BCI SOCIETY

Seventh International BCI Meeting

Abstract Book

BCIs: Not Getting Lost in Translation

May 21–25, 2018

Asilomar Conference Center

Pacific Grove, California

www.bcisociety.org

Table of Contents

Poster and Exhibitor Demonstrations Session 1

A- BCI Implant- Control

1-A-1 Thinking outside the motor cortex: Adding prefrontal cortex activity enhances decoding performance of a fully implanted motor cortex BCI

Erik Aarnoutse[1], Anouck Schippers[1], Sacha Leinders[1], Elmar G. M. Pels[1], Mariska Vansteensel[1], Mariana Branco[1], Nick Ramsey[1], Zachary Freudenburg[1]

[1]*Brain Center Rudolf Magnus, University Medical Center Utrecht*

Introduction: Communication for people who lost their ability for voluntary muscle control can be restored with a Brain-Computer Interface (BCI). Recently, we showed that a fully implanted BCI in an ALS patient can be successfully controlled, using attempted movement to self-regulate brain activity[1]. Activity from the primary motor cortex (M1) is translated into clicks, with which the user is able to control speech software. Since this BCI system is active 24/7, it is of utmost importance that it is reliable in its translation. Reliability can be increased by diminishing the occurrence of false positives: translation of brain activity into commands when this was not intended by the user. This is even more important in the no-control state, where the user is not engaged in communication. In this BCI system additional electrodes were placed over dorsolateral prefrontal cortex (dlPFC) to enable BCI control with working memory as well. In this study, we investigated whether the dlPFC is active during attempted movement and if so, whether including this signal will benefit performance. Material, Methods and Results: A late stage ALS patient (F, aged 58 at implantation) was implanted with ECoG electrodes (Resume II, Medtronic; investigational use) placed over motor cortex and over dorsolateral prefrontal cortex, and connected to an Activa PC+S amplifier (Medtronic, investigational device), implanted at the chest. Data is transmitted wirelessly and received ultimately by a tablet running custom software for signal processing. The translated signal is used to control an application, that can start and control speech synthesis software. The BCI is controlled by the activity of one bipolar electrode pair over M1. Data was collected during no-control state and during two types of tasks (continuous and matrix; 17 and 9 runs) in which the objective was to make clicks using the BCI system at specific time moments. Feedback of clicks was given on the basis of the beta and gamma activity in M1 (weighted -1 and 1, linear classifier). Coherence analysis (Mutual Information) between dlPFC and M1 electrodes showed that dlPFC signal may add information during motor attempt. The figure illustrates the temporal relation of the signals: correct (True Positive, TP) clicks showed a clear increase in the dlPFC gamma signal preceding the M1 gamma power increase leading a click. During unintended clicks (False Positive, FP) there was no increase in the dlPFC gamma signal prior to the click. This pattern was found in 12 of 17 runs of the continuous task and 6 of 9 runs of the matrix task. Subsequently, the gamma power increase preceding a correct click was exploited in offline simulation to assess the effect on BCI performance, using a cascading classifier (stage 1: M1, stage 2: dlPFC). FPs were assessed with no-control data (8 runs), TPs were assessed with the matrix task data. After optimization of parameters, a decrease of FPs of 2.3% is reached in the no control data, while the number of TPs is equal in the matrix data. Discussion: These results show the feasibility that additional information from areas outside of M1 can increase reliability. The dlPFC is an interesting target, since it is known to be involved in motor planning and the execution of tasks that require multiple steps. Prelocalization of the electrodes over dlPFC was geared towards using working memory tasks as control signal for BCI[2], and we have indications that motor planning requires a slightly more dorsal location. Significance: Reliability of a BCI is crucial for success, and ever more advanced methods should be used to maximize the true positive/false positive ratio. Here, we could make use of additional information from the dlPFC, which may guide design of BCIs with combined activity of multiple brain areas. 1 Vansteensel, MJ*, Pels, EGM*, Bleichner, MG, Branco, MP, Denison T, Freudenburg, ZV, Gosselaar, P, Leinders, S, Ottens, TH, Van Den Boom, MA, Van Rijen, PC, Aarnoutse, EJ*, & Ramsey, NF (2016). Fully implanted brain-computer interface in a locked-in patient with ALS. N Engl J Med 375 (21): 2060-66. doi:10.1056/NEJMoa1608085 2 Aarnoutse, EJ, Pels, EGM, Leinders, S, Freudenburg, ZV, Branco, MP, van den Boom, MA, Denison, T, Vansteensel, MJ, & Ramsey, NF (2017). Working memory as a control signal in a fully implanted brain-computer interface. Proceedings of the 7th Graz BCI Conference 2017. doi:10.3217/978-3-85125-533-1-01

1-A-2 Decoding grasps from supramarginal gyrus and ventral premotor cortex in tetraplegic human

Sarah Wandelt[1], Spencer Kellis[1], Michelle Armenta Salas[1], Luke Bashford[1], HyeongChan Jo[1], Matiar Jafari[1], Kelsie Pejsa[1], Dan Kramer[2], Brian Lee[2], Charles Liu[3], Richard Andersen[1]

[1]California Institute of Technology, [2]Keck School of Medicine of USC, [3]University of California, Irvine

Introduction: Grasping and manipulation of objects are important aspects of human independence and represent critical losses in paralysis due to spinal cord injury (SCI). Brain-machine interfaces (BMI) bypass the damaged spinal cord by implanting microelectrode arrays (MEA) in the motor areas of the brain to relay movement commands directly to prosthetic devices. By implanting cortical areas responsible for high-level movement plans and intentions, such as posterior parietal cortex (PPC) and ventral premotor cortex (PMv), these systems can provide fast, natural control of the prosthesis. In humans there are at least two areas with grasp selectivity in functional magnetic resonance imaging studies: the anterior intraparietal area (AIP) and one the supramarginal gyrus (SMG). The SMG and PMv have never been studied at the single neuron level in human. Here, we report the first simultaneous study of SMG and PMv neural population activity in human, during grasp behaviors and control of a robotic hand. Material, Methods and Results: In a task to study neuronal activity during grasp, trials began with a short inter-trial interval, followed by a cue of one of five grasps via images from the "Human Grasping Database". Then, after a brief delay, the subject imagined performing the cued grasp. Four-fold cross-validation classification with an LDA classifier, with 100 repetitions, was performed to examine decoding performance. Fig. 1 shows the classification accuracy obtained from classifying the different grasps during each phase based on data collected during the action phase. Using data from the ITI phase to classify the other phases resulted in accuracies at chance level (20%). Classification accuracy for SMG saturated at approximately 150 out of 168 features, while classification accuracy did not saturate for the

52 neurons of PMV. Discussion: These results indicate that grasp information is encoded in populations of single neurons in both SMG and PMv. Both areas supported decoding above the level of chance as soon as information was available about the cued grasp, and the highest accuracies were present during the action phase. These results indicate that both areas are involved in aspects of visual integration, motor planning, and motor execution during grasp behavior. Classification accuracy in PMV was lower than from SMG, but this result could be due, for example, to the smaller neuronal population or encoding of different aspects of grasp than were represented in the task. Significance: Incorporating activity from these cognitive-level components of the cortical grasp circuit could lead to a high performance brain-machine interface capable of dexterous hand manipulations. This capability would be critical to restoring independence for persons with spinal-cord injury.

1-A-3 Brain controlled epidural spinal interface reanimating forelimb function in spinal cord injury

Soshi Samejima[1], Abed Khorasani[1], Adrien Boissenin[1], Vaishnavi Ranganathan[1], Joshua Smith[1], Chet Moritz[1]

[1]University of Washington

Introduction: The restoration of hand and arm functions is the highest treatment priority for people with cervical spinal cord injury (SCI). Closed-loop neural interfaces can improve hand and arm function for individuals using intracortical recordings and direct muscle stimulation. As an alternative to muscle stimulation for reanimating hand and arm function, epidural stimulation of the spinal cord surface may offer fatigue resistance contraction and synergistic movement similar to intraspinal stimulation. In designing a cortically-controlled reanimation system for the upper extremity, population activity of neurons recorded from intracortical local field potentials (LFP) can be used as an alternative control signal since it shows longer term stability than spike-based decoding. LFP decoding of movement intention requires less computational power and may be translatable to less invasive brain recording techniques such as electrocorticography. To accelerate clinical translation, we use LFP recording and epidural stimulation below the spinal cord lesion in rodents. We demonstrate that this integrated system improves volitional control of the impaired forelimb after injury. Materials, Methods and Results: Long-Evans rats received implantations of intracortical microwires within the left forelimb sensorimotor cortex. In parallel, the animals were trained for a novel lever push task allowing us to measure forelimb elbow and shoulder extension force. During forelimb movement against the lever, we recorded brain activity from 16 intracortical electrodes. A Canonical Correlation Analysis Filter (CCA) algorithm was applied to the multi-channel envelopes of high-gamma LFPs (200-400 Hz) to extract the animals' movement intention. The CCA decoder combined the LFP envelopes to maximize correlation between the decoded output and lever presses in each trail. After several week recordings, the animals received a lateralized 200-kdyn contusion on the right side of spinal segment C4 and epidural implant on the right side of spinal segment C6. Subsequently, the decoder continually predicted forelimb movement and controlled spinal cord stimulation after injury (Figure 1A). Figure 1B represents the effectiveness of the LFP-controlled epidural spinal stimulation system. During stimulation-on period, whenever the decoded signal exceeded a predefined threshold, a train of 15 biphasic pulses (50 Hz, 300 µs, 1mA) were applied on the epidural electrodes. Later experiments graded the stimulation intensity and duration based on the decoded signal (not shown). During stimulation-off period, the decoded signal was computed, but no stimulation was delivered to the spinal cord. Figure 1C compares the functional performance during stimulation-on and stimulation-off periods. When the stimulation was on, the animal produced robust and natural movements. With stimulation off, the LFP decoder output still predicted the forelimb movements, but the animal produced significantly less force on the level ($p<0.001$). Discussion: This experiment demonstrates that LFP-controlled epidural spinal stimulation can reanimate volitional forelimb movement in rats with spinal cord injury. Contrary to functional muscle stimulation or peripheral nerve stimulation, epidural stimulation produced graded movement and fatigue resistant contractions in targeted muscles. Our multi-channel LFP based decoder reliably detected movement intention before the animals attempted to push the lever. The electrical stimulation artifact did not affect the decoding performance after removal of 2ms post-artifact signal using a sample-and-hold approach. This allowed the brain-controlled stimulation system to restore robust forelimb control after spinal cord injury. Significance: To our knowledge, this is the first study that demonstrates the effectiveness of closed-loop continuous control of epidural spinal cord stimulation based on LFP signals recorded from brain activity. LFP decoding required reduced user input compared to spike-sorting, and provided remarkably stable decoding performance across days without re-fitting the model. These are substantial benefits as we move toward implantable systems for clinical use.

1-A-4 Using a convolutional neural network for improved click detection in an implanted BCI setup

Julia Berezutskaya[1], Zachary Freudenburg[1], Erik Aarnoutse[1], Mariska Vansteensel[1], Sacha Leinders[1], Elmar G. M. Pels[1], Nick Ramsey[1]

[1]Brain Center Rudolf Magnus, University Medical Center Utrecht

Introduction A lot of current work in neuroscience is focused on providing a robust high-performance Brain-Computer interface (BCI) system to allow locked-in patients to communicate. Our lab has recently shown that one of the effective BCI strategies is detecting an attempted hand movement from motor cortex and translating it to a "click" for selecting options on the screen [1]. A late-stage ALS patient was implanted with a "click"-based BCI system for permanent use at home. The patient makes an attempted hand movement to generate a "click" and select letters of the screen to spell words. The system detects the "click" based on a combination of increase in brain activity in high frequency and its decrease in beta frequency band. Until now, this has been our default "click" detection strategy which overall provides reliable performance of 80-90% [1]. The present work aims at improving our default "click" detection strategy. Here we show that combining advanced machine learning techniques with effective preprocessing of the brain data can provide a 10% gain in performance. Materials, methods and results A locked-in patient was permanently implanted with a BCI system as described in [1]. We collected data from a channel implanted on the hand motor cortex (M1) while the patient was playing a whack-a-mole game. The brain signal was amplified with the Activa PC+S implant and transmitted with Nexus-1 (both Medtronic; investigational devices) to a tablet with custom software. In the game an 4 by 5 grid of holes is presented with a mole in one. Each position is highlighted sequentially at a rate of 2.5 s, first rows and then columns ('Scanning'). The patient was to generate a 'click' by attempting a hand movement only when the mole was highlighted. Overall, we collected 1386 trials (886 train and 502 test trials). Data for each trial (recorded at 200 Hz) consisted of 2 s preceding the moment a click (correct or incorrect) was detected. The time-frequency representation of the brain signal was obtained by convolving it with Gabor wavelets at different frequencies (1 to 100 Hz, 1 Hz bin spacing) with decreasing window length (4 wavelength full width at half max). A shallow 2D convolutional neural network (CNN) was trained on 2D brain input (time × frequency) to predict "click" (1) or "no-click" (0) class labels per trial. Ground truth labels were obtained based on the actual location of the mole and the selection box. The details of the CNN architecture are shown in Figure 1B. The CNN was trained using Adam optimizer in combination with early stopping. The network weights were regularized using a weight decay of 50. The CNN performance was cross-validated using a 20-fold cross-validation. Compared to the results using a default "click" detection strategy from [1] (85% correct), the CNN-based "click" strategy provided a considerable increase in performance, reaching 95% correct on average. Cross-validation ROC-curves are shown in Figure 1C. Confusion matrices in Figure 1D show that the improvement is due to decrease of both misses (false negatives) and false positives. Figure 1E shows examples of trials incorrectly classified by the CNN model. Figure 1F shows that when making a prediction the CNN model relies on combinations of spectro-temporal patterns across multiple frequency bands (see [2] for visualization details). Discussion The results show that using a combination of an advanced machine learning approach and efficient brain data processing leads to a considerable improvement in offline "click" detection accuracy by reducing the number of both false positive and false negative predictions. To make accurate predictions, the CNN model extracts complex combinations of spectro-temporal patterns. Future work tests feasibility of using this approach in real-time decoding. Significance The present work offers possible improvement to the default "click"-detection strategy of our BCI system. The present results can be useful for a future generation of BCI systems. References [1] M. J. Vansteensel et al., "Fully Implanted Brain-Computer Interface in a Locked-In Patient with ALS," N. Engl. J. Med., vol. 375, no. 21, pp. 2060-2066, Nov. 2016. [2] D. Erhan, Y. Bengio, A. Courville, and P. Vincent, "Visualizing higher-layer features of a deep network," Univ. Montr., vol. 1341, p. 3, 2009.

1-A-5 Simple vs. complex brain computer interfaces for restoring upper limb function via neuromuscular stimulation

Dawn Taylor[1], Tyler Johnson[2], Frank Willett[2], Harrison Kalodimos[2], Vishhvaan Gopalakrishnan[3]

[1]Cleveland Clinic & Louis Stokes Cleveland VA Medical Center, [2]Cleveland Clinic / Cleveland VA Medical Center /Case Western Reserve University, [3]Cleveland Clinic

Introduction: Desired movement commands can now be reliably decoded from paralyzed individuals using many types of brain computer interface (BCI) systems. By combining a BCI with stimulators that reanimate paralyzed muscles, we have the potential to restore a paralyzed person's own arm movements by thought. However, unlike using a BCI to control cursors or robots, restoring arm movement also requires solving the difficult problem of determining what muscle stimulation values need to be applied at each timestep in order to produce the desired limb motion. Instead of trying to design a complex non-linear algorithm to solve this very difficult problem ourselves, our lab took an alternative approach--we simply imposed a linear mapping directly between the recorded brain signals and the muscle stimulators with the hope that the brain would learn over time how to generate the neural signals that would produce accurate movements via this unnatural brain-to-muscle mapping. Material, Methods and Results: To test this theory, we trained macaques implanted with intracortical microelectrode arrays to control a realistic computational model of a human paralyzed arm that ran in real time. We used easy-to-collect empirical data about the arm's response to stimulation to generate an Nx6 linear matrix that we used to convert N firing rates into six muscle stimulation adjustment terms at each time step. During real-time brain control, these muscle adjustment terms were used to update the activation levels of the six muscles spanning shoulder and elbow joints in the model arm. The animals were rewarded with juice if they successfully moved the fingertip of the model arm to targets presented throughout the workspace. In spite of the simplicity of the brain-to-muscle mapping matrix, the animals were able to move the model arm to most targets immediately albeit using curved inefficient trajectories. However, with regular practice, the animals learned to produce new neural patterns that moved the arm to the desired targets using straighter, more efficient paths. Post hoc analysis of the neural data suggested the animals' neurons were actually still encoding just a low dimensional directional vector, which the animals learned to scale and rotate in a manner that would correct for the movement errors produced by mapping the neural firing rates directly to the muscle stimulators. The implications of this unexpected result is that even simple BCIs that produce low dimensional movement direction or velocity vectors, such as those driven by EEGs and ECoGs, should also be effective at controlling a paralyzed arm via our simple linear mapping process. Further simulation work has confirmed this to be true. Discussion: This study demonstrated that one can easily relearn to generate brain-controlled arm movements after paralysis by employing a simple linear mapping matrix to convert neural signals into muscle stimulation values in real time. Significance: Our simple, clinically feasible, empirical method of identifying an effective brain-to-muscle mapping matrix should make it easy to customize linear mapping functions for each unique user's paralyzed arm properties. Additionally, our results suggest useful arm movements can be achieved with both low-dimensional movement commands, such as those decoded from simple BCIs, as well as from mapping large numbers of firing rates directly to the muscle stimulators.

B- BCI Implant- Other

1-B-6 Primary motor cortex encodes a value function consistent with reinforcement learning that can be used for an autonomously updating BMI

Joseph Francis[1], Venkata S Aditya Tarigoppula[1], John Choi[2], John Hessburg[3], David McNiel[3], Brandi Marsh[3]

[1]University of Houston, [2]NYU, [3]SUNY Downstate Medical Center

Introduction: Our aim is to produce an autonomously updating BMI through the use of Reinforcement learning (RL). Specifically, Actor-Critic RL methods allow for designing a generalizable autonomous BMI. The Actor, in such a BMI, would compute intended actions by using the neural data from the primary motor cortex (M1) whereas the Critic would provide a qualitative feedback of the Actor's performance. The goal is to autonomously learn the optimal policy that dictates the BMI's actions such that it maximizes the expected reward/return of the user. The expected, temporally discounted reward, from a given state, is captured by the value function, synonymous with Critic. Necessary for this goal is our ability to decode the Critic signal from the user's neural activity itself. Here, we show that M1 encodes a value function in line with Temporal Difference (TD) RL. Material, Methods, and Results: We used two separate experimental paradigms with four non-human primates (NHP) as our subjects. Utah arrays were implanted in M1, S1, PMd, and PMv. In task 1 (a) NHPs either made movements to a single color-cued target manually or passively observed cursor motion to the target. The color indicated the reward value of the trial, which was awarded upon successful trial completion. Shown in (d) is the average activity from a single unit over time. Note the initial significant difference between the rewarding (R) (red) and non-rewarding (NR) (blue) trials as indicated by an asterisk (d.1-2). The separability moves forward in a trail with learning (d.4-9). In (e) we show a subpopulation of units that demonstrate the same learning-related activity pattern across sessions, reminiscent of the TD-RL value function as seen in (g). In (e.2-7, first column) we plotted the top 10% of units sorted with respect to their correlation to reward. To the right of these average plots are the full ensemble PSTHs in false color with a solid black line indicating the population average. In (e.1) we plotted the % units that show significant separability between R and NR trials for this purely predictable sequence version of the observation task. The sequence was R followed by NR repeated. Notice how the % units jump from session 1 to 2 and that the separability is pre-cue as the NHPs are predicting the next trial type after learning the sequence. M1 lost and regained its ability to encode the expected reward accurately during reversal learning. In our second set of experiments, NHPs controlled the grip force of an anthropomorphic robotic arm as seen in (b). In this work, the value of the trial could be between multiple levels depending on the session, up to 5 levels. (c) shows example units with linear representations of value, where the x-axis is reward value if successful and the y-axis is mean firing rate. In general, we found many more units that had a positive relation between value and rate, but there were units that had negative relations as seen in the figure. Plotted in (c) are the % of units with either positive or negative linear relationships with value. Finally, we plotted results from an RL simulation using the Microstimulus (MS) temporal encoding basis (f-g). These simulations used the same timing and structure as the real experiments performed by the NHPs. We did not explicitly optimize the model to reproduce the NHPs results but did run a small set of parameters to determin¬¬e what would¬ look similar. Note how the model also learns to predict the trial type as indicated by a peak in the value function pre-cue (f). The value function also peaks around the time of reward (f). Note the similarities between the neural data and model predictions, compare (d) and (f); (e.2-4) and (g). Discussion: Contra/ipsilateral M1 responds to the delivery of unpredictable reward, and shifts its value related response earlier in a trial, becoming predictive of expected reward, when the reward is predictable. This is observed in tasks performed manually or observed passively. The MSTD model, known to accurately capture RL related dopaminergic activity, extends to account for M1 reward-related neural activity. Significance: M1 encodes a value function consistent with RL. Therefore, M1 carries information not only useful for decoding the intended movement but also carries the evaluative information.

1-B-7 Injecting instructions into premotor cortex using intracortical microstimulation - implications for cortico-cortical BCI systems

Kevin Mazurek[1], Marc Schieber[1]

[1]*University of Rochester*

Introduction: Intracortical microstimulation (ICMS) is currently being used to deliver sensory information for users of brain-computer interfaces (BCIs). Given the somatotopically organized neural responses and percepts evoked by electrical stimulation in the primary somatosensory cortex (S1), for example, this cortical area frequently has been targeted for delivering bio-mimetic feedback using ICMS. Association areas of the cerebral cortex, however, may also be viable targets for delivering information with ICMS. The premotor cortex (PM) traditionally has been related to the preparation of motor plans for producing specific movements. PM receives inputs from parietal cortical areas representing processed visuospatial information, translates that information into plans for particular movements, and communicates those plans to the primary motor cortex (M1) for execution. Consistent with this general function, ICMS in PM of sufficient frequency, amplitude, and duration has been shown to evoke complex movements of the arm and hand that vary systematically depending on the locus of stimulation. Using ICMS at amplitudes and frequencies too low to evoke muscle activity, however, we found that through learned, conditional associations, ICMS in PM can provide instructions to perform specific actions. Material, Methods and Results: Two monkeys previously had been trained to perform a task using visual cues that instructed which of four objects to reach toward, grasp, and manipulate (RGM). We trained these monkeys to use low-amplitude ICMS at arbitrary PM locations as instructions for performing the same movements. Initially, low-amplitude ICMS was delivered at a different, arbitrarily-selected PM location concurrently with each of the four visual cues. As the visual cues then were gradually dimmed, the monkeys learned to associate even brief, low-frequency, PM-ICMS instructions with specific RGM movements. Eventually, using only the ICMS instructions, both monkeys performed the task with success rates, reaction times, and movement times equivalent to or better than when using visual cues. Performance was unimpaired when ICMS was delivered through a different single electrode to instruct each object, and remained unimpaired after frequency information was eliminated by delivering ICMS pulses at stochastically jittered inter-pulse intervals. Furthermore, after the assignments of ICMS at different PM loci to instruct particular RGM movements had been shuffled, the monkeys re-learned the shuffled assignments, confirming that the arbitrary associations were learned, not fixed. At the low current amplitudes used to deliver ICMS instructions, stimulus-triggered averaging of EMG activity showed a small output effect from only one PM electrode in one monkey, indicating that the monkeys could not have used twitches in different muscles as instructions for the four different movements. Discussion: Our findings demonstrate that low-amplitude, low-frequency, short-duration ICMS at different PM loci produces distinguishable experiences that the subject can report by performing arbitrarily-associated movements. Such ICMS in PM provides a novel means of injecting information into the nervous system. Both subjects were able to learn to associate ICMS at different electrodes with performing particular movements. The ability to deliver interpretable information using ICMS in cortical association areas will be valuable for future BCI systems, expanding the available "neural real-estate" through which information potentially can be delivered to the brain. Future work may identify additional association areas in which interpretable information can be delivered with non-biomimetic ICMS. Significance: Injection of interpretable information in cortical association areas has the potential to serve as the output limb of a cortico-cortical BCI. Focal neurologic diseases such as stroke or multiple sclerosis produce functional deficits in part by disrupting communication between cortical areas. Cortico-cortical BCIs could decode information from neural activity recorded upstream and inject appropriate information downstream to bridge over focal injuries in neural pathways, thereby restoring lost function to such patients.

1-B-8 Augmenting intracortical brain-computer interfaces in monkeys and humans with neurally driven error detectors

Nir Even-Chen[1], Sergey Stavisky[1], Jonathan Kao[2], Chethan Pandarinath[3], Paul Nuyujukian[1], Stephen Ryu[1], Leigh Hochberg[4], Jaimie Henderson[1], Krishna Shenoy[1]

[1]Stanford University, [2]UCLA, [3]Emory University, [4]Brown University

Introduction: Intracortical brain-computer interfaces (iBCI) recording from motor cortex have shown promising results in pilot clinical trials. While much work continues to be done to reduce iBCI errors by improving the accuracy and reliability of movement intention decoders, here we explore a complementary and less explored approach: attempting to automatically identify, using neural activity, when an error occurs so that the BCI system can automatically undo the error. This 'automatic error detect-and-undo' strategy takes advantage of the closed-loop nature of a BCI; the user has constant visual feedback and is aware of when the BCI performs an unintended action (i.e., an error). Somewhere in the brain, the user's neural activity will reflect this detection and recognition of an error. Here, we asked two primary questions: (1) does an outcome error signal exist in the motor cortex used for iBCI?, and (2) can decoding this signal benefit BCI performance?. To answer those questions we first investigated them in preclinical monkey experiments and then extended our results to the case of human participants in the BrainGate2 clinical trial. Material, Methods and Results: In both monkey and human experiments, the user controlled a 2D cursor through an iBCI system and performed a random grid task, in which they needed to select a cued target among a grid (e.g., 6 x 6) of selectable targets. During the task, the neural activity was recorded using 96-channel intracortical silicon microelectrode arrays (Blackrock Microsystems) implanted in the hand area of the motor cortex, and was decoded into a velocity control signal using previously described methods [Gilja et al 2012, Pandarinath et al 2017]. First, we investigated our questions with two monkeys. Surprisingly, we found task outcome neural correlates, and we were able to decode trial outcomes shortly after and even before a trial ended with 96% and 84% accuracy, respectively. This led us to develop and implement in real-time a first-of-its-kind intracortical iBCI error 'detect-and-act' system that attempts to automatically 'undo' or 'prevent' mistakes. The detect-and-act system works independently and in parallel to a kinematic iBCI decoder. In a challenging task that resulted in substantial errors, this approach improved the iBCI performance by up to 18%. After the encouraging results with monkeys, we investigated whether this task outcome-related neural signal was present in two human participants (T5 and T6). T5 was a 63 years old at the time of these experiments and was diagnosed with a C2-3 ASIA C spinal cord injury prior to study enrollment. T6 was a 51 years old at the time of these experiments and was diagnosed with ALS and had a resultant motor impairment (functional rating scale (ALSFRS-R) measurement of 16). We found that human motor cortex was also modulated by task outcome, and in offline analysis of previously collected data, we were able to decode errors with high accuracy (70-85%) with minimal (0-3%) misclassifications of successful trials. We also found that decoders trained on a random grid task could be generalized to a virtual typing task in which the targets are not cued for the participants. This suggests that these task outcome neural correlates were at least to some degree task-independent. Discussion: After showing the benefit of an automatic error detect-and-undo strategy in real-time in monkeys and subsequently showing similar error-related neural modulation in humans, our next step will be to augment a human clinical trial iBCI with real-time detect-and-undo capability . A detect-and-undo system could be used for various BCI applications. During typing this could be used for immediate character auto-deletion or for error tracking to improve upon word prediction algorithms. Detect-and-undo systems can also be utilized for returning to the previous menu during application use, and returning to a previous position when using a robotic arm. Though encouraging, whether or not similar task outcome error signals exist in more complex tasks such as prosthetic limb control remains an open question for future research. Significance: Detecting and undoing errors in real-time should make hard tasks feel easier, increase iBCI performance, and improve the user experience.

1-B-9 Retrospective analysis of the effects of nonstationarities on decoding performance in people using an intracortical brain computer interface

David Brandman[1], Thomas Hosman[1], Jad Saab[1], Jessica Kelemen[2], Brian Franco[2], Leigh Hochberg[1], John Simeral[3]

[1]Brown University, [2]Massachusetts General Hospital, [3]Rehabilitation R&D Service

Background: Intracortical brain computer interfaces (iBCIs) use information recorded from the cortex to provide people with paralysis the ability to control devices in their environment, such as computer cursors for communication. An ongoing area of research in iBCI systems is to ensure long-term robust and reliable control for the user. Degradation in neural control is often attributed to short-term nonstationarities in the recorded signals (Perge et al., 2013). The most common approach to addressing these nonstationarities involves recalibrating the decoder coefficients by incorporating recent neural data (Orsborn et al., 2014, Jarosiewicz et al., 2015). While recalibration has been shown to provide users with long-term control, the underlying nonstationarities have not been fully characterized. Gains in decoding performance could be made by understanding the frequency of nonstationarities and quantifying their effects on modern decoding algorithms. Material, Methods and Results: Participants T9 (52 year-old man right-handed man with ALS, ALSRFS-R=7) and T10 (35 year-old man with C4-AIS Grade A spinal cord injury) were enrolled in the ongoing BrainGate2 clinical trial. We retrospectively analyzed all closed-loop cursor control research sessions spanning 731 and 365 days, respectively. Channel spike counts and broad-band signal power were used as neural features (Brandman et al., 2017), recorded in non-overlapping 20ms bins. For each research session, a Kalman decoder was trained using a random subsample of data (without replacement), and then used to predict the decoded velocity vector of each time-step in the testing dataset. We quantified decoder performance for each session by computing the angular error between the kinematic cursor's decoded velocity and the assumed intended vector to target (Willet et al., 2017). We retrospectively analyzed 137 and 96 sessions for T9 and T10, respectively, where the participant performed closed-loop neural control of a computer cursor. Across all research sessions, we did not observe a linear trend in overall decoder performance for either participant (T9 R2 = 0.001, T10 R2 = 0.071). For individual research sessions, we found a linear relationship between decoding performance and z-score offsets in the observed neural features. To mitigate the effect of nonstationarities, we swept a variety of z-score threshold values and found that saturation above 2-zscores did not impact decoding performance (saturation below this level degraded decoding performance). We found that features with z-scores greater than 2 accounted for 5% of all observed values (once per second), including those features that were highly informative with high signal-to-noise ratios (Malik et al., 2015). Discussion: Intra-day nonstarionarities in closed-loop neural signals are detrimental to closed-loop control. We did not observe depredations in decoding performance over days. The linear relationship found between shifts in feature magnitude and closed-loop performance indicate that large z-score deviations are detrimental to decoding, and can be mitigated by principled feature saturation. Significance: These results suggest that additional and substantial gains can be made in decoding performance by addressing anomalous feature values, and mitigating their effects.

C- BCI Non-Invasive- Control

1-C-10 Integrating EEG and MEG information to enhance motor imagery classification in brain-computer interface

Marie-Constance Corsi[1], Mario Chavez[2], Denis Schwartz[3], Laurent Hugueville[3], Ankit Khambhati[4], Danielle Bassett[1], Fabrizio De Vico Fallani[1]

[1]INRIA-ICM, [2]CNRS, [3]ICM-UPMC-INSERM-CNRS, [4]University of Pennsylvania

Introduction: Brain-computer interface (BCI) is a potential tool for rehabilitation and communication. Most of the BCI experiments relies on the electroencephalography (EEG). Despite its clinical applications, BCI faces to both engineering and user-oriented challenges to improve its spreading. In this work, we assess the possibility of integrating electroencephalographic (EEG) and magnetoencephalographic (MEG) signals to enhance the classification performance in motor imagery-based BCI. Material, Methods and Results: We performed an offline classification from a dataset which gathers simultaneously recorded M/EEG signals from 15 healthy subjects (aged 28.13±4.10 years, 7 women). We used the one-dimensional two-target box-tasks experiment in which the subjects imagined a movement with the right hand or remained at rest, depending on the position of the target. During the first 5 runs, only the target was displayed (training phase) followed by 6 runs with a provided feedback (testing phase). For each modality (EEG, magnetometers -MAG and gradiometers -GRAD), we extracted the relevant features from training recordings. Then, we performed a classification of the testing data by integrating the classifiers' output from each modality via the Bayesian fusion approach, in which contribution of each modality is modulated via an attributed weight computed from the associated posterior probability. To compare classification performances between the fusion and the single-modality approach, the classification accuracy was estimated with the area under the curve (AUC). Significant changes of event-related de/synchronization appeared in alpha and beta band in all modalities. Results show that modality significantly affects the classification performance (ANOVA, $p<0.001$). Averages of 0.58±0.07, 0.58±0.09, 0.61±0.10, and 0.66±0.11 were obtained with EEG, MAG, GRAD and fusion classifiers respectively. In 13 subjects, the fusion led to an improvement of the AUC in comparison with single-modality approach, with relative increments ranging from 1.3% to 50.9%. Discussion: By using a rather simple classifier, we could include a reduced number of specific features involved in the motor-related neural mechanisms such as ERD in alpha and beta bands. More sophisticated approaches using the whole feature space, such as support vector machines and

Riemannian geometry as well as alternative fusion strategies, but also classification in source space to improve spatial resolution, can be further evaluated. Significance: The proposed fusion method led, in a large majority of subjects, to a reduction in the subjects' mental state misclassifications. Our weighting approach enabled to adapt the modality choice according to the subject and the session. Current searches focused on MEG sensors miniaturization will probably enable a larger diffusion of the integration of M/EEG features to further enhance BCIs performances.

1-C-11 A dynamic Chinese character writing based hybrid BCI paradigm for stroke rehabilitation

Cili Zuo[1], Yangyang Miao[1], Jing Jin[1]

[1]East China University of Science and Technology

Introduction: There were a number of publications have demonstrated the efficacy of Motor imagery (MI) based brain-computer interfaces (BCI) technology in post-stroke rehabilitation[1]. However, the accuracy of MI is often not sufficient to provide reliable control signals in practical applications[2], thus patients must passively accept which upper limbs to be trained. Therefore, a dynamic Chinese character writing based hybrid BCI paradigm was presented for patients to choose which upper limbs to be trained freely that may improve their training initiative. The paradigm was a combination of MI and P300 paradigm. The Chinese characters writing based MI paradigm was used due to its good efficacy in guiding subjects to modulate brain activity effectively for Chinese[3]. The P300 was evoked by the dynamic filling of Chinese characters which could provide reliable control signals. Material, Methods and Results: Three healthy subjects (3 male, aged 22-28 years) participated in the experiment. All subjects' native language was Mandarin Chinese. The experimental protocol consisted of an imagination of a Chinese character write task according to the screen cue. There were two dynamic Chinese characters and a forearm displayed on the screen. Figure 1 (a) illustrated an example of the screen cue shown to subjects where the first column represents left hand imagery, and the second column represents right hand imagery. Figure 1 (b) illustrated the process of a trial of the writing task. The 0-1.9s was preparation phase in which the Chinese character outlines (the first row of Figure 1 (a)) were displayed on the screen, and the subjects were asked to focus on Chinese character on the side of the forearm prompted. The 1.9-7.9s was imaging phase. In this phase, the outlines were filled stroke by stroke according to the writing order in a specific time series (the second row to the last row of Figure 1 (a)), while the subjects were asked to imagine writing the Chinese character follow the fill order. For classification, every stroke in right Chinese character was filled in 200 milliseconds later than the left one. When the subjects focus on the left character and performed the left hand motor imagery, the P300 signal was time lock with left time series. The right writing task was similarly to the left. The 7.9-10s was rest phase. In this paper, four Chinese character combinations ("生-正", "生-末", "仗-正", "仗-末") were used in the experiment. The EEG signals were recorded by 22 scalp electrodes according to the International 10-20 System, with a sampling rate of 256 Hz. The EEG signals were amplified by gHIamp. For P300, a third order Butterworth band pass filter was used to filter the EEG between 0.1 Hz and 12 Hz. The EEG was then down-sampled from 256 Hz to 36.6 Hz from the filtered EEG. In order to increase the distinguishability of the data, the five sub sections of each data segment were averaged. For MI, the EEG data were band-pass filtered from 8 to 30 Hz. Then common special pattern (CSP) was used to further extract features. Finally, both P300 and MI signals were classified by Bayesian linear discriminant analysis (BLDA). Table 1 shows the classification accuracy of MI and P300 using 10-fold cross-validation. Discussion: Preliminary result of three healthy subjects showed that although the classification accuracy of MI (73.02%±7.71%)was relatively low and unstable, but the average classification accuracy of P300 was 93.23%±1.91% which indicate that the hybrid BCI paradigm can meet the requirement of freedom to choose upper limbs for training. We will further proven the efficacy of this paradigm in stroke patients. Significance: The main contribution of this research is that a hybrid BCI paradigm was presented which allows stroke patients choosing which upper limbs to be trained proactive. References [1] Stefano Silvoni et al. Brain-Computer Interface in Stroke: A Review of Progress[J]. Clinical EEG and Neuroscience, 2011, 42(4): 245-252. [2] Blankertz B et al. Neurophysiological predictor of SMR-based BCI performance[J]. NeuroImage, 2010, 51(4): 1303-1309. [3] Qiu Z et al. Optimized motor imagery paradigm based on imagining Chinese characters writing movement[J]. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2017, 25(7): 1009-1017.

1-C-12 Query exploration for intended task state estimation with BCI

Aziz Kocanaogullari[1], Paula Gonzalez -Navarro[1], Tab Memmott[2], Betts Peters[3], Murat Akcakaya[4], Deniz Erdogmus[1]

[1]Northeastern University, [2]Oregon Health & Science University, [3]Institute on Development and Disabilities, Oregon Health & Science University, [4]University of Pittsburgh

Introduction: BCI communication systems have two main objectives; evaluating evidence from a user (e.g. EEG) using different queries (e.g. SSVEP, RSVP) and estimating user intent (e.g. intended symbol, string). BCI frameworks can be modeled as recursive state estimators, where the state is unknown user intent. For faster convergence to a correct/accurate estimate, queries can be optimized through objectives such as MMI [1], EPM [2]. BCI systems for language generation can be supported with a language model (LM) that provides prior information for state estimation. LM fusion increases typing speed, since languages are structured. In some cases, the user intent could be to express a phrase that is considered to be unlikely, in which case the user is forced to overcome the adversarial effect of the LM. This leads to slower estimate convergence due to the requirement to gather more evidence from the user (brain). As an edge case, if the user intent is least likely according to the LM prior, the user needs to react negatively to all other queries to be queried for the intended state. In this paper, we propose an exploration based querying mechanism to mitigate the negative effects of an occasionally adversarial LM. Material: We use RSVP Keyboard [3] with EEG data acquired using a g.USBAmp with 16 g.Butterfly electrodes (g.Tec, Graz, Austria), and a simulation framework developed in Python. Method: In this work, we investigated the use of a fixed temporal schedule that alternates between exploitation and exploration after a number of sequences have been spent on each strategy. Initially top letter candidates are shown, but if a confident decision is not possible after several sequences of stimuli, the query method switches to exploration mode and produces queries that maximize the Kullback-Liebler divergence between the expected posterior and prior. After several sequences, the query strategy switches to exploitation. Results: We used Monte Carlo simulations using generative models for EEG features developed based on real calibration data from 12 healthy users with different EEG separability levels, as described in previous work [4]. Simulations included an artificial LM for two cases; adversarial and supportive. In the figure, the performance of different algorithms are shown in different scenarios. In simulations deterministically scheduled exploitation-exploration method worked well; in the adversarial case, (70%) confident decisions were reached after 32 queries on average, while the competitor MMI case required 47. In the supportive case the proposed method works similar to the MMI case. Discussion: The proposed method achieves a confident decision faster in all scenarios. We note that user performance and required query counts are negatively correlated. Significance: BCI communication performance is significantly impacted by the level of assistance LMs provide to users. Especially for users with low EEG separability, performance is completely dictated by the LM. In order to help improve communication speed, adaptive querying methods that attempt to ensure users get a chance to provide the most useful evidence for intent inference. In this setting, stimulus subset selection can be posed as an active learning problem where exploitation and exploration needs to be balanced for maximum reward (speed). Acknowledgement: Our work is supported by NSF (IIS-1149570, CNS-1544895, IIS-1717654), NIDLRR (90RE5017-02-01), and NIH (R01DC009834). References: 1] M. Higger and et al., "Recursive bayesian coding for bcis," 2017, doi:10.1109/TNSRE.2016.2590959. [2] M. Moghadamfalahi and et al., "Active learning for efficient querying from a human oracle with noisy response in alanguage-model assisted brain computer interface," 2015, doi:10.1109/MLSP.2015.7324369. [3] U. Orhan and et al., "Rsvp keyboard: An eeg based typing interface," 2012, doi:10.1109/ICASSP.2012.6287966. [4] ----, "Probabilistic simulation framework for eeg-based bci design," 2016, doi:10.1080/2326263X.2016.1252621.

1-C-13 A novel detection method of driving emergency situations using EEG and surroundings

Luzheng Bi[1], Huikang Wang[1], Jinling Lian[1]

[1]*Beijing Institute of Technology*

1. Introduction: Living independence is always a significant problem for the disabled people with neuromuscular disorders. Brain-computer interfaces (BCIs) are considered as a solution because it does not depend on the users' speech or neuromuscular control. EEG-based BCIs have been studied to build brain-controlled wheelchairs [1] or brain-controlled vehicles [2]. However, when emergency situations (e.g., unexpected occurring of pedestrians or sudden braking of the leading cars) happen, the safety of brain-controlled vehicles becomes a new challenge. Obstacle detection system based on sensors, such as FIR camera [3] or RADAR [4], can only detect the 'potential' dangers rather than the 'real' dangers, which leads to brakes against the will of drivers. Researchers have begun to use EEG signals to detect driver braking intention to achieve a faster brake compliant with drivers [5-6]. However, the system performance (especially the false alarm rate) is not satisfying, which makes it difficult to apply this technique to the real world. In this paper, we first build a novel braking intention detection method by using EEG. Then the EEG-based braking intention detection result is combined with the surrounding information, which comes from the obstacle detection system, to develop a novel detection method of driving emergency situations with a low false alarm rate. 2. Experimental data: EEG signals were collected from 16 standard locations (i.e. F3, Fz, F4, C3, Cz, C4, T7, T8, P7, P3, Pz, P4, P8, O1, Oz, and O2) based on an international 10-20 system. The reference potential was set to be the mean of the

potentials on the left and right ear lobes. The EEG signals were amplified and digitalized with a sampling rate of 1000 Hz and a power-line notch filter was used to remove the line noise. Eight subjects participated in the experiment. 3. Method: Independent component analysis (ICA) is first used to remove artifacts (e.g. blinking artifact) in the collected EEG. After that, EEG signal is downsampled. Then baseline correction and common average reference are used to filter the signals. After that, common spatial pattern (CSP) is used to perform spatial filtering. Then the original power spectrum features are calculated. The final features are extracted through correlation analysis and then input to a regularization linear discriminant analysis (RLDA) classifier. Finally the output of BCI is combined with the output of a sensor-based obstacle detection system to get the final output of our system by the fusion rules we designed. 4. Results and Discussion: Figure 1 shows the system accuracy. The average accuracy reached 95.82% and the average detection time was around 480 ms. 5. Significance: This paper proposed a novel method to detect emergency situations by using EEG with surroundings. The proposed method performed well. To further improve the accuracy, more efforts are needed in feature extraction and classification methods. References: [1] Y. Yu et al., "Self-paced operation of a wheelchair based on a hybrid brain-computer interface combining motor imagery and P300 potential," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 25, no. 12, pp. 2516-2526, Dec. 2017. [2] X. Fan, L. Bi, T. Teng, H. Ding, and Y. Liu, "A brain-computer interface-based vehicle destination selection system using P300 and SSVEP signals," IEEE Trans. Intell. Transp. Syst., vol. 16, no. 1, pp. 274-283,Feb. 2015. [3] P. Hurney, P. Waldron, F. Morgan, E. Jones and M. Glavin, "Night-time pedestrian classification with histograms of oriented gradients-local binary patterns vectors," in IET Intelligent Transport Systems, vol. 9, no. 1, pp. 75-85, 2 2015. [4] M. Heuer, A. Al-Hamadi, A. Rain and M. M. Meinecke, "Detection and tracking approach using an automotive radar to increase active pedestrian safety," 2014 IEEE Intelligent Vehicles Symposium Proceedings, Dearborn, MI, 2014, pp. 890-893. [5] S. Haufe, M. Treder, M. Gugler, M. Sagebaum, G. Curio, and B. Blankertz, "EEG potentials predict upcoming emergency brakings during simulated driving," J. Neural Eng., vol. 8, no. 5, p. 056001, Jul. 2011. [6] S. Haufe, M. Treder, M. Gugler, M. Sagebaum, G. Curio, and B. Blankertz, "EEG potentials predict upcoming emergency brakings during simulated driving," J. Neural Eng., vol. 8, no. 5, p. 056001, Jul. 2011.

1-C-14 Reducing calibration time in BCI using transfer learning in classification domain

Ahmed Azab[1], Lyudmila Mihaylova[1], Mahnaz Arvaneh[1]

[1]*University of Sheffield*

Introduction: One of the major limitations of brain computer interface (BCI) is its long calibration time. Due to between sessions/subjects nonstationarity, typically a big amount of training data needs to be collected at the beginning of each session in order to tune the parameters of the system for the target user. In this research, we propose a new transfer learning algorithm on classification domain to reduce calibration time without sacrificing the classification accuracy of the BCI system. The proposed algorithm uses data from other subjects and combine it with the target subject's existing data to estimate the parameters of the classifier. Material, Methods and Results: The proposed transfer learning algorithm aims to correctly identify the label of a new trial performed by the new subject based on the classifier that is trained with a few trials from this subject and some labelled trials from other subjects or sessions.

The classification parameters (ws) refers to the individual features weights being used to predict the class label for subject/session s trials. Thus, when a new test trial arrives for a subject/session s, the class label can be predicted to be the sign of (classification parameter multiplied by the features of this trial). The proposed transfer learning algorithm calculate the classification parameters of the target subject, as follows: First, the classification parameters of each previous subject/session is calculated such that the classification error of that specific subject/session is minimised. Next, the classification parameters of the target subject is calculated such that not only the classification error of the target subject is minimised but also the classification parameters of the target subject is similar to the other existing subjects/sessions as much as possible. For this purpose a regularisation term is added to the objective function making a trade-off between minimising the error and the similarity of the classification parameters. Two baseline-training algorithms are used to be compared with the proposed algorithm. The first algorithm is the commonly used subject-specific BCI training model where the classifier is trained independent from other subjects using features extracted from the Common Spatial Patterns (CSP) algorithm. We refer to this algorithm as CSP. The second baseline algorithm is the multi-task learning-based classification algorithm (MT) proposed in [1]. From computational time point of view, the proposed transfer learning algorithm is much faster than the ML algorithm as it doesn't need to wait for the algorithm to converge in every iteration, as the proposed algorithm doesn't calculate the classification parameters of all the subjects jointly and together. In order to validate the proposed algorithm and compare it with the baseline algorithms, all algorithms are applied to BCI Competition 2008 - Graz data set A [1]. In this research, algorithms are applied only on the trials from the testing session by dividing it to two sessions one for training (different number of trials are used in different cases from the new subject) and one for testing (consists of 60 trials (30 trials per class). This is done to establish a practical case that new data of the test subject is coming from the same session. For each algorithm (subject-specific algorithm (i.e. CSP), multitask learning (i.e. ML) and the proposed transfer learning algorithm (i.e. TL)), the average classification accuracy over the nine subject is calculated using different number of trials (20, 40, and all trials) for training. Based on the statistical tests MT is neither significantly outperforming the state of art CSP nor the proposed TL algorithm. The classification accuracy of the proposed transfer-learning algorithm tends to be significantly better than the CSP results with P=0.97 when there are only 20 trials are available for training. Discussion: preliminary results showed that the proposed transfer learning algorithm outperformed the state of art BCI algorithms even when only few trials from the new subject are available. Statistical tests showed that using different number of trials did not have a main effect on the classification results. This finding strengthens the outcome of this research, which is reducing the calibration time without altering the overall accuracy of the system. Significance: Despite some advance, a successful transfer-learning framework for BCI is still a challenging task.

1-C-15 Co-adaptive learning improves efficacy of multi-day EEG-based motor imagery BCI training

Oren Shriki[1], Eyal Zakkay[1], Lior Shmuelof[1], Amjad Abu-Rmileh[1]

[1]*Ben-Gurion University of the Negev*

Introduction: BCIs based on motor imagery (MI) require training, during which the user gradually learns

to modulate relevant patterns of brain activity using feedback. In parallel, machine learning techniques are used to adapt the decoding algorithm to the user's brain [1,2]. Thus, to improve performance, both brain and machine need to co-adapt in a closed-loop manner. We set out to explore and quantify the effect of co-adapting the decoding algorithm on MI-BCI task performance across several consecutive training days. Materials, Methods and Results: We investigated the performance of two groups of subjects in a 4-day MI experiment using EEG. One group (n=9) performed the BCI task using a fixed classifier based on MI data derived from the first day (control group). In the second (experimental) group (n=9), the classifier was regularly adapted based on brain activity patterns expressed during the daily training sessions. To enhance subject engagement, we employed a video-game based feedback training environment. Concurrent EEG was recorded using the Laplacian configuration centered on C3 and C4 electrodes. Alpha and beta power were extracted from each of the two channels, and fed as features to an LDA classifier. Alpha and beta band ranges were adapted to each individual. Initial performance above 70% was employed as an inclusion criterion. We observed a significant difference in performance change between the two groups (mean reduction of 2.3% in performance for the control group compared to an increase of 5.8% in the experimental group, $p<0.05$). Further inspection of performance change within and between days showed that whereas the experimental group exhibited an initial decrease in performance between days, it was followed by a within-day increase in performance. The control group, however, exhibited decrease in performance in both comparisons. Further insight into co-adaptive learning can be gained from computational models of two-learner systems [3]. We explored different strategies for optimizing the training by developing such a computational model. Human learning was modeled as trial-by-trial exploration in the abovementioned feature space. To model between-day deterioration, noise was added to feature vectors at the end of each simulated day. To model the machine learning component, we again utilized an LDA classifier updating at the same rate as in the real data. The model qualitatively captured the changes in performance in both groups and exhibited gradual deterioration under the control group conditions and gradual improvement under the experimental group conditions. The model suggests that subjects with a higher propensity for exploratory behavior (greater exploratory noise) could improve even under the control group conditions. Discussion: Our results demonstrate that BCI training with an engaging video game and utilizing subject-specific frequency bands is not sufficient for eliciting improvement across days while undergoing MI-BCI training, and that improvement requires continuous adaptation of the classification algorithm. Classifier updating is necessary to utilize the improvement in neural representations due to learning, but also to account for changes in representation which are not directly related to learning and might reduce performance. Significance: Our study reveals that classifier co-adaptation is a key factor in BCI design for achieving optimal long-term performance. The proposed computational model allows for exploring the effect of different co-adaptation paradigms and could be utilized for optimizing training protocols.
Acknowledgements: This research was supported by the Agricultural, Biological and Cognitive (ABC) Robotics Initiative at Ben-Gurion University of the Negev.
References: [1] C. Vidaurre, C. Sannelli, K.R. Müller, and B. Blankertz, "Co-adaptive calibration to improve BCI efficiency", Journal of neural engineering, vol. 8, no. 2, p. 025009, 2011. [2] S. Perdikis, R. Leeb, and J. R. Millan, "Context-aware adaptive spelling in motor imagery BCI", Journal of neural engineering, vol. 13, no. 3, p. 036018, 2016. [3] J. S. Müller, C. Vidaurre, M. Schreuder, F.C. Meinecke, P. Von Bünau, P., and K.R. Müller, "A mathematical model for the two-learners problem", Journal of Neural Engineering, vol. 14, no. 3, p. 036005, 2017.

1-C-17 Developing a streaming-based P300 BCI paradigm with auditory and tactile stimuli: Effects of training on efficiency, effectiveness and satisfaction

Philipp Ziebell[1], Jana Stümpfig[1], Sonja Kleih[1], Andrea Kübler[1], Marc Erich Latoschik[1], Sebastian Halder[2]

[1]University of Würzburg, [2]University of Oslo

Introduction: P300 BCIs enable people to operate computer programs via electroencephalographic signals and have been successfully applied in various contexts [1]. A current major challenge is overcoming the gaze-dependence of the commonly used visual stimulation by developing eye-gaze independent BCIs, for example by using auditory or tactile stimuli [2]. Recent studies could show that auditory or tactile P300-BCIs can be intuitively used and that performance can be improved by training [e.g. 3, 4]. However, problems occurred regarding high subjective workload and still some users were not able to use the BCI successfully (BCI-Inefficiency [5]). As an alternative, streaming paradigms have been developed, altering the classical sequential presentation of stimuli in one stream by arranging them in two or more stimulus streams, and first positive results have been reported [e.g. 6]. Replicating these positive results and the training effects, using an auditory as well as a tactile streaming paradigm, was the aim of the present study. Figure 1. The two streaming paradigm versions used in the present study. Material, Methods and Results: Two streaming paradigm variations were designed, one version with two auditory and the other with two tactile streams (Figure 1), and the effects of training were examined with 20 healthy participants (age M = 25.30, SD = 5.17, 11 female) absolving three training sessions in 8 days on average. Emphasis was placed on avoiding typical study design flaws [e.g. 7], also using ideas from BCI gaming literature [e.g. 8]. Significant improvements could be shown in efficiency-measures (information transfer rate, subjective workload), further positive results were found regarding measures of effectiveness (online-accuracy), motivation and satisfaction, every participant managed to surpass the criterion for successful BCI-use (accuracy > 70%) in at least one session. Discussion and Significance: The training effects found in former studies using sequential paradigms could be replicated with both variations of the streaming paradigm, and the encouraging results like the absence of BCI-Inefficiency make it a promising candidate for future research, for example in a training study with locked-in patients. Acknowledgements: This work was supported by funding from the Alexander von Humboldt Foundation. References: [1] Fazel-Rezai, R., Allison, B. Z., Guger, C., Sellers, E. W., Kleih, S. C., & Kübler, A. (2012). P300 brain computer interface: current challenges and emerging trends. Frontiers in Neuroengineering, 5, 14, doi: 10.3389/fneng.2012.00014. [2] Riccio, A., Mattia, D., Simione, L., Olivetti, M., & Cincotti, F. (2012). Eye-gaze independent EEG-based brain-computer interfaces for communication. Journal of Neural Engineering, 9(4), doi: 10.1088/1741-2560/9/4/045001. [3] Baykara, E., Ruf, C. A., Fioravanti, C., Käthner, I., Simon, N., Kleih, S. C., ..., & Halder, S. (2016). Effects of training and motivation on auditory P300 brain-computer interface performance. Clinical Neurophysiology, 127(1), 379-387. [4] Herweg, A., Gutzeit, J., Kleih, S., & Kübler, A. (2016). Wheelchair control by elderly participants in a virtual environment with a brain-computer interface (BCI) and tactile stimulation. Biological Psychology, 121, 117-124. [5] Kübler, A., Blankertz, B., Müller K.-R., & Neuper, C. (2011). A model of BCI-control. In Müller-Putz, G., Scherer, R., Billinger, M., Kreilinger, A., Kaiser, V., & Neuper, C. (Eds.), Proceedings of the 5th International Brain-Computer Interface Conference. Graz: Technische Universität. [6] Hill, N. J., Ricci, E., Haider, S., McCane, L. M., Heckman, S., Wolpaw, J. R., & Vaughan, T. M. (2014). A practical, intuitive brain-computer interface for communicating 'yes' or 'no' by listening.

Journal of Neural Engineering, 11(3), doi: 10.1088/1741-882560/11/3/035003. [7] Chavarriaga, R., Fried-Oken, M., Kleih, S., Lotte, F., & Scherer, R. (2017). Heading for new shores! Overcoming pitfalls in BCI design. Brain-Computer Interfaces, 4, doi: 10.1080/2326263X.2016.1263916. [8] Kaplan, A. Y., Shishkin, S. L., Ganin, I. P., Basyul, I. A., & Zhigalov, A. Y. (2013). Adapting the P300-based brain-computer interface for gaming: a review. IEEE Transactions on Computational Intelligence and AI in Games, 5(2), 141-149.

1-C-18 A novel BCI speller combining dot-based visual stimuli and user voluntary sound-imagery task

Hong-Kyung Kim[1], Min-Ho Lee[1], Seong-Whan Lee[1]

[1]*Korea University*

Introduction: Event-Related Potential (ERP)-based speller allows people to write letters based on their brain signals. The P300 response is positive ERP component around 300ms after visual/auditory oddball stimulus that has mostly used in ERP-based BCI speller. To increase the spelling performance, previous studies have suggested various approaches for enhancing the ERP responses by modifying the system parameters such as stimulating a face [1], changing the size or color [2], and so on. However, the previous approaches highly relied on the specific type of the visual-stimulus; it is difficult to integrate these visual stimuli with some of BCI applications, such as a smart-phone or LED-based BCI systems that require the limited system environments. In this paper, we proposed a dot-based speller paradigm that dramatically reduces the size of a visual stimulus. The previous study reported that the small size of the visual stimuli deteriorated the spelling performance by reducing an amplitude of P300 component [2]. To compensate the reduction of ERP responses, a user voluntary sound-imagery task was simultaneously performed by a user. Methods and Results: The five participants (2 males) have placed 60 cm away from the monitor. The EEG signals were recorded using 32 electrodes according to ActiCap 32 channels standard-2. A normal speller and a dot-based speller layout were designed in our experiment (see Figure 1). On a 24-inch monitor, 36characters were displayed with the 4-inch size of a smart-phone layout. In the case of the dot speller, a tiny dot (less than 1mm) was positioned above every 36 characters (see Figure (A-b)), and the dot was flashed instead of the character itself. The experiment consisted of three conditions as follows; 1) Normal-gaze: focused on the normal speller stimulus, 2) Dot-gaze: focused on dot stimulus, and 3) Dot-imagery: focused on dot stimulus and performed the sound-imagery task (8000 Hz) in response to the flickering stimulus. Each condition was divided into training and test sessions; the RLDA classifier was generated based on the training data, while the test data were used for the performance validation. The decoding accuracy for the target character and the averaged ERP responses were validated in three different conditions (i.e., Normal-gaze, Dot-gaze, and Dot-gaze with sound imagery). The decoding accuracies (y-axis) were evaluated through the number of sequences (x-axis) from one to ten for individual subjects along with their averages (see Figure B). The averaged decoding accuracies achieved 65.3%, 46.7%, and 84.0% after sequence 3, and 94.7%, 72.0%, and 100% after sequence 10 for the Normal-gaze, Dot-gaze, and Dot-imagery, respectively. Averaged ERP responses indicated that the Dot-imagery condition showed relatively clear P300/N500 (at Cz) and N200 (at Oz) components compared to the Dot-gaze condition. Discussion: To confirm whether the practical and robust speller system can be constructed using the user-voluntary sound-imagery task, we mainly compared two different conditions of Normal-gaze and Dot-gaze with the sound- imagery task. The Dot-imagery condition showed relatively attenuated P300 responses compared to the Normal-gaze condition, however, the decoding accuracy showed the highest performance. We found the significant N400 component in the Dot-imagery condition that would be evoked by the user-voluntary sound-imagery task. Furthermore, a clear attenuation of the averaged amplitude for non-target trials in both Dot-based conditions was observed that could increase the discriminant of target vs. non-target class. Significance: Our study indicated that proposed dot-based speller could be successfully applied on the practical BCI systems by complementarily using it with the user voluntary sound-imagery task. Acknowledgements: This research was partly supported by the MSIT (Ministry of Science and ICT), Korea, under the SW Starlab support program (IITP-2015-1107) supervised by the IITP (Institute for Information & communications Technology Promotion) and partly funded by Microsoft Research Asia. References: [1] S.-K. Yeom, S. Fazli, K. R. Müller, and S.-W. Lee, "An Efficient ERP-based Brain-Computer Interface using Random Set Presentation and Face Familiarity," PLoS ONE, Vol. 9, No. 11, 2014, pp. 1-13. [2] M. Salvaris and F. Sepulveda, "Visual Modifications on the P300 Speller BCI Paradigm," Journal of Neural Engineering, Vol. 6, No. 4, 2009, pp. 046011.

1-C-19 Development of cognitive Brain-Machine interface based on visual imagery

Koji Koizumi[1], Kazutaka Ueda[1], Masayuki Nakao[1]

[1]*The University of Tokyo*

Introduction: In this study, to develop a new cognitive brain-machine interface (BMI) that is more intuitive and goal-directed than the existing BMI, we devised a "visual-imagery method," which allows visual imaging of the operation of the target. Here, we also investigated an "inner-speech method," which comprises internal pronunciation of words without emitting sounds, and an "inner-speech + visual-imagery method," which combines the two methods. Material, Methods and Results: Electroencephalography (EEG) signals from 16 participants were acquired and analyzed from 65 electrodes on all parts of the brain with the sampling frequency rate of 1000 Hz. During the inner-speech task, we measured EEG when repeating six Japanese words corresponding to the English words "up," "down," "left," "right," "forward," and "backward" in mind. During the visual-imagery task, participants visually imagined the movement of a drone in three planes (up/down, left/right, and forward/backward) while watching a drone hovering at the center position of three-dimensional space presented in the monitor. To reduce the individual differences in imagination, right before participants imagined the drone movement each time, they watched a movie in which the same drone moved in one direction. In the inner-speech + visual-imagery task, participants simultaneously imagined the movement of a drone and repeated in mind the word describing the direction in which the drone moves. EOG artifact was removed with ICA approach based on infomax algorithm. A total of 12 frequency band powers (0-10, 10-20, 20-30, 30-40, 40-44, 56-60, 60-70, 70-80, 80-90, 90-100, 100-110, and 110-120Hz) were extracted using the Welch periodogram algorithm; subsequently, each frequency band power was used for classification in a support vector machine (SVM) classifier. Multi-class classification was performed using a one-vs-one method; accuracy percentages were obtained by 20-fold cross validation. In all methods, the high-gamma band (60-120 Hz) yielded the best accuracy, compared with the accuracies obtained from lower frequency bands ($p < .05$). When solely high-gamma band power was used, the average accuracy of the 16 participants was 78.64% in inner speech, 80.31% in visual imagery, and 75.84% in inner speech + visual imagery. Experiments were conducted to determine the dominant EEG signals corresponding to different brain areas for the recognition of intended direction. We divided the 65 electrodes among six brain regions: prefrontal cortex, motor cortex, somatosensory cortex, temporal lobe, parietal lobe, and occipital lobe. Thereafter, the high-gamma band power of each region was extracted and used for classification. The accuracy in the prefrontal cortex was 82.18% in inner speech, 82.92% in visual imagery, and 78.75% in inner speech + visual imagery, which was significantly higher than the accuracies of other regions ($p < .01$) and of the whole brain ($F(1, 15) = 6.32$, $p = .0238$). Finally, we divided the electrodes in the prefrontal cortex into three regions: Dorsolateral prefrontal cortex (DL_PFC), Frontal pole (FrP) and Triangular part of inferior frontal gyrus (TrIFG). The accuracy in the FrP was 69.67% in inner speech, 74.48% in visual imagery, and 72.19% in inner speech + visual imagery. In inner speech, the accuracies of FrP and DL_PFC were significantly higher than the accuracy of TrIFG; however, there was no significant difference between FrP and DL_PFC. Additionally, during visual imagery and inner-speech + visual-imagery tests, there was a significant difference between FrP and DL_PFC ($p < .005$). Discussion: Here, we studied the probability of correctly identifying the direction in which an imagined drone moves, using visual imagery and a BMI system. Our results confirm that it is possible to detect different EEG signals that are specifically related to the visual image. However, this study has been performed with an offline classification method. A possible avenue for future work would be the creation of an online BMI system using visual imagery. Significance: In this study, we demonstrated that the high-gamma frequency band from EEG contains valuable information for the classification of inner speech and visual imagery. We also revealed that EEG signals from the prefrontal cortex are useful in the recognition of intended direction; in particular, the FrP is the most useful region in the prefrontal cortex.

1-C-20 Answering questions in Prolonged disorders of consciousness with a Brain-Computer Interface

Damien Coyle[1], Natalie Dayan[2], Jacqueline Stow, Jacinta McElligott, Aine Carroll

[1]Ulster University, [2]NeuroConcise

Introduction: A gold standard assessment tool for Prolonged Disorders of Consciousness (PDOC) is yet established and fallacious diagnoses are allegedly as high as 40%. Standard neurobehavioral rating scales: the JFK Coma Recovery Scale-Revised (CRS-R) and Wessex Head Injury Matrix (WHIM) depend on consistent overt behaviours and may have subjective bias. Sensorimotor rhythm (SMR)-brain-computer interface (BCI) augment behavioural assessments. SMR-BCIs enable intentional EEG modulation learning via motor imagery, and potentially communication or therapeutic technology interaction [1]. We present results of SMR-BCI awareness assessment; multisession stereo-auditory feedback BCI training; and a pilot question-answer system tested on PDOC patients. Material, Methods, Results: The study involved two male participants with Minimally Conscious (E) and Vegetative (JC) state diagnoses. Ethical approval granted by National Rehabilitation Hospital of Ireland. Informed assent given by participant's families. JC had no previous BCI experience. E had 20 BCI feedback training sessions(2011-2014)[2]. EEG was recorded via Fp1, Fp2, F3, Fz, F4, C3, Cz, C4, P3, Pz, P4 (gnautilaus 16 channel amplifier with active electrodes (g.tec)). Session 1 included block design assessment. Participants were asked to imagine one movement per block, cued with an auditory tone circa every 8s (6 blocks, 15 trials/block, E: right hand vs lift both feet; JC: left hand vs lift both feet). Blocks were combined and leave p-out cross validation (LpOCV; p=2 i.e, one trial from each class) was performed to determine average time-varying accuracy (see [2] for details). Pre-cue and peak accuracies were compared to determine activation significance, indicating patients may be aware of tasks and followed commands. Ensuing assessment, real-time feedback was given. E's visual acuity was unclear and JC was registered blind so stereo auditory feedback was given as broadband (pink) noise or music samples (see [1] for details), with 3-4 sessions of 1-5 runs (60 trials/run, randomized equal number per class) cued with voice command e.g. "left", "feet" or "right" to matching ear via earphones: cue at 3s, feedback at 4-7s. Feedback was modulated by continually varying the sound's azimuthal position between ±90° via imagined movement. Peak offline cross validation accuracies compared to baseline accuracy and online single-trial accuracies are reported in Figure 1. In session 4 a question-answer system based on a recent study in Amyotrophic Lateral Sclerosis was evaluated [2]. Biographical questions with known answer were posed. Most "yes" questions had semantically similar "no" questions e.g., "You are 33 years old" vs "You are 47 years old". Recordings of family members reading questions were played back to participants in timed paradigm. Participants responded for yes/no with respective hand/feet imagery. Figure 1 shows cross-validation analysis of EEG responses to 40 questions/run. E and JC scored median values of 6 and 4 (CRS-R) and 6/15 and 3/13 (WHIM) respectively, indicating behavioural unresponsiveness/communication inability. Yet both participants produced peak accuracies significantly higher than baseline during assessments, feedback and questions (4/5 runs), ($p<0.05$: Wilcoxon test), signifying wilful modulation of SMR. Discussion: The CRS-R and WHIM indicated indistinct visual acuity but preserved auditory startle, supporting stereo auditory feedback utility for PDOC patients, [1] but challenges with bias/non-stationarity due to artefacts attributed to reflexive movements/teeth-grinding/wheezing/cap-movement remain. While offline/online accuracy trends upwards, more sessions are vital to improve performance afore participants undergo open question sessions. Significance: Despite lack of behavioural responses, participants showed capacity to apply SMR strategies to answer questions: the first evaluation of multi-question system in PDOC. Trials are ongoing with larger cohort involving online feedback to questions. References: [1] D. Coyle, J. Stow, K. McCreadie, J. McElligott, and Á. Carroll, "Sensorimotor Modulation Assessment and Brain-Computer Interface Training in Disorders of Consciousness," Arch. Phys. Med. Rehabil., vol. 96, no. 3, pp. S62-S70, Mar. 2015. [2] U. Chaudhary, B. Xia, S. Silvoni, L. G. Cohen, and N. Birbaumer, "Brain-Computer Interface-Based Communication in the Completely Locked-In State," PLOS Biol., vol. 15, no. 1, p. e1002593, Jan. 2017.

1-C-21 Habituation of P300 in the use of P300-based Brain-Computer Interface (BCI)

Xiaoqian Yu[1], Theresa M Vaughan[2], Emanuel Donchin[1]

[1]University of South Florida, [2]National Center for Adaptive Neurotechnologies, Wadsworth Center

Introduction: P300-based BCI can provide a means of communication to people with amyotrophic lateral sclerosis (ALS), a progressive neurodegenerative disorder that mainly affects the motor system. Recent studies have suggested that up to 50% of individuals with ALS may experience some cognitive impairment. P300 amplitude is sensitive to the level of attentional resources allocated to the stimulus, and repeated presentation of identical stimuli may reduce the attentional resources allocated to the target. The degree to which the P300 habituates while using the BCI speller is unknown. The present study set out to test if the P300 habituates while individuals with ALS, and healthy volunteers (HVs), use the P300-based BCI. Material, Methods and Results: 2 ALS patients and 2 HVs were invited to use the BCI2000 system biweekly for 4 times in a lab setting. Eight EEG channels were recorded while subjects were using a checkerboard paradigm to respond to each of 25 predetermined letters. Subjects were instructed to silently count the number of times the target letter flashed, and moved on to the next target letter upon its selection. A stepwise linear discriminant function (SWLDA) was used to determine the item the subject intended to select. Offline analyses assessed the latencies and amplitudes of ERPs to the target and non-target items. No signs of habituation were found during these two months, the amplitude of the early negativity (N200), the late positivity (P300), and the late negativity (LN) were consistent across the 4 sessions. ALS patients achieved the same performance outcomes as HVs but displayed different ERP patterns from HVs: smaller P300 and LN, along with delayed latency in P300 and LN was observed for ALS patients when compared with HVs (Table 1). Important to note that the HVs are young college students, not age-matched with ALS patients. Discussion: The study aimed to test (1) if the P300 habituates in the use of BCI speller in both ALS patients and healthy volunteers, (2) whether the two groups' performance in the use of the BCI differed and (3) whether the two groups displayed a different pattern of ERP components generated during BCI use. The data aquired over 2 months did not show signs of habituation of the P300 in both ALS patients and HVs. Thus, P300-based BCI can be a reliable communication tool as it can reliably elicit ERP components over long period of time. ALS patients performed as well as HVs even though they showed different patterns of ERPs from HVs. Thus, it appears that the cognitive functionality of ALS patients meets the level of cognitive ability required for using the P300-based BCI. Significance: Despite literature suggesting that P300 may be sensitive to the amount of attentional resources allocated, and that fatigue or repeated presentation of stimuli may affect its amplitude, there are no studies addressing the potential impact of P300 habituation on long-term use of a P300-based BCI. P300 habituation is important to consider in the development of P300-based BCI as a reliable communication tool for people with ALS and other severe neuromuscular diseases. Acknowledgements: We thank all the people with ALS and their caregivers for their valuable time devoted to this study; and we thank National Center for Adaptive Neurotechnologies for the BCI2000 portable system. This work has been supported by the National Institutes of Health (NIH) (Grant P41: EB018783 (NIBIB)) References: Farwell, L. A., & Donchin, E. (1988). Talking off the top of your head: toward a mental prosthesis utilizing event-related brain potentials. Electroencephalography and clinical Neurophysiology, 70(6), 510-523. Geisler, M. W., & Polich, J. (1994). P300 habituation from visual stimuli?. Physiology & behavior, 56(3), 511-516. Lew, G. S., & Polich, J. (1993). P300, habituation, and response mode. Physiology & behavior, 53(1), 111-117. Phukan, J., Pender, N. P., & Hardiman, O. (2007). Cognitive impairment in amyotrophic lateral sclerosis. The Lancet Neurology, 6(11), 994-1003. Polich, J. (1989). Habituation of P300 from auditory stimuli. Psychobiology, 17(1), 19-28. Ravden, D., & Polich, J. (1998). Habituation of P300 from visual stimuli. International Journal of Psychophysiology, 30(3), 359-365. Ringholz, G. M., Appel, S. H., Bradshaw, M., Cooke, N. A., Mosnik, D. M., & Schulz, P. E. (2005). Prevalence and patterns of cognitive impairment in sporadic ALS. Neurology , 65, 586-590. doi:10.1212/01.wnl.00

1-C-22 The value-complexity trade-off for reinforcement-learning-based BCI

Hadar Levi Aharoni[1], Michal Moshkovitz[1], Stas Tiomkin[1], Bar Iluz[1], Sarel Duanis[1], Naftali Tishby[1]

[1]*The Hebrew University of Jerusalem*

Introduction: Several studies in recent years have shown that the reinforcement learning (RL) paradigm can be used for training a robotic device (agent) via a BCI, as a more efficient paradigm for movement control [1,2]. In this control approach an error-related potential (ErrP) is used as a negative reward on the agent's actions. An important factor affecting the performance of this control paradigm is the accuracy of the extracted ErrP, which may vary across individuals and in different conditions. Thus in order to design an RL-based BCI, one has to address the issue of finding an optimal control strategy under different noise levels. In the RL framework the optimal policy $\pi^*(s,a)$ defines the probability to take action a at each state s. This policy can be found by maximizing over a value function V which is the accumulated rewards. To handle the issue of a noisy reward in RL-BCI, we suggest to utilize the INFO-RL (IRL) algorithm [4], which defines the maximal achievable value for each level of complexity in the control. Rubin et al. have also shown that the IRL optimization finds low-complexity policies which are more robust in the presence of noise in the rewards, and thus, show a better generalization performance under noisy conditions. The IRL defines a free energy that combines both the value function and the control information (CI), a measure of the policy complexity [4]: $F(\beta) = CI - \beta V$, where β is a trade-off parameter. By minimizing this free energy, the IRL finds policies which maximize the value function, while giving preference to "simpler" policies, with a trade-off between them; the lower the β, the more important is minimizing the policy complexity compared to maximizing the value. Methods and Results: Based on the illustration given in [4], we defined a grid world with a 'minefield' area, and added a Gaussian noise to the rewards, simulating the noise in the ErrP feature extracted from the EEG. We then used the IRL algorithm to find the optimal policy, under different levels of noise. The solutions were explored for a range of β values, where high β is equivalent to the standard value maximization RL problem, and low β gives preference to policies with random actions. In fig. 1(left) we show the trade-off curves between the expected value (EV) and the CI, under different levels of noise in the reward. Two types of policies are typically found: a policy that crosses the minefield (fig. 1a) at high β, and a policy that bypasses the minefield (fig. 1b) at low β. While the high-β policies achieve high EV under low noise levels ($\sigma \leq 1$), the EV drops at higher noise levels. On the other hand, a lower-β policy which bypasses the minefield achieves a relatively high EV even under high noise levels, resembled by the maxima in the σ=2,2.5,3 curves. Therefore the low-β policy is the more robust solution. Under higher levels of noise (σ=3.5,4) the solution that bypasses the minefield is never reached, and therefore the maxima are absent in these curves. Discussion: In this paper we suggest that the INFO-RL paradigm is a principled method to control device movements using BCI. We explored the effect of noise in this paradigm and showed that it provides robust solutions under different levels of noise. We are currently testing the predictions of the INFO-RL paradigm in an RL-based BCI experiment. Significance: The application of the INFO-RL to the RL-BCI paradigm suggests a method to determine the optimal trade-off between the user- and machine-control in the adaptive-shared-control paradigm [3]. As discussed in [5], this may be particularly useful for restorative purposes, in cases where a specific user-control level is desired. References: [1] Iturrate et al. (2015). Teaching brain-machine interfaces as an alternative paradigm to neuroprosthetics control. Scientific Reports, 5. [2] Zander et al. (2016). Neuroadaptive

technology enables implicit cursor control based on medial prefrontal cortex activity. PNAS, 113(52), 14898-14903. [3] Chavarriaga et al. (2014). Errare machinale est: The use of error-related potentials in brain-machine interfaces. Frontiers in Neuroscience. [4] Rubin et al. (2012). Trading value and information in MDPs. Intelligent Systems Reference Library, 28, 57-74. [5] Bauer et al. (2015). Reinforcement learning for adaptive threshold control of restorative brain-computer interfaces: A Bayesian simulation. Frontiers in Neuroscience, 9(FEB).

D- BCI Non-Invasive- Other

1-D-23 Prediction of individual user's suitability for passive BCI applications using short resting EEG recordings

Ho-Seung Cha[1], Chang-Hwan Im[1]

[1]*Hanyang University*

Introduction: It has been frequently reported that some users have difficulty in using passive brain-computer interface (BCI) applications because of the small range of fluctuation of their EEG features. Customization of EEG features best suited to each user might be a solution to circumvent this issue, but it generally requires long and tedious training sessions before using the main passive BCI applications. Therefore, it would be of great value to develop a method to preliminarily decide whether an individual user can use the default feature without any training or needs additional training sessions for the customization. In this study, we searched for indices to predict individual user's variability of theta band power during meditation task using short resting EEG data acquired before the main task. Material, Methods and Results: 21 subjects were asked to participate in the first experiment, and EEG data were recorded from Fp1 and Fp2, with a mastoid reference, using Biosemi ActiveTwo, considering the electrode placements of typical wearable headband-type EEG devices (this database was denoted by [DB1]). Before the main meditation task, resting EEG data were acquired with eyes closed for one minutes. The meditation experiment was composed of three consecutive sessions. In the first session, participants were instructed to stare at a fixation cross for one minute. Then, in the second and third sessions, they conducted a controlled meditation task for five minutes with a one-minute inter-session interval. The prefrontal theta (5-8 Hz) power (PFTP) was chosen as the EEG feature during meditation [1]. To quantify the variability of PFTP, we computed interquartile range (IQR) of PFTP values of 180 epochs in each participant. Then, a resting-EEG index that showed the strongest correlation with the IQR of theta power of each participant was found. For the validation of the resting EEG index, we conducted the same experiment with 13 newly-recruited subjects (this database is denoted by [DB2]), and confirmed whether the optimal resting EEG index shows consistently strong correlation with the IQRs of theta power. As a result, strongest correlation was found between the average alpha power at Fp2 and IQR of theta power during meditation in DB1 ($r = 0.81$, $p = 9.99E-06$), as shown in Figure 1(left). After deciding the EEG index reflecting the variability of theta-band power during meditation using DB1, the same EEG index was applied to a new database DB2, and also also showed strong correlation with the IQR of theta power during meditation in DB2 ($r = 0.90$, $p = 0$), demonstrating the feasibility of the new

EEG index (see Figure 1(right)). Figure 1. Correlation between IQR of prefrontal theta power during meditation and IQR of left prefrontal alpha power during resting period. Left: DB1, Right: DB2. Discussion: The results of our study might be elucidated by the tight cross-frequency coupling of alpha and theta band activity during meditation task. If the level of basal alpha band power is low, there will be only a little room for the variation of theta band activity due to the tight theta-alpha cross-frequency coupling. We will continue to find new resting-EEG indices to predict the variability of EEG features for other passive BCI applications. Significance: In the present study, we investigated whether short resting EEG data could be used to predict individual variability of EEG features for passive BCI applications. It is expected that our study would contribute to the development of practical passive BCI applications. Acknowledgements :This work was supported by Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (2017-0-00432). references : [1] Baijal, S., Srinivasan N. Theta activity and meditative states: spectral changes during concentrative meditation. Cognitive processing, 11(1), 31-38. 2010.

1-D-24 A new paradigm for movement detection of self-paced movement imagination using movement-related cortical potentials

Joana Pereira[1], Andreea Sburlea[1], Gernot Müller-Putz[1]

[1]*Graz University of Technology*

<p>Introduction: Providing not only accurate, but also timely feedback about the user's intention is a crucial point in BCIs. BCIs based on movement-related cortical potentials (MRCPs) respond fast enough so that the Hebbian principle applies [1], and have therefore been used for movement detection. Training classifiers based on MRCP features for movement imagination (MI) detection can be a challenge, especially if one does not rely on cue-locked paradigms. In cue-locked paradigms, the participants are asked to perform MI after a GO cue and the signals elicited correspond not to a self-paced MRCP (Bereitschaftspotential) but to the so-called contingent negative variation (CNV). In this study, we tested offline a paradigm for detection of a self-paced MI task, inspired by Libet´s clock experiments [2].</p> <p>Material, Methods and Results: Fifteen healthy participants sat in front of a computer monitor and saw 5 glasses on a screen. Subjects were asked to select one glass and had 13 seconds to perform the self-paced reach-and-grasp MI towards it. We introduced a scroller with numbers and the subjects were asked, at the end of each trial, to report the number that was displayed on the scroller at the time they felt the urge to perform the MI. EEG (and EOG) was recorded using 61 (+3) active electrodes and sampled at 1 kHz. A trial-based removal of artefacts was performed and independent component analysis was used to remove components related with ocular or muscular artefacts. Offline, we downsampled the data to 10 Hz, band-pass filtered from 0.1 to 1 Hz using a zero-phase 4th order Butterworth filter, and time-locked the EEG to the reported number. We took amplitude features from 26 channels and 1-second windows around the reported number to train movement (and outside the MI period, to train rest), and performed both time-locked and asynchronous classification. </p> <p>A phenomenon consistent in morphology and spatial location with and MRCP was observed in 14 out of the 15 participants. The grand-average MRCP at channel Cz is shown in Figure 1a. An average accuracy of 82±9% was obtained for the time-locked classification. For the asynchronous classification scenario (Figure 1b), we slided 1-second windows over the trial-length

and had a trial-based evaluation with strict criteria: a trial was considered correct every time there was at least one true positive, but no false positives. An example of this evaluation for a subject with average performance is given in Figure 1c. The percentage of correct trials was at 53±17% - chance level was at 20% (calculated using label permutations). </p> <p>Figure 1: a) Grand-average MRCP. b) Asynchronous classification performance. d) Example of a testing fold of subject s3 with average performance for the asynchronous scenario. On the left single-trial image we show the classifier probability of the MI class (positive class) and on the right we show the correspondent detections based on the probabilities. </p> <p>Discussion: Both time-locking and asynchronous classification performances indicate the potential of such paradigm for online applications. One challenge is still to reduce the number of false positives in the case of the asynchronous scenario - as an example, a more suitable artefact correction could improve the performance. Further, it is still necessary to investigate the suitability of such paradigms in end-users (e.g. individuals with spinal cord injury). </p> <p>Significance: With this study we show a new paradigm which allows the estimation of time-locking points for training movement detectors based on MRCPs in a self-paced MI task. </p> <p>Acknowledgments: This work was supported by the ERC Consolidator Grant ERC-681231, Feel Your Reach.</p> <p>References: </p> <p>[1] Mrachacz-Kersting, N., Kristensen, S. R., Niazi, I. K., & Farina, D. Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity. The Journal of physiology, 590(7), 1669-1682 (2012). </p> <p>[2] Libet, B., Gleason, C. A., Wright, E. W. & Pearl, D. K. Time of conscious intention to act in relation to onset of cerebral activity (readiness-potential). The unconscious initiation of a freely voluntary act. Brain 106 (Pt 3), 623-642 (1983).</p>

1-D-25 Robustness of single-hand classification against other-hand activity in EEG

Christian Niethammer[1], Wolfgang Rosenstiel[1], Martin Spüler[1]

[1]*University of Tübingen*

Introduction: It is commonly accepted that neural activity measured with EEG during motor execution can be used to control prostheses [1]. So far, research focuses mainly on detecting the movement related neural activation. However, this focus can lead to models that are not robust in everyday life. Although left- and right-hand movements can be measured in EEG on different hemispheres, the neural activity still overlaps. When a person holds an object with a BCI controlled prosthesis and moves the other, healthy hand, this movement could wrongly be detected as trigger for the prosthesis to open. Therefore, it is important to investigate the robustness of a model against other-hand activity and how this robustness could be increased by additional features. Methods: Seven subjects performed a motor execution experiment. Using two PlayStation® Move-Motion Controller, subjects controlled the x- and y-axis of a cursor on a computer screen. The position of the cursor could be altered by pronating and supinating the hands. The subjects had to reach different positions on the screen in a random sequence, which resulted in left hand (LH, e.g. horizontal), right hand (RH, e.g. vertical) and bimanual (BI, diagonal) movements, or rest (RE) on the same position. Brain activity was recorded using 32 electrodes (29 EEG, 3 EOG). Ocular artifacts were corrected offline using a regression-based method. EEG data was separated in four groups (LH, RH, BI, RE), power spectral density was calculated of 14 electrodes distributed over right, left and central areas and used as features for the classifier from 8-30 Hz. A linear support vector machine was used for classification. Features for class one contained RH and/or BI and for class two RE and/or LH. To investigate the robustness of each model considering right-hand movements, they were tested on the full spectrum of possible hand movements (RE, RH, LH and BI). Results: The average classification accuracies over all subjects for all models in consideration of right-hand activity are shown in Table 1. The classification results varied subject dependent from 56% to 90% for RH. Using only RE and RH features results in 70%, 72% and 71% average classification accuracy for RE, RH and BI respectively. However, only 41% of LH were classified as non-right-hand movement. Adding bimanual and left-hand movement features does significantly increase the accuracy of classifying LH (t-test, $p < .05$). However, the accuracies for RE, RH and BI decrease significantly, as well. Therefore, the average accuracy for all movements is still highest with the right-hand movement and rest features in the classifier. Table 1: Averaged classification results with different feature sets and classifier approaches (first column), tested on RE, RH, LH and BI. Asterisks indicates significance (alpha = .05) compared to Right vs. Rest feature set. Discussion: In this work we illustrate the serious problem of models having a very low robustness against other-hand activity. There is a high chance that left-hand movements will be classified as right-hand movement which decrease the overall classification results. By using additional features, such as bimanual movements and left-hand movements to train a classifier, the low accuracy of left-hand movements can be improved. However, these models lack in accuracy rates of right-hand and bimanual movements. The overall performance of successfully classifying whether the right hand is active, does not improve by adding other features. With spatial filter methods based on the source activity of a specific region, e.g. beamforming techniques, these results could be improved. Significance: This investigation shows that results reached in an isolated condition (e.g. right-hand vs. rest) can not be replicated including left-hand and bimanual movements. Applying BCIs to medical devices like prostheses, can only be done successfully by considering all possible influences on the used features. Acknowledgements This work was supported by the Baden-Württemberg Stiftung(KONSENS-NHE). References: [1] D. J. McFarland, and J. R. Wolpaw. Brain-computer interface operation of robotic and prosthetic devices. Computer, 41(10):48-52, 2008

1-D-26 A new BCI-based rehabilitation possibility: Sensorimotor rhythm amplitude control affects the size of a spinal reflex

Hanna Carruth[1], Rachel Haywood[1], Jeremy Hill[2], William Sarnacki[3], Lynn M McCane[4], Jonathan R Wolpaw[4], Dennis J McFarland[4]

[1]University of Glasgow, [2]Burke Medical Institute, [3]New York State Department of Health, [4]National Center for Adaptive Neurotechnologies, Wadsworth Center

Introduction Many studies have shown that people with or without neuromuscular disabilities can learn to control sensorimotor rhythms (SMRs) in the electroencephalogram (EEG) through a series of training sessions; they can learn to increase or decrease SMR amplitudes in the mu (8-12 Hz) and/or beta (18-26 Hz) frequency bands over sensorimotor cortex (e.g., Electroencephalogr Clin Neurophysiol (1991) 78:252-259; (1994) 90:444-449). BCI-based SMR training might help to improve recovery of motor function in people with CNS disorders by guiding activity-dependent brain plasticity (Lancet Neurol (2008) 7:1032-1043). Since activity-dependent brain plasticity is believed to guide spinal cord plasticity in motor skill learning (Neuroscientist (2010) 16:532-549), it is possible that BCI-based SMR training could also affect spinal reflex excitability, and thereby affect motor control. To test this hypothesis, we studied the impact of SMR (mu-rhythm) amplitude change on the size of the H-reflex (the electrical analog of the spinal stretch reflex) in the forearm muscle flexor carpi radialis (FCR). Materials Methods and Results Six adult participants with no known neurological conditions and two participants with chronic incomplete spinal cord injury (SCI) were trained to increase (SMR-up) and decrease (SMR-down) mu-rhythm amplitude over the right hand/arm area (i.e., at/around the C3 or CP3 electrode locations over left hemisphere), using a BCI- based cursor-control task. Once trained over >10 training sessions to control SMR amplitude, participants then performed the same SMR cursor task while the H-reflex was elicited in the right FCR muscle by median nerve stimulation. H-reflex trials occurred at random intervals during SMR-up trials, during SMR-down trials, and in between trials. In all six normal volunteers, the H-reflex was larger during SMR-up trials and smaller during SMR-down trials, compared to in-between trials. The group mean�SE values were 112�6% of the in-between value for the SMR-up trials and 92�1% for the SMR-down trials, significantly different from the in-between trials ($p<0.05$ for both, paired t-test). In one of the two people with SCI, the results were similar to those in healthy people, whereas in the other person with SCI there was no clear difference in the H-reflex between SMR-up and SMR-down trials. Interestingly, in both people with SCI, spastic FCR EMG activity (i.e., clonus and spontaneous low-frequency firing) decreased during the cursor-control training sessions. Discussion and Significance These initial results indicate that SMR amplitude affects spinal reflex excitability. They suggest that SMR training might be developed as a new therapeutic approach to enhance recovery of motor control in people with reflex abnormalities due to spinal cord injury or other chronic neuromuscular disorders (e.g., J Neurosci (2013) 33:2365-2375). Support from: NIH Grants NS069551 (NINDS) and P41EB018783 (NIBIB).

1-D-27 A ternary hybrid EEG-NIRS Brain-Computer Interface for the classification of brain activation patterns during mental arithmetic, motor imagery, and idle state

Jinuk Kwon[1], Jaeyoung Shin[1], Chang-Hwan Im[1]

[1]*Hanyang University*

Introduction: Many studies have been carried out to find appropriate mental tasks for multi-class EEG-BCI and NIRS-BCI; however, multi-class hybrid EEG-NIRS BCI (hBCI) has not been well studied. Here we propose the use of an hBCI for the classification of three brain activation patterns elicited by mental arithmetic (MA), motor imagery (MI), and idle state (IS: relax without performing cognitive task), with the aim to elevate the information transfer rate (ITR) of hBCI by increasing the number of classes while minimizing the loss of accuracy.
 Material, Methods and Results: EEG data were recorded with 21 active electrodes placed on both frontal (Fz, F1, F2, F3, and F4) and motor (FC3, FC4, Cz, C1, C2, C3, C4, C5, C6, CP3, and CP4) areas. NIRS data were collected using a portable NIRS system with 16 NIRS channels placed on the forehead over the PFC. The participants imagined complex finger tapping at a rate of approximately 2 Hz (MI) or continuously subtracted a one-digit number (between six and nine) from the result of a former calculation (MA) or stayed relaxed without performing any specific mental imagery task. The participants were performed the three types of tasks 30 times each. The ternary classification problem was decomposed into three binary classification problems in order to apply the "one-versus-one" classification strategy where classification was performed for all binary combinations of classes and the estimated class was decided by majority voting. EEG feature vectors were constructed using the log-variance of the first three and last three common spatial pattern (CSP) components selected after filter-bank CSP filtering. NIRS feature vectors were constructed using the temporal mean values of HbR and HbO in the 5-10 s and 10-15 s temporal windows in NIRS epochs from all channels. A 10×10-fold cross-validation was performed using shrinkage linear discriminant analysis for each of the three binary classification problems. The ternary classification accuracies for EEG-BCI, NIRS-BCI, and hBCI were 76.1±12.8, 64.1±9.7, and 82.2±10.2%, respectively. The classification accuracy of the proposed hBCI was thus significantly higher than those of the other BCIs ($p<0.01$).
 Discussion: The results of our study showed the feasibility of the combined use of EEG and hemodynamic variations at the PFC to enhance the performance of ternary BCI. The main drawback of the current hBCI is the high complexity of the system, which might make it difficult to apply in practical BCI applications. Therefore, it is necessary to minimize the system complexity using an optimal channel selection method and by manufacturing a unified EEG-NIRS recording system.
 Significance: We proposed a ternary hybrid BCI system simultaneously using EEG and hemodynamic variations from the PFC, which showed improved BCI performance compared to the conventional ternary BCI systems.
 Acknowledgements: This work was supported in part by the Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (2017-0-00432, Development of non-invasive integrated BCI SW platform to control home appliances and external devices by user's thought via AR/VR interface).

1-D-28 EEG-based neglect assessment

Murat Akcakaya[1], Aya Khalaf[1], Safaa Eldeeb[1], Jessica Kersey, Gazihan Alankus[2], Emily Grattan[3], Laura Waterstram, Elizabeth Skidmore[1]

[1]University of Pittsburgh, [2]Izmir University of Economics, [3]Medical University of South Carolina

Introduction: Spatial neglect is a neurological disorder that is one of the most common consequences of right-side brain damage after stroke. Patients with neglect are characterized by their inattention to stimuli appearing on their contralesional side which is usually the left visual side. The aim of this work is to introduce a novel electroencephalography (EEG)-based passive BCI system that can be used as a robust and objective neglect assessment test. In this test, EEG signal is recorded in response to visual stimuli shown on a screen at random locations. We performed a feasibility study and showed the performance of the system through the participation of both healthy individuals and neglect patient. The aim behind starting the experiments with healthy participants is to validate the proposed system under less complex conditions compared to those associated with neglect patients. Materials, Methods and Results: EEG was collected using 17 electrodes placed according to the 10-10 system over frontal, central, parietal, occipital lobes as well as the visual cortex. Compared to the original Starry Night Test [1] that requires keyboard inputs from the user, the proposed test uses the participant's EEG to assess neglect. At the beginning of each trial, as seen in Figure 1, a random number of distractors (green dots) were shown on the screen. At every random period of 50-250 ms, the visibility of a randomly selected distractor was toggled. During a trial, a target appeared once on the screen after a randomly chosen delay range of 700 ms to 2200 ms in which distractors were continuously changing as described above.

The target was shown on the screen for 66 ms and a new trial started after this target disappeared. To simulate neglect in healthy participants, all the targets on the left visual field (left side of the computer screen) were hidden to shift the attention to the right side. To assess the system's ability to recognize absence or existence of a target based on the EEG data, a two-class problem that utilizes naïve Bayes classifier was formulated. The used features included EEG data segments corresponding to 500 ms measured EEG time-locked to target onset. Wilcoxon test with 0.05 p-value was used for feature selection. The results were obtained using data collected from 10 healthy participants and 5 neglect patients. The results for healthy participants showed that when the neglect was simulated, the proposed system achieved successful separation between the hidden (neglected) and shown (observed) targets. Distinguishing between hidden and shown targets allow to detect if there is neglect. Detecting if the targets are hidden simulates the case in which the participant neglected the targets while detecting if the targets are shown represents the case in which the participant perceived the targets. For this reason, we define sensitivity as the accuracy of detecting the perceived targets. Specificity is defined as the accuracy identifying the neglected targets. Overall accuracy shows the identification among perceived and neglected signals. The system achieved average accuracy, sensitivity and specificity of 74.24%, 75.17% and 71.36% respectively. As for the neglect participants, on average, the system achieved 75.66% accuracy, 71.66% specificity and 72.01% sensitivity. Discussion:These significant results achieved for both healthy participants and neglect patients suggest that the proposed EEG-based system is a promising objective tool for neglect assessment. Significance: Neglect is assessed using paper and pencil tests that are subjective and require physical response from participants. That response can be absent or very slow depending on the severity of stroke. Here, the EEG-based assessment method we propose does not depend on direct physical human response and subjective evaluations. Moreover, an EEG-based neurofeedback training version of the current test will be developed and used by patients in a virtual reality environment. Such system is cost-effective and can be used to speed up the recovery process of neglect patients since it can be administered at home without requiring supervision from a rehabilitation therapist. Acknowledgement: Our work is supported by NSF IIS-1717654. References: [1]L. Y. Deouell and et al, "Assessment of spatial attention after brain damage with a dynamic reaction time test.," DOI:10.1017/S1355617705050824

1-D-29 Brain-Computer Interface in virtual reality

Reza Abbasi Asl[1], Mohammad Keshavarzi[1], Dorian Yao Chan[1]

[1]*University of California, Berkeley*

Introduction: We study the performance of Brain-computer interface (BCI) system in a virtual reality (VR) environment and compare it to 2D regular displays. Material, Methods and Results: The integrated system consists of three components: a wearable electroencephalography (EEG) device, a VR headset, and an interface. Recordings of brain and behavior from human subjects, performing a wide variety of one-minute tasks using our device are collected. The tasks consist of object rotation or scaling in VR using either mental commands or facial expression (smile and eyebrow movement). Subjects are asked to repeat similar tasks on regular 2D monitor screens. The performance in 3-D virtual reality environment is considerably higher compared to the to the 2D screen. Particularly, the median number of success rate across trials for VR setting is double of that for the 2D setting. Significance: Our results suggest that the design of future BCI systems can remarkably benefit from the VR setting.

1-D-30 Motor imagery classification based on deep convolutional neural network and its application in human-robot interaction

Taochun Zhou[1], Shiwei Cheng[1]

[1]*Zhejiang University of Technologys*

Introduction: Brain-Computer Interface (BCI) based on motor imagery (MI) has been applied to recognize human intent by collecting and classifying electroencephalogram (EEG) signals widely. Convolutional neural network (CNN) is a variant of multi-layer perceptron (MLP), and it has been widely used in speech recognition[1] and image recognition[2]. And compared with the manual selection of EEG signals, CNN is more time-saving and labor-saving in feature extraction and largely solves the classifying problems without relying on experience features. Therefore, according to the EEG signal's that combining temporal and special features, we constructed a CNN model to classify the MI. Material, Methods and Results: As shown in Figure 1, firstly, in order to collecting the experimental data of MI, we designed a MI experimental paradigm based on imagining left/right hand movement, foot movement and stay silent; secondly, according to the EEG signal's features, we constructed a 3-layer CNN model to classify the MI; thirdly, the proposed method was used in the experimental data set of 10 subject to build classification model, and it was compared with the other methods (Mu[3], CSP+SVM[4], WPD(wavelet packet decomposition)+SVM[5] and SAE(sparse auto encoder)); finally, the classification model which achieved the best classification performance was applied in real-time control of NAO to validate the effectiveness of our proposed method. Besides, subject got visual feedback through the NAO robot's movement and voice. The results demonstrate that CNN can further improve classification performance: the average accuracy of experimental data set (87.68%±2.18%) using CNN is higher than that using the other methods. Furthermore, in real-time control of NAO robot, the average accuracy of all subjects reaches to 85.36%±3.31%, which validate the effectiveness of our CNN method. The proposed method can recognize MI, and provides theoretical basis and technical support for BCI applications in the field of human-robert interaction. Discussion: The traditional EEG classification methods need to first extract the pattern features and require priori knowledge. But, CNN allows the computer to automatically learn the pattern features and incorporate feature learning into the modeling process which reduces the subjectivity and imperfection caused by feature manually selection. The results show that this method can be more accurate than the traditional classification methods. Our method also has some limitations, for example, it only recognizes four classes of motor imagery EEG signal now. The next step will be carried out in the following aspects: (1) Improve the EEG experimental paradigm and collect more complex EEG data, and the CNN model is used to identify more complex EEG signal. (2) To furtherly optimize the network structure of CNN, and adjust the appropriate parameters, and combined with other methods, such as deep belief network (DBN) to get higher classification rate; (3) Facing the massive and complex EEG data emerging in practical application, we consider to use SPARK framework to realize the distributed processing and to further improve the real-time application of BCI. Significance: These results provide further evidence that the proposed method can recognize MI, and provide theoretical basis and technical support for BCI applications in real-time application, such as human-robert interaction. References: [1] Abdel-Hamid O, Mohamed A, Jiang H, et al. Applying convolutional neural networks concepts to hybrid NN-HMM model for speech recognition//Proceedings of the 2012 lEEE ICASSP, Kyoto, Japan, 2012: 4277-4280 [2] Krizhevsky A, Sutskever I, Hinton G E. Imagenet classification with networks for image classification//Proceedings of the 2012 IEEE CVPR, Providence, USA, 2012: 3642-3649 [3] Pfurtscheller G, Brunner C, Schlogl A, et al .Mu rhythm (de) synchronization and EEG single-trial classification of different motor imagery tasks [J] .Neuroimage, 2006, 31(1):153-159. [4] Samek W, Vidaurre C, Müller K R, et al. Stationary common spatial patterns for brain-computer interfacing [J]. Journal of neural engineering, 2012, 9(2): 026013. [5] Zhou Z X, Wan B K. Wavelet packet-based independent component analysis for feature extraction from motor imagery EEG of complex movements [J]. Clinical Neurophysiology, 2012, 123(9): 1779−1788

1-D-31 Effects of positive and negative reinforcement on performance accuracy in behavioral and P300 speller-based sound discrimination tasks

Owen Adams[1], Daniele Ortu[1], Traci Cihon[1]

[1]*University of North Texas*

Introduction: Brain-computer interfaces (BCIs) have varied in their training methods. Some studies have used aversive learning tasks where the participants attempted to avoid monetary loss or other negative outcomes (Ruf et al., 2013). Other studies have used appetitive learning tasks where participants worked to gain money or contact other positive outcomes (Kleih, Nijboer, Halder, & Kubler, 2010). What remains to be seen is a direct comparison of these teaching methods, both for behavioral measures and brain activity. Material, Methods and Results: The current study used a simple sound discrimination task to compare aversive and appetitive teaching methods. The participants' goal was to identify whether a tone was longer or shorter than 600 milliseconds. In the appetitive learning trials, referred to hereafter as the positive reinforcement trials, participants only received feedback and gained 10 cents if they correctly identified the length of a tone. In the aversive learning trials, hereafter referred to as the negative reinforcement trials, participants only received feedback and lost 10 cents if they incorrectly identified the tone length (the participants started with a "bank" of 4 dollars to equalize the salience of money gain and loss). 80 trials of each condition were randomly presented to participants with subsequent comparisons made on performance accuracy and reaction times. Unique pictures were presented before each trial type to signal whether the upcoming trial would involve an appetitive or aversive contingency. Discussion: Results indicated negative correlations between comparison stimulus duration and reaction time with different slopes between positive and negative reinforcement trials. Accuracy was shown to be similar between positive and negative reinforcement trials. Significance: These findings may have implications for improving training techniques and are evaluated within the context of BCIs such as the P300 speller device. Specifically, the P300 speller device is highly dependent on brain activity within a particular timeframe after stimulus presentation. Any differences observed between behavioral reaction times when comparing appetitive and aversive contingencies would also likely show up as a confounding variable if attempting to use the two teaching techniques interchangeably. Awareness of differences between the two is important because the eventual goal of speller training should be to enable the participant to respond quickly and accurately, both when attempting to approach and avoid situations. The findings will now be applied to EEG-based BCIs to compare P300 activity and speller accuracy between positive reinforcement contingencies where participants answer "yes" to questions and negative reinforcement contingencies where participants answer "no" to questions. This is potentially significant in that people using BCIs are likely to encounter situations in which they wish to avoid or escape stimuli as well as those in which they wish to approach stimuli. Up until this point, the former situation has been the primary focus of study, making avoidance and escape important to compare with positive reinforcement in the context of BCIs. Future research will work toward the integration of behavioral psychology and neuroscience toward the aforementioned goal. References Kleih, S. C., Nijober, F., Halder, S., &; Kübler, A. (2010). Motivation modulates the P300 amplitude during brain-computer interface use. Clinical Neurophysiology, 121(7), 1023-1031. Ruf, C. A., Massari, D. D., Furdea, A., Matuz, T., Fioravanti, C., van der Heiden, L., Halder, S., & Birmbauer, N. (2013). Semantic classical conditioning and brain-computer interfaces: Encoding of affirmative and negative thinking. Frontiers in Neuroscience

1-D-32 EEG-based visual attentional state decoding using convolutional neural network

Soheil Borhani[1], Reza Abbasi Asl[2], Jabril Ibrahim Muhammad[1], Yang Jiang[3], Xiaopeng Zhao[1]

[1]University of Tennessee, Knoxville, [2]University of California, Berkeley, [3]University of Kentucky, Lexington

Introduction: Maintaining sustained visual attention to a cognitive task is of high importance [1]. Recent studies in Brain-Computer Interface (BCI) using electroencephalography (EEG) shows a promising capability to reveal moment-to-moment attentional states [2]. A number of studies highlight the implication of Event-Related Potentials (ERPs) such as N170 or P300, yet some other studies identified the significance of alpha and beta bands elicited from specific parts of human scalp in spotting level of attention. In the present study, we developed a deep learning approach to analyze the neurophysiological signals collected during a visual attention task. An individualized EEG-based classifier was developed to probe and extract underlying subject-specific features of early visual attention. Material, Methods and Results: Thirty-eight healthy volunteers (11 females; 21.3±1.9 years and 27 males; 23.1±5.2 years) were recruited to conduct tasks on visual attentional state evaluation. The participants were exposed to 8 blocks of 50 images, each of which lasted for 1 second. A blank screen was shown between the images, where the duration of the blank was randomly determined between 1 and 1.5 seconds. We also collected the behavioral response via keyboard button presses. A Convolutional Neural Network (CNN) classifier was developed. Two different representations of the EEG data were used as input to the CNN classifier. The first approach utilizes a spatio-temporal representation and the second one utilizes a spatio-spectral representation. We included a dropout probability of 0.6 in the fully connected layers to reduce overfitting and Rectified Linear Unit (ReLU) activation function to address the gradient vanishing problem. We also used Adam optimizer to adapt the learning rate while preventing the fluctuations of the gradient descent. The first approach achieved an average accuracy of 55% and the second approach achieved an average accuracy of 70%. Discussion: This study shows that EEG signals can be used to distinguish attentional state using visual stimuli. Two different representations were studied. The spatio-spectral representations lead to more accurate results compared to spatio-temporal representations. The size and architecture of the model are designed in a way that train the model considerably fast and enable it to run on small machines.

Significance: The proposed deep learning approach has advantages over the conventional selective visual attention decoding procedures; instead of using engineered features of the EEG, we developed a classifier based on the convolutional neural network using learned features [3]. The findings of this study may be beneficial to people with attention deficit and attention disorder. Also, the platform may improve the understanding of the causal attributes of human visual attention. References: [1] R. Abiri, S. Borhani, X. Zhao, and Y. Jiang, 2017. Real-Time Neurofeedback for Attention Training: Brainwave-Based Brain-Computer Interface, Organization for Human Brain Mapping (OHBM 2017), Vancouver, Canada, June 25-29, 2017. [2] Y. Jiang, R. Abiri, X. Zhao, Tuning Up the Old Brain with New Tricks: Attention Training via Neurofeedback, Frontiers in Aging Neuroscience, 239996, 2017. [3] P. Bashivan, I. Rish, M. Yeasin, and N. Codella, Learning representations from EEG with deep recurrent-convolutional neural networks, arXiv preprint arXiv:1511.06448, 2015.

1-D-33 Effect of stimulation frequency band on SSVEP-based BCI

Ga-Young Choi[1], Soo-In Choi[1], Hyung-Tak Lee[1], Hyun-Wook Kim[1], Jae-Hong Jang[1], Han-Jeong Hwang[1]

[1]Kumoh National Institute of Technology

Introduction: Brain-computer interface (BCI) based on steady-state visual evoked potential (SSVEP) has been intensively studied due to its high classification performance with little training [1]. One of the important factors that influence the performance of SSVEP-based BCI is selection of stimulation frequencies. In this study, we investigated the impact of stimulation frequency bands on BCI performance. Material, Methods and Results: EEG data were recorded with fifteen subjects using thirty-one electrodes while focusing on LEDs flickering at different frequencies. To see the effect of stimulation frequency bands on the performance of SSVEP-based BCI, we used four different stimulation frequencies each in low (5, 5.5, 6, 6.5 Hz), medium (21, 21.5, 22, 22.5 Hz), and high (40, 40.5, 41, 41.5 Hz) frequency bands [2-3]. Each frequency band was independently tested, where the subjects attended on one of the four stimuli for 6 s according to the instruction. A total of 20 trials were tested for each stimulation frequency. Canonical correlation analysis (CCA) was used for classification. As a result, the medium frequency band shows significantly higher performance than low and high frequency bands (Friedman test: $X^2 = 14.13$, $p < 0.05$; Bonferroni corrected, $p < 0.05$). Discussion: In this study, we presented the impact of stimulation frequency bands on the performance of SSVEP-based BCI to provide a guideline for selecting an optimal stimulation frequency band. More solid results will be presented with additional datasets in the conference and we will open our dataset for public use. Significance: To our best of knowledge, this is the first study that systematically investigates the impact of different stimulation frequency bands on the performance of SSVEP-based BCI.

1-D-34 EEG assisted VR streaming: Reducing delays by predicting head rotation

Anne-Marie Brouwer[1], Jasper van der Waa[1], Hans Stokking[1]

[1]TNO

Introduction:<p> Real time streaming of 360° video across consumer networks to a VR headset, e.g. for watching a soccer match in the stadium, is challenged by bandwidth limitations. Therefore, Field-of-View based approaches only stream the content part of the 360° video that falls within in the viewing window of the headset. However, when the VR user rotates the head, other content parts are not instantly available, resulting in visible delays. A solution is to also stream parts adjacent to the viewing window, but this takes up bandwidth and trades low delays against low spatial resolution. We propose to use EEG signals of the VR user to predict when he or she is going to rotate the head and in which direction. Information about (likely) upcoming head movements allow for better choices about how to spend bandwidth: higher resolution of the currently viewed part, or retrieving adjacent parts so that they are in time for display when rotation actually takes place. Predicting head rotations may be possible given the literature on EEG correlates of upcoming movements, even though as far as we know, this has not been investigated for head rotations.<p> Material, Methods and Results:<p> We asked participants to generate 'random' left- and rightward head rotations, self-paced but leaving a few seconds in between movements, while wearing a VR headset and 32 EEG electrodes. Head movements were tracked using the motion sensing system embedded in the headset. After defining rotation onset and the direction of rotation on the basis of data from the motion sensing system, we trained personalized multi-layer perceptron models to distinguish EEG epochs preceding rightward, leftward and no rotation, using equally sized classes. Single epochs of unseen test data could be classified as belonging to one of the three rotation categories with accuracies ranging between 32% (chance level) to 79%. For four participants, accuracy was below 40%, for four participants it was over 70% and three ended up in between. The main difference in performance was caused by the strength of the bias to label data as preceding 'no rotation'. Simulating a real time scenario by applying these models to streaming EEG data that was withheld from the training also showed that the probability of 'no rotation' was consistently high but started to decrease at around 400 ms before rotation onset. Slightly earlier, the probabilities of an upcoming right- or leftward rotation started to diverge in the correct directions.<p> Discussion:<p> This study showed the feasibility of predicting whether a head rotation is coming up, and in which direction, based on EEG data. Simulations of a real time scenario shows that in order to use this information, it is wise to not simply take the most probably class as prediction but to take the development of probabilities of the three classes into account. Improvements in the classification models, especially with respect to feature selection and reducing observed overfitting, are still possible. <p> Significance:<p> The proposed BCI technology could significantly enhance VR imagery, enabling new types of immersive applications. From the perspective of the BCI research field, we think that this application provides an excellent, concrete case of how information derived from EEG could smooth man-machine interaction in a real life setting. It can be used to put the field's achievements to the test and to further develop in the context of a large scale, real life application. The main reason for its suitability is that acquiring training data with accurate labels (whether and which head movement took place) as well as monitoring the quality of the predictive model can happen on the fly without the user even noticing. Starting with the default situation of not making use of the EEG signals at all, the application can only improve over time. EEG sensors could be integrated with the headset and may be used for other purposes as well (e.g. monitoring cognitive or emotional state).<p>

Acknowledgements:<p> We thank Liselotte Kroon, Alessia Cacace, Benjamin de Graaff and Ingmar Stel for help in setting up the experiment and collecting data. We thank Gert-Jan Schilt for ideas and support. This research is part of the project Networked Virtual Reality, TKI (Topconsortium for Knowledge and Innovation) Consortium Agreement 0100294530 with KPN as Industrial Partner.

1-D-35 EEG fatigue classifier for distracted driving

Leili Tavabi[1], Nazgol Tavabi[1], Marissa Powers[2], Bruna Girvent[3], Esther Jun Kim[4], Hector Cordourier Maruri[2], Olufemi Oluwafemi[2]

[1]University of Southern California, [2]Intel Corporation, [3]Northeastern University, [4]Volkswagen Group

Introduction: Daydreaming is the cause for 66% of distracted driving accidents according to a study in 2013 by Erie Insurance. The inability to maintain concentrated attention over prolonged periods of time is termed as Vigilance Decrement in modern psychology. This problem highlights the need for a driver assistance system that can predict vigilance decrement and alert the driver with the appropriate feedback to remain attentive on the road. We provide a solution by using EEG signals from the brain to predict vigilance decrement and provide visual feedback to the driver/rider to return them to the desired physiological state. A smart fatigue-detecting helmet is built as a proof of concept integrating the EEG headset and classifier. Material, Methods, Results: For our study, we used a Mackworth Clock Test - a well known task in psychology used to study the effect of long-term vigilance on the detection of rare signals. Participants were asked to respond to the rare signals as fast as they can. Their responses were considered either hits or misses based on their reaction time within a predefined threshold. We used a commercially-available headset called Muse with four channels [TP9, AF7, AF8, TP10] and collected EEG data from 14 subjects while they went through this 1-hour task. It is prior knowledge that EEG frequency bands are loosely associated with different cognitive states. The higher frequency bands beta(12-30Hz) and gamma(30-50Hz) are associated with consciousness and engagement whereas lower frequencies theta(3-8Hz) and alpha(8-12Hz) are associated with calmness and meditation. Using this prior knowledge, we identified the following three frequency band combinations to have noticeable correlation with users' responses: (i) (gamma + beta)/theta, (ii) theta/alpha, (iii) (alpha + theta)/beta. These features were calculated for 20-second windows prior to the stimulus and were fed into an SVM classifier as indicators of vigilance decrement to classify instances of fatigue versus alertness. Artifact rejection techniques were applied in the time domain to reduce the effect of eye blinks and artifacts on the data. Three subjects were removed from the analysis due to low signal quality or high number of artifacts. The classification reached an accuracy of 72% across the remaining 11 subjects post-eyeblink removal and using data from all four channels. Discussion: In this work, we propose an EEG fatigue classifier that utilizes the signals obtained from a low-cost, less intrusive and more comfortable alternative to the medical-grade EEG headsets. The proposed EEG fatigue classifier is device-agnostic and can be used with any EEG headset that includes the same electrode locations. EEG provides the added value of being able to 'predict' fatigue before dangerous behaviors manifest. Image processing techniques, in contrast, only detect fatigue with head nodding, eyelid closure, and lane drifting. Significance: EEG signals are effective means of detecting different cognitive states including fatigue. However the high cost and burdensome form-factor of medical-grade EEG headsets remain a barrier to entry for real-world app Abbood, H., et al, "Prediction of driver fatigue: Approaches and open challenges", Computational Intelligence (UKCI), 2014 14th UK Workshop on. IEEE, 2014. Joyce, C.A., et al, "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation", Psychophysiology, 41(2), 2004.lications. The results of this research implicate the ability to predict fatigue for the aim of developing fatigue countermeasure devices for day-to-day use. The solution is designed around comfort and cost by using limited number of dry electrodes. It can be integrated into multiple head-worn devices and applied in several domains including driver and workplace safety and air traffic control. footnote: All authors were full-time or intern employees at Intel when this work was conducted. References: Ji, Q. et al, "Real-time nonintrusive monitoring and prediction of driver fatigue." IEEE transactions on vehicular technology 53.4 (2004): 1052-1068. Abbood, H., et al, "Prediction of driver fatigue: Approaches and open challenges", Computational Intelligence (UKCI), 2014 14th UK Workshop on. IEEE, 2014. Joyce, C.A., et al, "Automatic removal of eye movement and blink artifacts from EEG data using blind component separation", Psychophysiology, 41(2), 2004.

1-D-36 Fronto-central theta oscillations reflect cognitive monitoring processes in collision avoidance tasks

Ruslan Aydarkhanov[1], Marija Uscumlic[2], Ricardo Chavarriaga[1], José del Millán[3]

[1]EPFL, [2]Nissan International SA, [3]Ecole Polytechnique Fédérale de Lausanne (EPFL)

Introduction: Interaction with the environment requires perceptual processing of the scenes before taking actions. Typical everyday tasks, e.g. driving, include stimuli which cannot be instantly interpreted. In case of driving we need to observe and predict the behavior of pedestrians and other drivers when deciding whether to accelerate, to brake, to change lane or to turn. A BCI system can decode the driver's engagement in scene understanding and action preparation so as to provide seamless assistance [1]. In this study we focused on EEG signatures of the cognitive processes enabling the prediction of collisions of moving stimuli in a 2D environment and the upfollowing action to prevent it. Material, Methods and Results: Two experimental sessions were split into 8-minute long runs with short trials of ~5s. In the beginning of the trial 2 circular objects appear on the screen: one in the center (i.e. target) and the other one at the specified distance from the target at a random angle. After 1s delay the second object starts moving in the direction of the target with a constant speed. In fifty percent of the trials the second object collides with the target, while the rest end up as misses. Subjects (N=16) must identify as soon as possible whether the objects will collide. The angle of the movement defines the trial outcome and the difficulty level of the task: angles close to the tangent to the target lead to greater variability in response time. If the subjects predict the collision, depending on the given instruction, they press the button immediately or report the decision after the trial finishes. EEG signals were acquired with a 64-channel BioSemi ActiveTwo system. Eye movements and index finger flexion were recorded with 3 EOG and 2 EMG electrodes. We applied CAR referencing and SPHARA artifact removal method, followed by filtering with Butterworth filter in the range 1-30 Hz. We then estimated the time course of θ-power in each channel using continuous wavelet transform with a complex Morlet wavelet (averaged over several frequencies in the range 3-8 Hz). Stimulus-locked and response-locked signals were analyzed with baseline of 100 ms period prior to the movement onset of the object. We considered only collision trials with motor responses (110 trials per subject on average) and binned them based on the response time (Slow, Medium and Quick) thresholding at 0.33 and 0.66 quantiles. The fronto-central θ-power consistently increased from the stimulus movement onset and reached its peak value at about the motor action (Figure 1). The Pearson correlation between response time and θ-power confirmed the correlation with fronto-central region before the response. Binary classification was applied to trials binned into Quick and Slow thresholded at median response time. Regularized QDA on θ-power at 7 fronto-central channels at [-800, -200] ms window before the response produced AUC value of 0.77 on average across subjects in leave-one-run-out cross validation (13 subjects above chance level). Discussion: The obtained results demonstrate that fronto-central increase in θ-power is linked to engagement in the analysis of visual stimuli when subjects need to make a decision about the upcoming action. This signature is distinguishable from motor-related increase in theta-power only in longer trials. Relatively low correlation values along with high classifier performance suggest non-linear development of theta. High classifier performance allows for further exploration in an online regime. Significance: The fronto-central theta increase is known to be related to cognitive processes, e.g. evidence accumulation [2]. This study reports for the first time the same type of modulations in a collision avoidance tasks. Single-trial detection of such process will provide a valuable information on monitoring and decision making processes in dynamic situations. For instance, such information can be exploited by the driver-assistance systems to infer the driver's cognitive state and readiness to perform an action. Acknowledgements: This project was supported by Nissan Motor Co Ltd, under the 'Research on Brain Machine Interface for Drivers' project. References: [1] Chavarriaga, R. et al. (2013). Detecting cognitive states for enhancing driving experience. 5th Intl BCI Meeting. [2] van Vugt et al. (2012). EEG oscillations reveal neural correlates of evidence accumulation. Front Neurosci 6.

1-D-37 Noise-tag BCI for covert selective attention in different modalities

Sara Ahmadi[1], Marzieh Borhanazad[1], Peter Desain[1]

[1]Radboud university, Donders Center for Cognition

Introduction: Exogenous brain-computer interface (BCI) support communication through brain activity recorded by EEG in response to the external stimuli such as visual, auditory or tactile. Various methods, such as transient evoked potentials (P300) or steady-state evoked potentials (SSEP), have been proposed and applied in different modalities. Despite many achievements, these paradigms failed to be used in a practical BCI system due to their limitations like poor accuracy, low speed or difficulties increasing the number of stimuli. These issues are recently addressed using pseudo-random code evoked potentials. A successful example of such a method is noise-tag BCI [1] implemented in the visual domain having reliability, high speed and the possibility to work without calibration phase. However, the visual application is dependent on eye gaze. In this study, we will extend the noise-tagging method to covert selective attention and evaluate it in auditory and tactile modalities. Material, Methods and Results: The noise-tag method exploits specific pseudo-random bit sequences known from telecommunication. Our auditory stimuli consisted of two stories narrated by a female and a male speaker which were amplitude modulated using two code signals. The stimuli were simultaneously presented using a pair of loudspeakers placed at the sides of the subject and the subjects were instructed to attend to the male or female voice. The tactile stimuli were two codes which were presented simultaneously to the subjects' left and right index finger using braille tactile stimulators. Subjects were asked to attend to one of the fingers and count the deviant. In order to analyze the recorded EEG signals to identify the attended stimuli, we used a generative model, reconvolution [1] to predict the responses to the codes. Reconvolution is based on temporal dynamics (transient response) and the spatial distribution. Both can be learned at once by applying Canonical Correlation Analysis

(CCA) which maximizes the correlation between spatially filtered data and the convolution of the stimulation sequence and the transient responses. Once the transient responses and spatial filter are learned, the response to any new stimulation sequence can be predicted by convolution. Here we designed a novel CCA technique to deal with lateralized activation of brain signals in auditory and tactile modalities. The novel method, called dual-CCA, results in two spatial filters corresponding to two attended sides. Subsequently, a template matching classifier was used to identify the attended side. Our preliminary results show the viability of noise-tagging method also in auditory and tactile modalities. Figure 1 shows an example of the resulting activity pattern and transient responses obtained from both single CCA [1] and our novel dual CCA method in the auditory task. We observed a classification accuracy significantly above chance level in the auditory task. Our preliminary results of the tactile experiment show evidence that our method is applicable and provides reasonable activity pattern and transient responses. Discussion: We designed our dual CCA based on the assumption that the transients from the left and right attention have the same behavior and time course while the brain activities have different spatial distributions. Therefore we expect our dual-CCA to provide more discriminating pattern leading to more accurate classification. The activity patterns obtained using single and dual-CCA illustrated in Figure 1a shows the capability of dual-CCA to segregate the brain activity assigned to the attended side. Furthermore, the obtained transient responses show a similar pattern to what is reported in the literature on dichotic listening task (eg.[2]). Significance: We extended the noise-tag method to auditory and tactile modalities and provide an effective analysis tool to obtain the patterns of latralization seen in brain activities. Based on the preliminary results, we foresee to be able to design BCIs that can be effectively used by people who are not able to benefit from visual BCI. [1] J. Thielen, et al. Re(con)volution: Accurate response prediction for broad-band evoked potentials-based brain-computer interfaces. In Brain-Computer Interface Research. Springer 2017. [2] J. A O'sullivan, et al. Attentional selection in a cocktail party environment can be decoded from single-trial EEG. Cerebral Cortex, 25(7),2014.

1-D-38 Towards multiclass Brain-Computer Interface for joint human-computer image analysis

Steven Gutstein[1], Brent Lance[2], Anthony Ries[3], Vernon Lawhern[2], David Slayback[1]

[1]Army Research Laboratory, [2]U.S. Army Research Laboratory, [3]Army Research Labs

Introduction: Advances in Brain-Computer Interface (BCI) technologies include techniques allowing humans to triage images using Rapid Serial Visual Presentation - RSVP (Sajda et al., 2010). These techniques utilize machine learning to analyze electroencephalography (EEG) signals when a person sees a sparsely occurring target image. However, they are limited to binary target/non-target classification problems, and are sensitive to the target/non-target ratio. Yet, most practical image classification tasks are multi-class. Here, we present a novel, multi-class RSVP method that may also be more robust to the target/non-target ratio. We call it Mismatch Rapid Serial Visual Presentation (M-RSVP). M-RSVP is based on differences in EEG signals between viewing images with matched and mismatched labels. We define the M-RSVP paradigm and present initial results. Material, Methods and Results: During M-RSVP, we rapidly show subjects individual images. Shortly after each image is displayed (0.25-1s), a label is superimposed. After another brief interval the process repeats. Stimuli (i.e. images and labels) are drawn from the Places2-365 dataset, which consists of 365 locations, each with 5,000-30,000 images [3].

The labels may or may not correctly describe (i.e. match) the images. We used a standard counting procedure, where subjects counted the number of incorrect labels (i.e. mismatched stimuli) in an experimental block. A 38 year old male performed ten 2-minute M-RSVP blocks. Image-label pairs were presented sequentially for one second each, giving a presentation rate of 0.5 Hz to minimize ERP overlap, but early testing indicates higher presentation rates are possible. Further reducing overlap, image and label onset were randomly jittered by up to ±100ms. The match/mismatch ratio was 80/20. EEG data were recorded at 256Hz using a Biosemi ActiveTwo system with 64 active Ag/AgCl electrodes. Vertical (VEOG) and horizontal (HEOG) electrooculogram were recorded with VEOG electrodes centered superior and inferior to the left eye and HEOG electrodes placed along the outer canthus of each eye. Additionally, reference electrodes were placed on both mastoids. Discussion: EEG data were re-referenced to averaged mastoids, high/low pass filtered at 0.1Hz/40Hz. The EEG data was epoched into 1-second epochs timelocked to the onset of label events. Averaged ERPs were generated for matching and mismatched stimuli. An ERP showing their difference was generated. The resulting ERPs are shown in Figure 1. A separation between the matching and mismatched stimuli appears approximately 400ms after label presentation. Preliminary results show an N400 response in the data. A negative deflection in the EEG voltage 400ms after label presentation characterizes this response. The N400 is evoked through semantic discrepancies in image or text stimuli [1]. A presentation rate of 0.5 Hz was used to maximize ERP separation. Preliminary testing indicates the possiblity of running the M-RSVP at rates up to 2 Hz. The M-RSVP will likely show higher performance levels when the semantic distinctions between the labels are broad. However, this may not be a major limitation - previous work shows computer vision provides higher performance than humans at fine-grained recognition in domains with large numbers of labels[2]. Significance: We introduced a novel BCI paradigm of potential use for joint human-computer vision analysis of large image databases. Our preliminary results, have several promising implications in joint human-computer image analytics. M-RSVP should be more amenable than RSVP for non-binary classification problems and could potentially be used with Active Learning to iteratively update a computer vision system Acknowledgements: This project sponsored by the U.S. Army Research Laboratory under CAST 076910227001 and ARL-H70-HR52. References: [1] Kutas, M., & Federmeier, K. D. (2011). Thirty years and counting: Finding meaning in the N400 component of the event related brain potential (ERP). Annual Review of Psychology, 62, 621-647. [2] Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., ... Fei-Fei, L. (2015). ImageNet Large Scale Visual Recognition Challenge. International Journal of Computer Vision, 115(3), 211-252. [3] Zhou, B., Khosla, A., Lapedriza, A., Torralba, A., & Oliva, A. (2016). Places: An Image Database for Deep Scene Understanding. arXiv:1610.02055 [Cs]

1-D-39 An EEG measure for individual written text difficulty assessment in neuroadaptive learning environments

Lena Andreessen[1], Peter Gerjets[2], Detmar Meurers[3], Thorsten Zander[4]

[1]TU Berlin, [2]Leibniz-Institut für Wissensmedien, [3]Eberhard-Karls-Universität Tübingen, [4]Zander Laboratories B.V.

Introduction: In online-learning environments students are presented a variety of written text material for information conveyance. The difficulty with which a text can be read and consequently understood is highly individual, depending on factors as years of education, professional knowledge, etc. This work presents an approach to identify an EEG measure which is reflective of workload changes in individuals as a result of reading at different levels of written text difficulty and reading speed. When employed in an online-learning environment such a measure could be used to keep the text difficulty of learning material at an optimal level for the individual learner. Material, Methods and Results: Seven participants read six easy and six difficult texts of approx. 500 words each. The text difficulty was determined according to the established readability measure Flesch Index (Felsch, 1948). A pre-test confirmed (n=6) that easy texts resulted in lower subjective workload than difficult texts according to NASA-TLX scores. EEG was recorded from 64 electrodes while each participant read all twelve texts with the RSVP (Rapid serial visual presentation) presentation technique. Instead of presenting the full text in a continuous fashion, here each word is presented by itself in a sequence at a constant position on the screen. Half of easy and difficult texts was presented at a self-adjusted presentation speed to the reader and the other half with an increase of 40 percent. The pre-test had also confirmed that subjective workload is significantly higher for such an increase in presentation speed. A participant specific predictive model derived from a task-independent workload paradigm each participant had completed, was applied off-line to EEG data recorded during text reading. This resulted in predictive values ranging between 0 and 1 for each word in a text, 0 indicating low workload and 1 high workload. Predictive values were subjected to a repeated-measures two-way AVOVA. Results showed a significant effect for the factor text difficulty ($F(1,6)=6.719$, $p=.041$) and no significance for the factor presentation speed ($F(1,6)=3.601$, $p=.107$). There was no significant interaction ($F(1,6)=.081$, $p=.785$). Discussion: Though there is high variance in workload prediction for single words in easy and difficult texts, statistical testing revealed an overall significant increase in predictive values of workload for difficult texts. Predictions for texts presented with an increase of 40 percent were not significantly higher. Therefore predictions made by task-independent workload classifier could be used as an individual measure to distinguish between levels of texts readability. This approach should be tested for a larger variety of text material. It also should be tested for its robustness and include a larger population of participants. Significance: We successfully trained a BCI which can distinguish between levels of written text difficulty. In an online-learning environment the individual user model built by the system could be enriched by feeding it the output of such a BCI. Over time the system could learn about the individual user's readability skills and neuroadaptively generate personalized texts. Reading at balanced levels of workload would be established to improve learning efficiency for the learner. References: Flesch, R. (1948). A new readability yardstick. Journal of applied psychology, 32(3), 221.

1-D-40 Active inference for adaptive BCI : An application to the P300 speller

Jelena Mladenovic[1], Jérémy Frey[2], Emmanuel Maby[3], Mateus Joffily[4], Fabien Lotte[5], Jérémie Mattout[3]

[1]Potioc Inria, and CRNL Inserm, [2]Ullo, [3]Lyon Neuroscience Research Center, [4]Gate CNRS, [5]Inria, LaBRI (Univ. Bordeaux, CNRS, Bordeaux-INP), France / RIKEN BSI, Wakoshi, Japan

Introduction: Adaptive BCIs have shown to improve performance [1], however thorough adaptation is far from being reached, and a general and flexible framework to implement adaptive features is still lacking. We appeal to a generic Bayesian approach, called Active Inference (AI), which tightly couples

perception and action [2]. Endowing the machine with AI, enables: (1) to infer user's intentions or states by accumulating observations (e.g. electrophysiological data) in a flexible manner, as well as (2) to act adaptively in a way that optimizes performance. We illustrate AI applied to BCI using realistic P300-speller simulations. We demonstrate it can implement new features such as optimizing the sequence of flashed letters and yield significant bit rate increases. Material, Methods and Results: Active Inference rests on an explicit probabilistic model of user and task. Key variables include observed data, user's hidden states , and machine's action, as follows. The observed data, here EEG responses to target/non-target (P300 or not) and feedback stimuli (Error Potentials - ErrPs or not), allow the machine to infer user's hidden states, here the intention to spell a letter or pause as well as the user's recognition of a target/non-target or a correct/incorrect feedback. Depending on the hidden states inferred, the computer can conduct possible actions, here to flash in order to increase confidence about the target, to stop flashing and display the chosen letter, or to switch off the screen if it infers an idle state of the user, i.e. no P300 response has been observed for some time. Each hidden state is mapped onto observations through the data likelihood matrix which can be learned from calibration data. Given the machine's actions, the transitions between hidden states are modelled by a probability (Markov) matrix. We also predefine the preference over all possible outcomes. Typically, the preferred outcome is to be in the state of observing a correctly spelled letter. Finally, a parameter γ sets the exploration-exploitation tradeoff for action selection. We compared AI to two classical approaches: 1) P300-spelling with a fixed flash number (12) of repetitions and pseudo-random flashing; 2) P300-spelling with pseudo-random flashing but optimal stopping [3]. To do so, we used data from 18 subjects from a previous P300-speller experiment [4]. For each algorithm and subject, we simulated the spelling of 12000 letters. Furthermore, to demonstrate AI's flexibility, we implemented a "LookAway" feature, in which the machine would infer the user to be in idle state and would switch the screen off. We also simulated an ErrP classification enabling the automated detection of a wrongly spelled letter. In case of such detection, AI picks the next most probable letter to spell or choose to continue flashing to strengthen its confidence. AI showed significantly higher bit rate (54.12bit/min) than the second best strategy (optimal stopping, 45.70b/m), see fig 1. Its performance increased even further when a perfect ErrP classifier is used (73b/m). Finally, when idle user states are simulated, it accurately switches off the speller around 89% of the time, after about 24 flashes. Discussion: Our results demonstrate a great potential for implementing adaptive BCI beyond existing approaches, showing an increase of 18% and 59% (using ErrP classifier) in bit rate. Significance: AI outperforms other algorithms while offering a possibility of unifying various adaptive implementations within one generic framework. Thanks to such generality, with only a few tuning of its parameters, AI can incorporate many features, such as automated correction or accounting for an idle user state. It can adjust to signal variability by inferring about the user, but it can also take into account the influence of its actions onto the user. This approach lays ground for future co-adaptive systems.
References: [1] Mladenovic et al. 2018. A Generic Framework for Adaptive EEG-Based BCI Training and Operation, BCI Handbook -Technological and Theoretical Advance [2] Friston et al. 2006. A free energy principle for the brain, J. Physiol.100, 1-3, 70-87 [3] Mattout et al. 2015. Improving BCI performance through co-adaptation: applications to the P300-speller. Annals phys-rehab-med 58.1 : 23-28. [4] Perrin et al. 2011. Detecting and interpreting responses to feedback in BCI, GBCI, 116-119

1-D-41 HAIL: A human-autonomy crowdsourcing approach to image classification

David Slayback[1], Vernon Lawhern[2], Nicholas Waytowich[1], Addison Bohannon[1], Steven Gutstein[1], Brent

Lance[2]

[1]Army Research Laboratory, [2]U.S. Army Research Laboratory

Introduction: With the expansion of collected image data and its applications, the ability to efficiently sort and classify that data is critical. Expert human labelers are accurate but untenable for large datasets. Computer vision (CV) algorithms have made huge advances, achieving comparable accuracy to human labelers in many tasks several orders of magnitude faster [1]. However, such breakthroughs have been limited to domains where extremely large, labeled image datasets are available. CV still performs poorly on tasks where it is impractical to obtain such datasets. To address these deficiencies, we combine human and CV agents in an iterative process, leveraging human input to improve accuracy without slowing to the rate of manual labeling, similar to how the large-scale Places image database was developed. The initial pass queried search engines for images of desired categories, which Amazon Mechanical Turk workers verified. Then an AlexNet classified the images; images classified with high confidence were passed back to the AMT worker [2]. We propose to rapidly perform this process using the Human Autonomy Image Labeler (HAIL), a system that iteratively distributes images among human and CV agents for classification. HAIL determines its distribution based on the inferred speed and accuracy of each agent, minimizing the number of human labels required and maintaining the speed of CV. Additionally, we introduce a brain-computer interface (BCI) labeling modality, using electroencephalography (EEG) data generated during rapid serial visual presentation (RSVP) of task images to provide a faster method for human input [3]. While this version of HAIL worked well on small problems, we continue to make improvements in order to move towards the goal of processing large-scale image data. Material, Methods and Results: We developed a crowdsourcing framework for labeling images with several types of interchangeable agents: pretrained CV models (currently running on Raspberry Pis), manual human labelers, and BCI human labelers. These agents are linked to the system with the LabStreamingLayer (LSL) framework. We evaluated the system on a subset of 10 categories from the Places scene image database, classifying images from 1 category as targets and others as nontargets. This evaluation used 1 manual, 1 BCI, and 8 CV labelers. Our system achieves comparable accuracy to a manual labeler with only 1 tenth of the time. Discussion: Early testing of HAIL demonstrates marked improvements over both CV and human labeling alone. The Places dataset is difficult for standard CV due to its focus on scenes rather than objects, but HAIL was able to achieve human-level accuracy at nearly the same speed. Using a modular approach allows HAIL to adapt to the availability of different labeling agents as well as future advances in CV and BCI. Extensions of HAIL will incorporate multi-class labeling [4] and more sophisticated reinforcement learning methods for image distribution, expanding its potential use cases. Significance: Many tasks within image classification and other domains still require manual human input for adequate performance. HAIL illustrates the value of human-autonomy collaboration for these tasks by providing a successful test case of a crowdsourcing approach. In the future, HAIL and systems like it can be extended to new domains of data processing that might otherwise be intractable. Acknowledgments: This project was sponsored by the U.S. Army Research Laboratory under ARL-H70-CYB, ARL-H70-HR52, and through Cooperative Agreement Number W911NF-17-2-0153. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. Government. References: [1]Russakovsky, O. et al., ImageNet Large Scale Visual Recognition Challenge, International Journal of Computer Vision, vol. 115, no. 3, pp. 211-

252, 2015. [2]Zhou, B. et al., Places: A 10 million Image Database for Scene Recognition, IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. PP, no. 99, pp. 1-1, 2017. [3]Saproo, S. et al., Cortically Coupled Computing: A New Paradigm for Synergistic Human-Machine Interaction, Computer, vol. 49, no. 9, pp. 60-68, 2016. [4]Lance, B. et al.,Towards Multiclass Brain-Computer Interface for Joint Human-Computer Image Analysis in AAAI HCOMP, 2017.

1-D-42 Neurofeedback improves SSVEP BCI performance on subjects with both 'high' and 'low' performance

Qi Tang[1], Wenya Nan[1], Feng Wan[2], Yong Hu[3]

[1]Shanghai Normal University, [2]University of Macau, [3]The University of Hong Kong

Introduction: Our previous work has demonstrated that the SSVEP BCI users with low performance (i.e. classification accuracy <80%) can be improved by alpha down-regulation neurofeedback training (NFT) [1]. However, it is unclear whether the NFT benefits on a larger population with both 'high' and 'low' initial performances. Furthermore, whether the improvement of BCI performance after NFT is predictable using initial BCI performances is an important question for subject selection in the NFT. Thus, this study aims to answer the above two questions. Material, Methods and Results: In total 12 subjects (age: 28 ± 6 years, 4 females) including 8 subjects with high classification accuracy completed the 10 NFT sessions in two consecutive days. The experiment protocol and settings remain consistent with previous work [1]. Results show that IAB is reduced during NFT and the protocol is effective to improve the BCI performance for subjects with both 'high' and 'low' initial performances in SSVEP trials in analysis time length starting form 1s to 3.5s. Using 3s analysis time length of SSVEP flashing as an example (see Fig. 1), a paired t-test revealed a significant improvement on both the SSVEP signal SNR ($t(11) = 4.168$, $p = 0.002$) and the BCI classification accuracy ($t(11) = 3.310$, $p = 0.007$) for all subjects. More specifically, the 'high' performance group showed an average increase of 11.9% in the SSVEP signal SNR and an average increase of 15.11% in the BCI classification accuracy. For the 'low' performance group, the signal SNR has increased 16% and the BCI classification accuracy has increased 45.29%. Furthermore, Spearman correlation test showed that the percentage change of accuracy after NFT was significantly correlated with initial BCI accuracy ($r=-0.796$, $p=0.002$) in 3s analysis, and such correlation was also found in the analysis data with 2s, 2.5s and 3.5s. Discussion: The results indicate that NFT can benefit wide range users with both 'low' and 'high' BCI performances. However, the improvement of BCI accuracy in 'high' group is much smaller than the 'low' group, which may be explained by ceiling effect and one outlier (accuracy increased from 48% to 94%) in total 4 subjects with 'low' initial performance. Significance: This study verifies that alpha down-regulation neurofeedback training can improve the SSVEP BCI performances for subjects with both high and low initial BCI performances, and the improvement of BCI accuracy is predictable using initial BCI accuracy. Acknowledgements: Supported in part by Macau Science and Technology Development Fund (036/2009/A, 142/2014/SB and 055/2015/A2) and Univ. of Macau Research Committee (MYRG: 139-FST11-WF, 079-FST12-VMI, 069-FST13-WF, 2014-00174-FST, 2016-00240-FST and 2017-00207-FST). Reference: [1] F. Wan, J. N. da Cruz, W. Nan, C. M. Wong, et al., "Alpha Neurofeedback Training Improves SSVEP-Based BCI Performance", J Neural Eng, vol. 13, no. 3, p. 036019, 2016.

1-D-43 Brain functional connectivity associates with fatigue in SSVEP-BCI applications

Chi Man Wong[1], Feng Wan[1], Yong Hu[1], Agostinho Rosa[2]

[1]University of Macau, [2]University of Lisbon

Introduction: Fatigue is considered as a major challenge of practical use of steady state visual evoked potential (SSVEP) based brain-computer interfaces (BCIs) as it brings hazard to health and degradation of system performance [1]. In this work, we performed EEG based brain network analysis to study the fatigue development in SSVEP-BCIs applications. An experiment has been designed to induce fatigue to 2 subjects during an SSVEP-BCI task. The connectivity in frequency bands of delta, theta, alpha and beta based on magnitude square coherence of EEG signals between electrodes has been calculated to build the functional network. The network parameters have been investigated according to fatigue references based on subjective self-assessment and system performance. Material and Methods: The experiment protocol is concisely presented in the sub-figure a: The subjective fatigue evaluation is conducted with Stanford Sleepiness Scale. It is a well-accepted and very concise fatigue scale, so that the recurrent fatigue assessment would not be too disturbing to the subjects. The threshold for connectivity was chosen individually to deal with the individual difference [2-4]. Results: Between pre- and post- baseline measurement, delta and alpha bands connectivity show most active changes. The connectivity in delta band decreased in right frontal and increased in left central and occipital area while alpha band connectivity increased in right frontal area in eye-closed baseline measurement. The connectivity between pre- and post open-eyes baseline did not show consistent results across subjects. In SSVEP task sessions, alpha and beta bands connectivity show most active changes. Active changes happen in frontal, central and occipital areas. As subjects' fatigue level increase, the alpha and beta bands connectivity within these areas decrease; when subjects refreshed during the rest intervals, the connectivity increased. Some results of changes from both subjects are shown in the sub-figure b. Discussion: The changes in frontal area in right frontal agreed with studies [2], which reflected the changes in attentions between alert and fatigue states in baseline measurement. The changes in central and occipital areas during the SSVEP tasks are highly possibly due to the increasing workload in visual cortices and the drowsiness of subjects accumulated during the experiment. Significance: Investigated the changes of brain dynamic state in the fatigue development during SSVEP-BCI tasks. More information about the mechanism of fatigue in SSVEP-BCIs is explored. Acknowledgement: Supported in part by Macau Science and Technology Development Fund (036/2009/A, 142/2014/SB and 055/2015/A2) and Univ. of Macau Research Committee (MYRG: 139-FST11-WF, 079-FST12-VMI, 069-FST13-WF, 2014-00174-FST, 2016-00240-FST and 2017-00207-FST). References [1] Gao SK, Wang YJ, Gao XR, Hong B. Visual and auditory brain-computer interfaces. IEEE Trans. Biomed. Eng. 61(5): 1436-1447, 2014. [2] Sun Y, Lim J, Meng J, et al. Discriminative analysis of brain functional connectivity patterns for mental fatigue classification[J]. Annals of biomedical engineering, 2014, 42(10): 2084-2094. [3] Kar S, Routray A, Nayak B P. Functional network changes associated with sleep deprivation and fatigue during simulated driving: validation using blood biomarkers[J]. Clinical Neurophysiology, 2011, 122(5): 966-974. [4] Liu J P, Zhang C, Zheng C X. Estimation of the cortical functional connectivity by directed transfer function during mental fatigue[J]. Applied ergonomics, 2010, 42(1): 114-121.

1-D-44 Hybrid BCI development based on SSVEP and RSVP for the neurogaming with a purpose

Li-Wei Ko[1], Yun-Chen Lu[1], Yufei Huang[2], Tzyy-Ping Jung[3]

[1]*National Chiao Tung University,* [2]*University of Texas at San Antonio,* [3]*University of California, San Diego*

Introduction: A brain-computer interface (BCI) is a direct communication channel between the human brain and an external device. Despite the immense advancements in recent years, the current BCIs have not been used widely in real-world applications, which require robust performance over a long period of time. The fluctuations in BCI performance might be in part attributed to changes of users' brain states (caused by fatigue, motivation, etc.) over time. This study aims to explore the effects of brain-state changes on the BCI performance the electroencephalogram (EEG). However, the current BCI paradigms are not engaging participants to perform experiments for a longer duration. BCI paradigm embedded into games with a purpose (GWAP) is a promising approach overcomes the issue. Method: This study seamlessly integrates Rapid Serial Visual Presentation (RSVP) and Steady State Visually Evoked Potential (SSVEP) BCIs into a hybrid BCI-based GWAP. The GWAP resembles a popular match-three puzzle game (e.g. Candy Crush), where the player manipulates icons to make them disappear according to a matching criterion. Figure 1 shows a snapshot of the proposed GWAP. In the GWAP game design, an SSVEP BCI is used to identify one of the multiple target positions and an RSVP BCI is used to recognize the target icon. This study adopted a commercial EEG system to collect 32-channels EEG data (Neuroscan NuAmp System). We also propose a hierarchical classification process to analyze the EEG data collected during the experiments. The first layer used Canonical Correlation Analysis (CCA) to classify the SSVEP signals for identifying the target position. The second layer used machine-learning classifiers such as Bagging Tree, SVM, LDA, and BLDA to classify the event-related potentials (ERP) in RSVP for detecting the target icons. Results: Experiment results showed that the SSVEP classification accuracy achieved 97.90%, while the RSVP classification performance reached 83.45%. The resultant overall performance of the hybrid BCI system was 81.56%. In addition, we observed a constant drop in the RSVP performance after section 4, which could be due to physiological state changes. By comparing RSVP performance to the theta band power in the occipital lobe (related to mental fatigue) and alpha band power of frontal lobe (related to attention), we observed an inverse relation between the performance and both the band powers. Conclusions: In this study, a new hybrid BCI-based GWAP was developed for recognizing multiple targets through the SSVEP and RSVP in the real environment. SSVEP was used for predicting the participants' selected visual option (one option out of the four), and RSVP was used to for recognition target item embedded in the visual stimulation. The overall performance of the hybrid BCI system obtained through hierarchical classification was 81.56%. Study results also showed that the subjects' BCI performance significantly affected by the changes in their physiological states. We found a negative correlation between the accuracy of target detection across different sessions and the frontal alpha and occipital theta powers, during the sustained use of RSVP.

1-D-45 Toward automatized placement of visual stimuli for gaze-independent SSVEP-BCI

Anibal Cotrina[1]

[1]Federal University of Espirito Santo

Introduction: In a SSVEP-BCI based on depth-of-field [1], two LED-based stimuli are properly placed in the center of the field of view but at different distances. This placement allows users to select one stimulus by focusing on it, so that the other one is distanced and non-focused. Since both stimuli are projected close to each other in the center of the field of view, the gaze redirecting is not demanded. In the present work, a robotic-based system is proposed for visual stimuli placement (Fig. 1a). The aim is to (re)adjust automatically the positions of two stimuli to ensure they are properly placed in the user's field of view (top inset of Fig. 1b); mainly when involuntary movements arise during the BCI operation (see two examples in the bottom inset of Fig 2b). Material, Methods, and Results: The placement system of two visual stimuli is composed by two articulated robots (with 3 servo-based joint and 2 plastic links of 10 cm) connected to two visual stimuli (7×5 green LED arrangements flickering at 5.6 and 6.4 Hz), and a video camera (30 fps), as shown in Fig 1a. Robots adjust the stimuli positions by using information of a camera. The Control system block represents the algorithm that computes the next position of each stimulus. For this purpose, face markers (such as point center of the face, eyes, and midpoint) are detected in online mode and associated to the position of a stimulus (by computing distances) when it is properly placed. It allows to apply feedback control to update positions when distances vary; and inverse cinematic to move the stimulus to the updated position. In current stage of the work, the stimuli placement process; which includes markers detection, distances computing, updating positions and movement of the robot, is performed under a time window of 1s. First visual stimuli are relocated and then they are turning on for sending a BCI command. Discussion: People with paralysis may have involuntary movements during the operation of SSVEP-BCIs that can reduce the performance of the interface. Visual stimulus must be projected on the fovea, the region of the retina with high density of photoreceptors [2]. The accuracy of the command detection can achieve 0.93 for a time window (TW) of 4s [3]. A right stimulation process can increase the accuracy that can reduce time of command recognition. In the present stage of the work, the reallocation time increase the TW and consequently reduce the bit of rate; however, in future experiments the automatic placement will be done when stimuli are on. Significance: Due to the high performance of SSVEP-BCI systems, gaze-independent SSVEP-BCI systems are being developed to overcome the demanding of muscular control and make them suitable for people with paralysis [4]. Devices that ensure the stimulation units are placed in the right position regarding to the users must be considered in the development of gaze-independent systems, mainly during the BCI operation. References <p>[1] Cotrina A. Toward brain-computer interaction in paralysis: a new approach based on vep and depth of field. Springer 2017</p> <p>[2] Seiple et al. The spatial distribution of selective attention assessed using the multifocal vep. Vision Research, 42(12), 1513-21, 2002</p> <p>[3] Cotrina A et al. A SSVEP-BCI setup based on Depth-of-Field. IEEE Trans.of neural system and rehabilitation eng. 25(7): 1245-45, 2017</p> <p>[4] Riccio et al. Eye-gaze independent EEG-based brain-computer interface for communication. J. Neural Eng. 9, 045001, 2012</p>

E- Signal Acquisition

1-E-46 Comparison of conventional and tripolar EEG electrodes in BCI paradigms

Charles Anderson[1], Walter Besio[2], Saleh Alzahrani[1]

[1]Colorado State University, [2]University of Rhode Island

Introduction: The hypothesis driving our work is that the limitation in the reliability of BCI systems is primarily due to a lack of precision in EEG recorded from scalp electrodes. Activity from relatively large areas of the brain affect the signal that is recorded by one electrode, so differences in brain activity in neighboring brain regions cannot be detected. This poster will summarize our recent work investigating W. Besio's new EEG sensor, the Tripolar Concentric Ring Electrode (TCRE), which has been shown to be capable of recording more localized activity and activity at higher frequencies than is possible using conventional EEG electrodes [1]. Here we summarize preliminary experiments using TCRE electrodes in BCI-related applications. <p>Material, Methods and Results: We will present results from the analysis of P300 ERPs and motor-related potentials using EEG recorded with conventional EEG electrodes and Besio's new TCREs. Initial results of P300 analysis were obtained using EEG recorded at position Pz simultaneously with a conventional electrode and a TCRE while a subject performed a common P300-Speller task. As expected, classification accuracy of P300 ERPs increased by averaging over multiple trials with both electrodes. However, classification accuracy of EEG recorded with the TCRE electrode was up to 20% higher than that obtained with conventional electrodes. <p> For our initial experiments with motor-related potentials we recorded EEG from conventional electrodes and TCREs from Cz, C1, C3 and C5 during finger tapping. By averaging EEG over multiple trials, synchronized to the finger tap, we obtained averaged motor-related potentials (MRPs) shown in the following figure. We found that the MRPs from TCREs were much clearer than those from conventional EEG. More importantly, the shape and amplitudes of the MRPs are different among the TCRE electrodes, even though they are quite close on the scalp. This difference is not seen in the MRPs from conventional EEG electrodes. This result agrees with Besio's earlier study of MRPs [2]. A study of R2 correlations between energy in frequency bands and movement versus rest reveals a strong correlation with movement in data from TCREs that is more spatially focused than seen in data from conventional EEG electrodes. <p> Discussion: Results indicate that tripolar TCRE electrodes provide EEG recordings with higher spatial resolution and higher frequencies that what can be obtained with conventional EEG electrodes. <p> Significance: The increased spatial resolution and higher frequencies provided by the new TCRE electrodes may lead to breakthroughs in the reliability of BCI applications based on noninvasive EEG recording technology. <p> References
 [1] Liu, X. and Besio, W., Comparisons of the Spatial Resolution between Disc and Tripolar Concentric Ring Electrodes, in Proceedings of the Fifth International Brain-Computer Interface Meeting, 2013.
 [2] Koka K. and Besio, W., Improvement of Spatial Selectivity and Decrease of Mutual Information of Tri-Polar Concentric Ring Electrodes, Journal of Neuroscience Methods, vol. 165, pp. 216-222, 2007.

1-E-47 Acquisition and classification of haptic P300 signals for Brain Computer Interface

Kup-Sze Choi[1], Guanjin Wang[1], Shuang Liang[2], Zhaohong Deng[3]

[1]Hong Kong Polytechnic University, [2]Shenzhen Institutes of Advanced Technology, [3]Jiangnan University

Introduction: Human vision is largely exploited for developing brain computer interface (BCI). Among them, the P300 speller has achieved major success in assisting paralyzed people to communicate with the world, where the odd ball paradigm is implemented by the appearance of visual information anticipated by users to evoke characteristic brain signals. However, such systems require constant focus of the eyes that can lead to visual fatigue. For virtual reality applications, it may distract the attention of users from the virtual environment that they are concurrently interacting with. In this study, the haptic counterpart of visual P300 is explored for BCI development. The haptic sensation can provide additional degrees of control and flexibility for BCI system design. The experimental paradigm for acquiring haptic P300 electroencephalogram (EEG) signals and the classification are presented. Material, Methods and Results: The haptic P300 EEG signals concerned in the pilot study were event related potentials resulting from vibrotactile stimuli applied to user's limbs. It investigated the feasibility to classify EEG signals due to vibration at each individual limb, which could be used to implement haptic-based BCI systems. The stimuli were generated by attaching a small vibration motor to each of the four limbs. The motors were programmed so that the user felt one second of vibration at one limb, followed by four-second rest, and then one-second vibration at another limb, and so on; sequentially from the left forearm (LF), right forearm (RF), left lower leg (LL) to the right lower leg (RL). In one session of the experiment, the above vibration sequence repeated 20 times. A subject was recruited to undergo four sessions of experiment. The subject was required to pay attention to the vibration to be applied to a specific limb in each session. That is, there were 4 labels (LF, RF, LL and RL), one for each limb. For each session, 20 samples of target class and 60 samples of non-target class were obtained. The EEG signals were collected from 16 electrodes of the international 10/20 system, i.e., Fz, FC1, FC2, C3, Cz, C4, CP1, CP2, P7, P3, Pz, P4, P8, O1, Oz and O2. 80% of the acquired EEG data were randomly selected for training and the remaining 20% for testing. The EEG signals were bandpass filtered in the range of 8-35Hz. Features of the signals were extracted by using common spatial pattern filtering. Classification was achieved by linear discriminant analysis (LDA) and support vector machine (SVM) with Gaussian kernels (kernel width σ = 20; penalty parameter C = 1000). The mean and standard deviation (SD) of the classification accuracy resulting from 100 runs of the two algorithms are shown in Table 1. (See the PDF file attached) Discussion: This study attempts to exploit the haptic perception channel to provide additional degrees of flexibility for BCI design and to relieve the burden of visual attention. The results show that haptic P300 EEG signals, acquired by user's anticipation of vibration at a specific limb, can be identified by classification algorithms, where SVM (over 0.7) outperforms LDA (0.64 to 0.69). The classification accuracy is expected to be further improved by collecting more data and using more advanced machine learning algorithms. However, unlike the acquisition of visual P300 signals where paying attention to visual stimuli is simply achieved by gazing at target locations on computer screen, the act of concentrating on the vibration to occur at a specific limb is relatively an abstract concept. It is unclear about how this could be carry out consistently among different users, which may present challenges against the robustness of classification algorithms. Significance: The results of the study show that haptic stimulus can potentially be leveraged to develop BCI systems and enhance the performance. For paralyzed people whose haptic sensation remains intact, BCI system involving haptics can enhance their controllability and interactivity with world, and reduce fatigue due to over reliance on vision. Further research will be conducted to increase the size of the dataset, develop advanced classification algorithms and build online haptics-based BCI system. Acknowledgement: This work is supported in part by the Hong Kong Research Grants Council (PolyU 152040/16E)

1-E-48 Free Wally: A game for measuring meaningful motor intentions

Ceci Verbaarschot[1], Pim Haselager[1], Jason Farquhar[1]

[1]Radboud University; Donders Institute for Brain, Cognition and Behaviour

Introduction: Predicting motor intentions from brain activity has been achieved in previous research [e.g. 1]. However, while these studies measure self-paced limb movements, these have no noticeable consequences and participants are instructed to perform them spontaneously, i.e. for no apparent reason. It has been called into question whether motor intentions for such movements are ecologically valid and whether the achieved predictions would remain successful in real-life situations. Moreover, previous studies focus mostly on 1 out of 3 possible components of an intention: either the what, when or whether [2]. Because everyday motor intentions likely involve all 3 components at a time, these studies arguably collect incomplete datasets. To address both issues, we developed a computer game called "Free Wally", where players perform deliberate movements to achieve a specific goal. Stimuli provide reasons to move and movements have consequences. The game offers a choice of whether to move, what movement to perform and when to perform the movement, incorporating all 3 components related to an intention. As a control, we tested Free Wally against another game called the "Object Game", which mimics the traditional designs of previous research. By comparing these games, we investigate potential differences in neural preparation and participants' awareness of their intentions between spontaneous and deliberate movements. Material, Methods and Results: We recorded EEG data of 41 participants who performed 144 trials of the Free Wally or Object Game. The stimuli of both games are similar in terms of shape and timing. However, in contrast to Free Wally (Figure 1A), the Object Game stimuli have no meaning. In both games, participants can choose to move (i.e. perform a left/right hand button press) or do nothing on a single trial basis. While participants are playing either game, an auditory probe may be presented, similar to [3]. When a probe is presented and the participant: 1. did not intend to move: they should ignore the probe and continue the game 2. did intend to move: they should veto the movement and wait for the trial to end A cluster-permutation test on pre-movement data detected no significant differences between the two games in terms of brain signals, i.e. (Lateralized) Readiness Potential or alpha/beta ERD (Figure 1B). No significant differences were found between the two games in terms of the intention onset or point of no return. Discussion: Brain signals recorded during both games were comparable, suggesting that at least the late stages of movement preparation are similar for spontaneous and deliberate movements. This increases confidence that these signals can serve as reliable predictors of intended movement in real-life situations. Significance: Free Wally can measure meaningful motor intentions by invoking reasons and consequences. Furthermore, it allows the collection of training data to classify the content, occurrence and timing of a motor intention in a motivating and fun way. We hope our game enables future research into the formation and content of motor intentions, specifically during the early stages of movement preparation that have been left unexplored by the current study. [1] Schultze-Kraft, M., Birman, D., Rusconi, M., Allefeld, C., Görgen, K., Dähne, S. & Haynes, J. D. (2016). The point of no return in vetoing self-initiated movements. Proceedings of the National Academy of Sciences, 113(4), 1080-1085 [2] Brass, M., & Haggard, P. (2008). The what, when, whether model of intentional action. The Neuroscientist, 14(4), 319-325 [3] Matsuhashi, M., & Hallett, M. (2008). The timing of the conscious intention to move. European Journal of Neuroscience, 28(11), 2344-2351

1-E-49 EEG based emotion classification with cross frequency coupling in music listening with continuous response

Juanli Zhang[1], Amna Ghani[1], Petra Ritter[1], Randy McIntosh[2]

[1]Charite, [2]University of Toronto

Introduction The ongoing brain activity recorded by EEG is used to investigate the mechanism of music emotional regulation because of its informative characteristics during various emotional states. The real-time continuous response of emotion could provide a more accurate tie to how emotion evolve in the real world. In this study, our participants were allowed to perform the real-time subjective response to how they feel during music listening. Based on the fact that the emotion classification performance normally spanned from 55% to 72%[Lin et al., 2017] and that cross frequency coupling has the potential to provide differential insights into emotional states recognition[Schutter DJLG et al., 2012], this study aimed to research the different feature extraction methods to classify the emotional states. Especially, we concentrated on different forms of cross frequency coupling method and explored the best way to apply them into music emotion detection based on EEG signal. Material, methods and results Data were collected from 18 subjects in total. Forty pieces of music with an average length of 40s were selected for their capacity to induce various emotions mapped to valence and arousal levels. Subjects were seated in front a computer monitor and they used the mouse to indicate consistently their real-time ratings during listening a musical piece. The rating screen is shown with a two-dimension map, the horizon axis representing the valence (from unpleasant to pleasant)while the vertical axis is the arousal level(from relaxing to stimulating). EEG data were down sampled to 512 Hz, re-referenced to the average, eye blink artifacts removed by ICA, and band-pass filtered to 1-90Hz. Two forms of CFC, namely PSI (phase synchronization index) and PAC (phase amplitude coupling) were applied to classify the emotional states, and compared with normally used methods PSD (power spectral density) and DLAT (difference in left-right laterality direction). PSI was calculated in each of seven frequency bands (delta, theta, low-beta, high-beta, low-gamma, high-gamma) between each two of 11 channels (FP1, FP2, F3, F4, C3, C4, P3, P4, O1, O2, PZ), while PAC was formed by calculating the phase amplitude coupling index in each of 11 sites between each two of seven frequency bands. In order to explore how the frequency bands influence the classification performance, we also separated the frequency band 1-45 Hz into 11 intervals with a bandwidth of 4Hz. The methods were named PSI_4Hz and PAC_4Hz. After feature selection by Fisher Ratio, classifier SVM was applied to classify the different emotions with cross validated by leave-one-out (LTO). The results showed that the best performance was obtained by features derived from PAC_4Hz at mean accuracies of 93.49% 92.42% separately for valence and arousal binary classification, while PSI_4Hz method could attain the performance at accuracies of 88.78% and 85.71% respectively. Both in valence and arousal level, all the EEG coupling features outperformed the performance of feature types PSD and DLAT. Discussion Different methods captured diverse features of EEG dynamics and all of them could perform a better classification than chance level as shown in Fig.1. Our results demonstrated that the cross frequency coupling was more sensitive to characterize the EEG variation in response to emotional states. Significance: Our findings coincided with previous studies which highlighted the role of the measure of cross frequency coupling in indicating interaction among brain areas varying with frequency band during various emotional states. Acknowledgements: The authors acknowledge the support of the James S. McDonnell Foundation (Brain Network Recovery Group JSMF22002082), the German Ministry of Education and Research (US-German Collaboration in Computational Neuroscience01GQ1504A, Bernstein Focus State Dependencies of Learning 01GQ0971-5, the Max-Planck Society Minerva program) and the European Union Horizon2020 (ERC Consolidator BrainModes 683049) References: Lin Y-P, Jung T-P. Improving EEG-Based Emotion Classification Using Conditional Transfer Learning. Frontiers in Human Neuroscience. 2017;11:334. doi:10.3389/fnhum.2017.00334. Schutter DJLG, Knyazev GG. Cross-frequency coupling of brain oscillations in studying motivation and emotion. Motivation and Emotion. 2012;36(1):46-54. doi:10.1007/s11031-011-9237-6.

1-F-50 A new method for localizing activity in the brain based on empirical mode decomposition and entropy function

Maximiliano Bueno-Lopez[1], Eduardo Giraldo[2], Marta Molinas[1]

[1]Norwegian University of Science and Technology, [2]Universidad Tecnológica de Pereira

Introduction: <p>Empirical Mode Decomposition (EMD) is an adaptive time-frequency analysis method, which is very useful for extracting information from noisy nonlinear or nonstationary data. The applications of this technique to Biomedical Signal analysis has increased and is now common to find publications that use EMD to identify behaviors in the brain. In this work, a novel identification method of relevant Intrinsic Mode Function (IMF), obtained from EEG signals, using an entropy analysis is proposed. The idea is to reduce the number of IMFs that are necessary for the reconstruction of neural activity. The efficacy of the proposed method has been demonstrated in a simulated and real data base. A relative error measure has been used to validate our proposal.</p> Material, Methods and Results: <p> Brain Mapping: The Inverse Problem The forward problem of EEG generation can be formulated as y(tk)=Mx(tk)+ε(tk); being y(tk) the EEG, and x(tk) the neural activity, with tk=kh the time at sample k being k=1,...T the total number of samples, h the sample time and M<span style="text-align: justify;"> the lead-field matrix that relates the neural activity with the EEG. It is possible to formulate an iterative inverse problem [1] in order to estimate the neural activity.<p> Empirical Mode Decomposition The aim of the EMD method is to decompose the nonlinear and non-stationary signal into a sum of intrinsic mode functions (IMFs). EMD is applied over the EEG to obtain the IMF. Having obtained the IMF, we can apply the Hilbert transform to each component, and compute the instantaneous frequency.<p> Optimal IMF selection: Entropy Function In order to reconstruct the EEG signal, an optimal selection of the IMFs is proposed based in one threshold value obtained from the entropy function.<p> Experimental Setup The performance of the method is evaluated by using simulated and real EEG signals with epileptic activity. The methodology is shown in the attached figure.</p> Discussion: <p>This strategy avoids the use of the common methods that include expert clinicians with visual observation of EEG signals, which tends to be time consuming and sensitive to bias. The threshold value proposed was obtained after several tests with the values of entropy and retained energy in each IMF. The first validation using simulated databases allowed us to calculate the relative error and to affirm that the technique presented provides an accurate detection of sources associated to epileptic seizures. The decomposition using IMFs allows us to reconstruct the neuronal activity using only the information that is considered relevant for this application.</p> Significance: <p>We have proposed a new and simple methodology based on an entropy function and EMD that allows to reconstruct the neuronal activity using only the information that is considered relevant. This method also mitigates the problem of mode mixing that has been reported in previous papers [2].</p> Acknowledgment <p>This work was carried out during the tenure of an ERCIM 'Alain Bensoussan' Fellowship Programme.<p> References: <p> [1] E. Giraldo-Suarez, J.D. Martinez-Vargas, and G. Castellanos-Dominguez. Reconstruction of Neural Activity from EEG Data Using Dynamic Spatiotempora Constraints. International Journal of Neural Systems (2016), 1-15.<p> [2] M. Bueno-Lopez, E. Giraldo, and M. Molinas. Analysis of Neural Activity from EEG Data based on EMD frequency bands. In 24th IEEE International Conference on Electronics, Circuits and Systems (ICECS) (2017)

1-F-51 Optimizing the multi-orthogonal-space classifiers separately to get the global optimal EEG classification performance

Qiqi Zhang[1], Ying Liu[1]

[1]*Beijing Institute of Technology*

Introduction: The electroencephalogram (EEG) is the reflection of electrical activity of the brain upon the scalp, which is the summed synaptic potential of millions of neurons [1]. And how to extract and recognize the useful information to reflect the physiology and anatomy features of brain activities from EEG signals is the key role for brain-computer interface systems(BCI). So we present a novel approach to improve EEG classification accuracy by optimizing the classifiers separately in different orthogonal feature space to get the global optimal classification performance. Material, Methods and Results: We used the tensor method to get different orthogonal space, then feature extraction and classification were executed in the different orthogonal space separately and the final classification results were obtained by voting mechanism. To evaluate the performance of our approach, we validated its performance by BCI competition dataset [2]. The dataset consists of MI task experiments for right hand and left hand movements with C3, Cz and C4 channels' signals. And the powerful feature extraction method common spatial pattern (CSP) and several common classifiers including Linear discriminant analysis (LDA), Logistic regression (LR), K-nearest neighbor (KNN), Naïve Bayes (NB), Support vector machine (SVM), Decision Tree (DT) and the ensemble classifiers were used to make the comparison. The performance of the classification methods was evaluated by validation accuracy and test accuracy using 10 fold cross-validation method. The validation accuracy and test accuracy were calculated in validation set and test set respectively. Discussion: Instead of optimizing the classifiers or the ensemble classifiers in the same feature space, we extracted the information in different orthogonal subspace and optimizing the classifiers in different subspace separately. And this approach could get relevant independent classification results in different feature subspace. Significance: The proposed method could exploit the different classifiers' potentialities in their feature subspace and get an optimal classification performance in the whole space by voting mechanism. References: [1] Lopes da Silva, F., 1987. EEG analysis: theory and practice. In: Neidermeyer, E., Lopes da Silva, F. (Eds.), Electroencephalography Urban and Schwartzenberg. [2] Schlögl A 2003 Outcome of the BCI-Competition 2003 on the Graz Data Set (Berlin: Graz University of Technology)

1-F-52 Towards decoding speech: Effects of prior phonemes on sensorimotor cortex activity during sequential vowel production

Efraim Salari[1], Zachary Freudenburg[1], Mariska Vansteensel[1], Nick Ramsey[1]

[1]*Brain Center Rudolf Magnus, University Medical Center Utrecht*

Introduction: The potential of speech BCIs to restore communication in severely paralyzed subjects have been investigated previously [eg 1,2]. However, accuracy levels and the number of degrees of freedom usually do not suffice for patients to use these systems at home. In order to improve these systems, more research is needed to better understand the neural dynamics during speech. Here, we investigate the effect of one vowel on the temporal neural activity dynamics of a subsequent vowel in the sensorimotor cortex. Material & Methods: Electrocorticography (ECoG) was recorded in three epilepsy patients (A-C) who were treated at the UMC Utrecht hospital. In one subject (A; right hemisphere), the standard clinical coverage was used and in two subjects (B-C; left hemisphere) a high-density electrode grid was used. HD-grids were placed with the subject's permission for research purposes. All subjects had coverage over the mouth sensorimotor areas. Subjects pronounced the /i/ sound (ca. 1000 ms) in three conditions with differing vowel transitions: preceded by either a /u/ or /a/ sound (ca. 1000 ms), or no sound. The task was presented on a screen, placed approximately 1 m from the subject. Recorded signals were preprocessed (line noise removed, common average re-referenced) and the high frequency band (HFB; 75-135Hz) power was extracted, normalized and smoothed. Trials were epoched and a correction was applied for differences in voice onsets and voice transitions. Sensorimotor electrodes showing a significant response during vowel transition were identified and for these electrodes we determined if there was a significant difference in HFB-power over conditions. We averaged per condition the amplitudes of all significant sensorimotor cortex electrodes and determined what was the most common difference between conditions. Results: Of all sensorimotor cortex electrodes, 39.3 % (11/28; A), 71.1 % (27/38; B) and 49.1 % (56/114; C), showed a significant response for the vowel transition. Of these electrodes, 54.6 % (6/11; A), 63.0 % (17/27; B) and 66.1 % (37/56; C), show a significant difference between conditions. For subjects B and C, the HFB power during an /i/ production was highest when it was preceded by a /u/ and for subject A the amplitude was highest when the /i/ sound was not preceded by any sound (Fig. 1). Discussion: The results indicate that pronouncing the same sound doesn't necessarily have to be accompanied by the same neural activity in the mouth motor cortex. One possibility is that these differences reflect co-articulation effects. Another possibility is that there is a non-linear relationship between neural activity and behavioral performance. It has been shown for instance that for repeated finger movements, neural activity was different over the course of repetitions, even though the behavioral performance was equal [3]. A similar effect could also be possible for vowel pronunciation, where the same vowel pronunciation may have different neural dynamics, depending on the previous utterance. Differences between subjects A and B/C may be explained by exact grid coverage. Significance: The current results show that neural activity of a single speech unit is depending on previous utterances. This is important for BCI systems that try to classify speech units, as we show that a single speech unit may be accompanied by a set of neural activity patterns, rather than one single pattern. References: [1] Ramsey NF, Salari E, Aarnoutse EJ, Vansteensel MJ, Bleichner MB, Freudenburg ZV. Decoding Spoken Phonemes from Sensorimotor Cortex with High-Density ECoG Grids. NeuroImage, 2017 [2] Herff C, Heger D, de Pesters A, Telaar D, Brunner P, Schalk G, Schultz T. Brain-to-Text: Decoding Spoken Phrases from Phone Representations in the Brain. Neural Technology, 2015 [3] Hermes D, Siero JCW, Aarnoutse EJ, Leijten FSS, Petridou N, Ramsey NF. Dissociation between Neuronal Activity in Sensorimotor Cortex and Hand Movement Revealed as a Function of Movement Rate. The Journal of Neuroscience, 2012

1-F-53 EEG-guided electrotactile stimulation for haptic feedback

Doug Weber[1], Safaa Eldeeb[1], Aya Khalaf[1], Murat Akcakaya[1], Deniz Erdogmus[2]

[1]University of Pittsburgh, [2]Northeastern University

Introduction: The long-term vision of our team is to enhance haptic perception in artificial interfaces in a multitude of applications including prosthetic limbs, telepresence and virtual/augmented reality. Modern approaches to provide haptic feedback focus mainly on robotic manipulators, vibrators, and tactors, which tend to be cumbersome, and limited to a small number of contact points. On the contrary, electrotactile displays are compact and wearable, and recent discoveries demonstrate that naturalistic sensations of touch can be provided by electrical stimulation of peripheral nerves [1]. To date, only two state-of-the-art attempts show the feasibility of real-time adaptation of stimulation through the guidance of EEG measurements: a virtual path-following task [2], and real-time computer graphics adaptation to improve the perceptual and emotional response of a VR user [3]. We suggest a powerful approach for real-time closed-loop control of haptic electrotactile stimulation using EEG to directly measure brain activity associated with perceptual responses elicited by sensory stimulation. The aim of this study is to develop techniques to extract EEG features that are markers for real world haptic interactions. The extracted EEG features will be used to model the EEG evidence that will later be employed in the closed-loop guidance system to adaptively control the electrical stimulation. Methods and Results: We first identify EEG channels that would be most responsive to haptic input through electrical stimulation and then extract salient EEG features corresponding to real world haptic interactions. EEG was recorded according to the 10-20 system from 14-channels, using electrodes (gUSBAmp) placed in the frontal and somatosensory cortex focusing around the motor planning and sensorimotor integration regions, respectively. First, an electrical stimulation (3mA pulses with 1Hz frequency for 30 seconds) was applied to the right index finger of a righthanded participant while recording EEG, and electrode located at C5 is identified as the most informative channel based on the power spectral density of the recorded EEG (see Figure). In the second step, five different textures have been generated and used in this study, (a smooth surface, and surfaces with large ridges, large bumps, small ridges, and small bumps). These surfaces were securely attached to a force transducer which is fixed on a table. The induced force and EEG were recorded synchronously while the participant was rubbing each surface roughly with 1Hz frequency for 30 seconds We denoted one complete rub over the surface as a trial, and used the recorded force data to segment the EEG for different trials. Accordingly, we obtained roughly around 30 segments of EEG data for each surface. The power spectral densities of the EEGs averaged over different trials were computed, see Figure. Figure shows that haptic inputs from different textures induce significantly different EEG responses. For each trial, we extracted features based on the spectral properties of the corresponding EEG segment. We used leave-one-out cross-validation to train a 5-class Naïve Bayesian classifier. The accuracy for 5-class classification was obtained as 82:2% (chance level is 20%) and the sensitivity of the classifier for smooth, small ridges, large ridges, small bumps and large bumps were computed as 72:2%, 61:1%, 88:9%, 100% and 100%, respectively. Discussion: Our results show that it is possible to discriminate among surfaces with different textures using EEG, and as the roughness of the surface increases so does the sensitivity of the EEG. Significance:The aim of this study is to develop analysis techniques to extract EEG features that are markers for real world haptic interactions. These markers will be used to design principles for model-based optimal EEG-guided closed-loop haptic feedback. Acknowledgements: Our work is supported by NSF (IIS-1149570, CNS-1544895, IIS-1717654) References: [1] Daniel W Tan and et al., "A neural interface provides long-term stable natural touch perception," 2014, DOI: 10.1126/scitranslmed.3008669 [2] Anatole Lecuyer and et al., " Toward adaptive VR simulators combining visual, haptic and brain-computer interfaces," 2013, DOI: 10.1109/MCG.2013.80 [3] Maryam Mustafa and et al. " Electroencephalographics: Making waves in computer graphics research," 2014, DOI: 10.1109/MCG.2014.107

1-F-54 Post-hoc labeling of arbitrary EEG recordings for data-efficient evaluation of neural decoding methods

Sebastián Castaño-Candamil[1], Andreas Meinel[1], Michael Tangermann[1]

[1]*University of Freiburg*

Introduction: Many behavioral processes have correlates in oscillatory neural sources. Decoding such processes from M/EEG usually requires data-driven methods. The evaluation of such decoding algorithms is difficult: the amount of labeled M/EEG data available is limited, labels can be unreliable, and raw signals often are contaminated with artifacts. As an alternative, simulation frameworks can be used. To generate artificial brain signals, however, most simulation frameworks make unrealistic assumptions about brain activity, which limits the generalization to real-world conditions. Here, we thrive to remove many shortcomings of current frameworks and propose a versatile alternative, that allows for objective evaluation of data-driven decoding methods for neural signals. Its central idea is to utilize posthoc labeling of arbitrary M/EEG recordings. This strategy makes it paradigm-agnostic and allows to generate comparatively large datasets with noiseless labels. An extended version of the present contribution, including a use case scenario has been made available online recently [1] and is under review for publication. Materials, Methods, and Results: Our novel dataset generation framework relies upon an unsupervised projection of an arbitrary M/EEG dataset onto a source space. Afterwards, an arbitrary source found in the projected space may be used to form label information for assessing of

a neural decoding algorithm. Any projecting function could be used to realize the aforementioned projection, however, we propose two strategies for its choice: 1) Anatomic constraints or 2) a data-driven approach. Anatomic constraints may be introduced using a source reconstruction method. Exemplarily, we have drawn on the minimum norm estimate [2], using the New York Head [3] containing anatomically plausible neural sources. As for the data-driven approach, a set of underlying independent components can be selected using, for example, the FastICA algorithm [4]. The optimization criterion utilized to find independent component is, in this case, maximization of the non-gaussianity of the sources. After a source has been declared target source the required labels can be extracted, e.g.~via segmentation and extraction of bandpower values. Fig. 1 illustrates the posthoc labeling strategy. An implementation of the framework and an EEG dataset for testing has been made available for practitioners (github.com/bsdlab/Post-HocLabeling, dataset DOI: 10.5281/zenodo.1065107). Regarding the EEG dataset provided, it was recorded from seven healthy subjects with a mean age of 28 years. 73 minutes of EEG data on average at a sampling rate of 1kHz from 31 passive Ag/AgCl electrodes with impedances below 20k were recorded within a single session while subjects sat in front of a computer screen and switched between calmly performed motor tasks and pauses. Given the paradigm-agnostic character of our framework, details about the motor task are out of the scope of this contribution. Discussion and Significance: Our framework implements a posthoc labeling of paradigm-agnostic M/EEG signals. The framework allows generating labeled datasets containing real neural signals and prescinds from making assumptions about neural dynamics. As a clear advantage, the generated labels are extracted directly from the data. Thus, they are noise-free and describe the neural target source perfectly. However, a practitioner is free to add arbitrary levels of label noise to examine an algorithm's robustness. Furthermore, the posthoc labeling of paradigm-agnostic M/EEG recordings offers greater efficiency in terms of data usage. Compared to real datasets whose labels depend on the paradigm they were recorded on, our posthoc labeling can also exploit recorded idle periods or preparatory intervals. In the data provided, this led to an exploitation of effectively 55% of the original M/EEG after performing standard artifact rejection procedures. Consequently, we envision the adoption of our framework as a tool for development and testing of decoding algorithms for oscillatory neural phenomena. Acknowledgements: This work was supported by the DFG grant number EXC 1086.
References: [1] S. Castaño-Candamil et al. arXiv CoRR, abs/1711.08208, 2017. [2] R. Grech et al. J. of Neuroengineering and Rehabilitation, 5(1):25, 2008. [3] Y. Huang et al. NeuroImage, 140:150-162, 2016. [4] A. Hyvärinen et al.. Neural networks, 13(4):411-430, 20

1-F-55 Estimating P300 latency and amplitude using LMS adaptive filtering

Md Rakibul Mowla[1], Jane Huggins[2], Bala Natarajan[1], David Thompson[1]

[1]Kansas State University, [2]Direct Brain Interface Laboratory, University of Michigan

Introduction: The P300 event-related potential (ERP) is a positive deflection approximately 300ms post-stimulus, used in P300-based BCI speller systems. P300 latencies and amplitudes are correlated with memory and mental status [1]. We have also shown that estimated P300 latency can help and improve P300 speller based BCIs performance [2]. Since the commonly-used grand averaging technique does not allow single-trial analysis, here we have proposed a least mean squares (LMS) adaptive filtering method for single-trial estimation of P300 latencies and amplitudes. This will help to improve the speed of speller BCIs. Material, Methods and Results: In this work, P300 latencies and amplitudes are estimated using data from [3]. To estimate the P300 signal from single trials, the LMS adaptive filter requires a reference signal. Grand averages of target trials of training data have been used as reference signals for an LMS filter. Let the estimated P300 be denoted as \hat{p}(t) and the reference signal as r(t). Then the estimated latency is L = argmax_{\tau} E[r(t)\hat{p}(t-\tau)] and the amplitude is A = max \hat{p}(t). Figure 1 (left & middle) shows 20 single target trials before and after applying an LMS adaptive filter at electrode location Pz of a participant with ALS. From the figure, we can see that the LMS filter improved P300 visibility on single trials. Figure 1(right) shows the histogram of the estimated latency for the same subject. [Figure] Figure 1: Single trials before (left) and after (middle) applying LMS filter from an ALS subject and estimated latencies (right). Table 1 shows the mean and standard deviation of the estimated latencies for subjects with ALS. Subjects K143 K145 K146 K147 K152 K155 K156 K158 K159 K160 Mean (ms) 324.8 583.3 307.2 251.2 237.5 293.9 232.7 280.3 477.3 301.7 S.D (ms) 53.04 51.68 45.63 42.16 38.96 38.00 40.14 36.10 48.38 40.29 Table 1: Mean and standard deviation (S.D) of estimated latencies for subjects with ALS. Discussion: The aim of this work is to estimate the latency of P300 ERPs in a speller BCI paradigm. However, the work is not compared with any existing method and still under development. Our goal was to investigate the efficacy of the LMS adaptive filtering method. From the above figure, it appears that LMS has the potential to improve P300 ERPs signal-to-noise ratio, which should improve latency estimates. Significance: This method will help to estimate P300 latency in single trials, and will allow analysis of trial-to-trial variations of P300 ERPs. However, further validation is required. Acknowledgements: The data were collected under NIDRR grant H133G090005 and award number H133P090008. The opinions and conclusions are those of the authors, not the respective funding agencies. References [1] E. R.Braverman, K. Blum. "P300 (latency) event-related potential: an accurate predictor of memory impairment." Clinical Electroencephalography, 2003;34: 124-39. [2] M. R. Mowla, J. E. Huggins, and D. E. Thompson. "Enhancing p300-bci performance using latency estimation." Brain-Computer Interfaces, vol. 4, no. 3, pp. 137-145, 2017. [3] Thompson, D. E., Warschausky, S., & Huggins, J. E. Classifier-based latency estimation: a novel way to estimate and predict BCI accuracy. Journal of neural engineering, 10(1), 016006, 2013.

1-F-56 A data-driven EEG spatial filter for estimating pre-movement sensorimotor integration signals

Mark Pflieger[1]

[1]*Cortech Solutions, Inc.*

Introduction: An EEG spatial filter is defined by a matrix with M columns corresponding to scalp channels (input) and D rows corresponding to derived channels (output). Typically, D<M (e.g., M=128, D=4) so that the spatial filter reduces the data, and the derived channels selectively enhance particular brain signals of interest for an application. Because matrix multiplications are faster than typical multi-channel EEG sampling rates, spatial filters are well-suited for real-time applications such as BCI, augmented cognition, neurofeedback, and closed-loop brain stimulation. The design of an EEG spatial filter may be model-driven (e.g., beamformer estimators of regional brain signals) or data-driven (e.g., common spatial patterns). Envisioned here are potential BCI or augmented cognition applications for which data-driven spatial filters are designed from event-related stimulus-response experiments in order to derive signals that reflect sensorimotor integration per se, apart from experimentally induced

sensory and motor brain signals. This study aims to show that the Volterra-Hansen theory [1] can derive plausible sensorimotor integration signals from reaction-time (RT) EEG data by (i) linearly separating overlapping sensory and motor ERP waveforms, and (ii) estimating a 2nd-order Volterra kernel that characterizes bilinear RT-related modulations of motor ERPs. The desired sensorimotor spatial filter matrix is obtained by analyzing the Volterra kernel in a time interval that precedes overt movement. Material and Methods: Volterra-Hansen methods [1] were implemented in the EMSE framework to analyze continuous event-related EEG data (128 channels, nose reference, 1000 Hz) recorded by Saron et al. [2] using the visuomotor Poffenberger paradigm. Checkerboard wedge stimuli were presented briefly to lower-left or to lower-right visual quadrants. In different conditions, the participant responded with the hand ipsilateral or contralateral to the stimulated visual field. Thus, each trial had one visual event and one behavioral event, which were separated by the RT interval. RTs ranged from ~200 ms to ~500 ms. Analysis used epochs of 2048 ms per trial with a pre-stimulus baseline of 500 ms, a post-response interval of 700 ms, and the remaining points set to the average value of the data. 1st-order modeling separated the overlapping visual-related and motor-related ERP waveforms. 2nd-order analysis of RT-modulated motor responses was performed on the residual after removing the 1st-order modeled waveforms. Results and Discussion: Inspection of the 2nd-order kernel revealed an RT-related modulation from -162 ms to -48 ms preceding movement. Figure 1 shows 4 InfoMax-rotated spatial components that account for ~90% of the kernel variance in this interval. The theory posits that these topographies may reflect "pure" sensorimotor processes. Plausibly, the pronounced parietal-negative peak of the 1st spatial component (~60% variance) may relate to stimulus-response mapping. Thus, the 4-by-128 spatial filter matrix defined by the 4 topographies could be used to derive sensorimotor integration signals in real time. Significance: Considering that human participants readily configure arbitrary stimulus-response mappings for different tasks, and that brain processes strictly between sensory and motor processes are needed to support these mappings, it follows that sensorimotor integration signals per se may reflect brain processes (a) that are abstracted from actual stimulus presentations and overt behaviors, and (b) that are readily configured by ordinary mental operations. Thus, Volterra-Hansen plus spatial filtering methods for estimating sensorimotor integration signals--as illustrated here--may prove useful for BCI and augmented cognition applications. Acknowledgements: Cliff Saron provided the visuomotor EEG data [2]. References: [1] Pflieger ME. Volterra-Hansen theory of event-related transients modulated by inter-event intervals. IJBEM. 2011;14(1):34-9. [2] Saron CD, Foxe JJ, Simpson GV, Vaughan HG. Interhemispheric Visuomotor Activation: Spatiotemporal Electrophysiology Related to Reaction Time. In: Zaidel E, Iacoboni M, editors. The Parallel Brain: The Cognitive Neuroscience of the Corpus Callosum. Cambridge, Massachusetts: The MIT Press; 2003. p. 171-219.

1-F-57 Decoding mPFC activity contributes to better prediction of movement intention

Xiang Zhang[1], Shuhang Chen[1], Yiwen Wang[1]

[1]*Hong Kong University of Science and Technology*

Introduction: Brain-machine interface (BMI) enables people with disability to control neural prosthesis by translating the brain signals into the motion intentions. One of the key challenges could b that the subjects need to brain control the neural prosthesis by adapting to prosthesis performances through learning. Therefore, the learning of the prosthesis control procedure needs the participation of the corresponding cortical areas including the primary motor cortex (M1) and the medial prefrontal cortex (mPFC). It is generally accepted that M1 plays a role of executing an intended movement in the past two decades. The area of mPFC has been argued that is ideally involved in the retrieval of memories and the decision making, including the reward-guided learning. We are interested to explore computationally if decoding the mPFC activity could contribute in the learning process of the neural prosthesis control. Material, methods and results: Sprague Dawley(SD) rats were used in the experiment. Prior to the behavioral tasks, the subjects were implanted with two 16-channel microelectrode arrays in the upper limb area of M1 and mPFC separately. The rats were trained to do a lever press task. In the task, a 10kHz tone is first presented, and the rats need to press and hold the lever at least 540ms within a 3 second window. A feedback tone will be given to the subject in the 90ms pips if the rat accomplishes a correct trial. Early release or omission will be treated as an unsuccessful trial and the rat will not be rewarded water. Inter-trial breaks randomly range from 4 to 6 seconds. During the experimental session, the neural signals of M1 and mPFC are simultaneously collected from the microelectrode. The original signal is collected by Plexon (Plexon Inc, Dallas, Texas) at a sampling frequency of 40kHz, then high-pass at 500Hz. The spike timing info is restored using offline sorter. Spike rates are counted using a window of 100ms. Totally up to 35 neurons are collected over 3 days. All the movement events are recorded using the behavior box, and synchronized through Plexon digital input. There are 204 trials in day 1, 115 trials in day 2, and 105 in day 3. We apply the Kalman filter to derive the states of movement (start and press) from the neural spike rates. All the successful trials are segmented and connected from 500ms before start and 500ms after success. The discrete movement of the start and press is smoothed using sigmoid function. We predict the continuous movement from the observation of the spike rates in M1 only, and compare the decoding results with that using neural spikes of both M1 and mPFC. The decoding performance is evaluated using the correlation coefficient (CC) between the predicted movement state and desired movement state. Figure1. (a) A segment of decoding results using M1 only (green dashed line) and using both M1 and mPFC (blue solid line). The x-axis is time in second. The y-axis is the movement after smoothing, where state 0 represents the start and state 1 means the press. Red dotted curve is the desired movement. (b) the decoding correlation coefficients using M1 only (green line) and using both M1 and mPFC (blue line) over the three days. We can see the correlation coefficient between the ground truth and the decoding results increases when adding mPFC neural activity. In figure 1(a), the improvement mainly happens at the state of the start (as illustrated in red arrows), indicating the participation of mPFC may help to anticipate the start of the trial. We also plot in figure 1(b) statistically decoding results over 3 days. Comparing with the results only using M1 (cc is 0.5642, 0.6251, 0.6083 respectively over three days), Adding the neural spikes of mPFC to the observations in Kalman filter, the cc is 0.6658, 0.6681, 0.8268. which demonstrates a steady improvement. We also see the decoding performance using both M1 and mPFC increases over 3 days, potentially indicating better learning procedure of the prosthesis control. Discussion: From our current results, we conclude that involving the mPFC in the decoding procedure will contribute to better movement state prediction. We need to further validate the results using more subjects. Significance: Our preliminary results demonstrate that the mPFC could participate in early anticipation of the movement start, which consequently contributes to the better learning of the neural prosthesis control.

1-F-58 Towards Generating A Task-Independent Workload Classifier with EEG

Xixie Zhang[1], Laurens Krol[1], Thorsten Zander[2]

[1]*Technical University of Berlin,* [2]*Zander Laboratories B.V.*

Introduction: EEG signals are non-stationary and could be influenced by factors, like slight electrode drift during the experiment, or changes in subject's brain processes due to fatigue or other factors. Brain activity is heavily context-dependent, thus currently we still need to calibrate classifiers for different tasks and separate sessions, even within individual subjects. Therefore, we are engaged in investigating whether we could calibrate a classifier that is robust against non-stationarities and transferable between different sessions and tasks. Mental workload is an important state in safety-critical environments and has great influence on performance in many tasks, such as in learning, driving, or monitoring (e.g. [1]). It can be reflected in the oscillatory power of specific frequency bands. In particular, there is an increase in frontal theta power and a decrease in parietal alpha power during high workload [2]. Band power estimates can be obtained continuously from ongoing EEG and may thus provide a continuous measure of workload. Here we present a study for generating a task-independent classifier for workload detection with EEG, aiming at validating the classifier trained on calibration task on other tasks. Material, Methods and Results: This experiment was conducted in a well-controlled laboratory and 7 healthy subjects took part in the experiment (the experiment is still ongoing and there'll be 9 more subjects). All participants performed a calibration task (subtraction task vs. relaxing) and five testing tasks of two different workload levels (high/low workload) and a relaxing session (no workload). The five testing tasks include n-back task, backward digit span task, addition task, word recovery task and mental rotation task, and all of them have 20 blocks lasting 30s each, whose sequence is randomized. After first and last blocks of two workload levels the subjects were asked to report their subjective ratings on mental workload. The data were collected using a 64 active Ag/AgCl electrode system by Brain Products mounted according to the extended 10-20 system. To investigate the task-independence of the workload classifier, individual classifiers were firstly calibrated based on data from the calibration phase. The data were divided in consecutive 1-second epochs of high versus low condition data. Filter bank common spatial patterns were applied to extract features describing the power in theta (4-7 Hz) and alpha (8-13 Hz) bands using three patterns per band and linear discriminant analysis (LDA) was used to separate the classes with a 5-fold nested cross-validation with margins of 5. The calibrated classifiers were then applied to 1-second epochs taken from the other five tasks and classification was made between two different workload levels (high vs. low workload) as well as between high workload and no workload conditions. Discussion and Significance: Table 1 lists all classification accuracies of applying the classifier trained in calibration phase in five different testing tasks. For almost all participants and all tasks, the classifiers calibrated with the method above were unable to separate the high and low workload levels. Otherwise, the classifiers performed rather well on classifying high workload and no workload conditions; especially for addition task, word recovery task and mental rotation task, the average classification accuracies are above 74%. It can be concluded that this task-independent workload classifier is applicable in classifying whether there's workload or not. This could greatly simplify the calibration session and could be applied to a number of new tasks, thus enhancing its applicability in workload detection in more practical environments. Since these are preliminary results of our study, we'll further investigate the other classification methods to see whether it's still possible to classify between two different workload levels with acceptable accuracy. References: [1] Berka, C., Levendowski, D. J., Lumicao, M. N., Yau, A., Davis, G., Zivkovic, V. T., ... & Craven, P. L. (2007). EEG correlates of task engagement and mental workload in vigilance, learning, and memory tasks. Aviation, space, and environmental medicine, 78(5), B231-B244. [2] Klimesch, W. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. Brain research reviews, 29(2), 169-195.

1-F-59 Primitive shape imagery classification from electroencephalography

Attila Korik[1], Laura Hay[2], Sam Gilbert[3], Madeleine Grealy[2], Alex Duffy[2], Pei Ling Choo[2], Damien Coyle[1]

[1]Ulster University, [2]University of Strathclyde, [3]University College London

Introduction: Brain-computer interfaces (BCIs) augment traditional interfaces for human-computer interaction and provide alternative communication devices to enable the physically impaired to work. Imagined object/shape classification from electroencephalography (EEG) may lead, for example, to enhanced tools for fields such as engineering, design, and the visual arts. Evidence to support such a proposition from non-invasive neuroimaging techniques to date has mainly involved functional magnetic resonance tomography (fMRI) [1] indicating that visual perception and mental imagery show similar brain activity patterns [2] and, although the primary visual cortex has an important role in mental imagery and perception, the occipitotemporal cortex also encodes sensory, semantic and emotional properties during shape imagery [3]. Here we investigate if five imagined primitive shapes (sphere, cone, pyramid, cylinder, cube) can be classified from EEG using filter bank common spatial patterns (FBCSP) [4]. Material, Methods, and Results: Ten healthy volunteers (8 males and 2 females, aged 26-44) participated in a single session study (three runs, four blocks/run, 30 trials/block (i.e., six repetitions of five primitive shapes in random order)). Trials lasted 7s as shown in Fig. 1 and ended with an auditory tone. Thirty EEG channels were recorded with a g.BSamp EEG system using active electrodes (g.tec, Austria). [Fig.1 HERE] EEG channels with high-level noise were removed. Signals were band-pass filtered in six non-overlapped, 4Hz width bands covering the 4-40Hz frequency range. Filter bank common spatial pattern (FBCSP) based feature extraction and mutual information (MI) based feature selection methods provided input features for 2-class classification using linear discriminant analysis (LDA) for target shape versus the rest, separately. The final 5-class classification was decided by assessing the signed distance in the 2-class discriminant hyperplane for each of the five binary classifiers as shown in Fig. 1. Classifiers were trained on two runs and tested on the one unseen run (i.e., 3 fold cross-validation). A Wilcoxon non-parametric test was used to validate the difference of DA at end of the resting period (-1s) and at the maximal peak accuracy occurring during the shape imagery task (0-3s) is significant ($p<0.001$). Fig. 1 shows the between-subject average time-varying classification accuracies with standard deviation (shaded area). Discussion: The results indicate that there is separability provided by the shape imagery and there is significantly higher accuracy compared to the ~20% chance level prior the display period with maximum accuracy reaching 34%. In [5] classification of five imagined primitive and complex shapes with 44% accuracy is reported using a 14 channel Emotiv headset. Differences in performance reported may be influenced by EEG recording (EEG in [5] appears to have different dynamics (significant mean shifts)), the study had more sessions/trials, applied ICA for noise removal and the participants had designer experience whilst our study did not. Improvement of our methods is required to achieve higher accuracy rate. It is unclear if an online feedback to shape imagery training and learning will an impact performance - a multisession online study with feedback is the next step in this research. Significance: To best of our knowledge this is only the second study of shape imagery classification from EEG. Acknowledgement: supported by the UK EPSRC grant nos. EP/M01214X/1 and EP/M012123/1 References [1] T. Horikawa and Y. Kamitani, "Generic decoding of seen and imagined objects using hierarchical visual features," Nat. Commun., vol. 8, no. May, pp. 1-15, 2015. [2] G. Ganis, W. L. Thompson, and S. M. Kosslyn, "Brain areas underlying visual mental imagery and visual perception: An fMRI study," Cogn. Brain Res., vol. 20, no. 2, pp. 226-241, 2004. [3] D. J. Mitchell and R. Cusack, "Semantic and emotional content of imagined representations in human occipitotemporal cortex.," Sci. Rep., vol. 6, no. December 2015, p. 20232, 2016. [4] Kai Keng Ang, Zheng Yang Chin, Haihong Zhang, and Cuntai Guan, "Filter Bank Common Spatial Pattern (FBCSP) in Brain-Computer Interface," 2008 IEEE Int. Jt. Conf. Neural Networks, pp. 2390-2397, 2008. [5] E. T. Esfahani and V. Sundararajan, "Classification of primitive shapes using brain-computer interfaces," CAD Comput. Aided Des., vol. 44, no. 10, pp. 1011-1019, 2012.

1-F-60 Prediction of subject-specific affective states in music listening using SPoC

Amna Ghani

Charite

Introduction: Musical emotions have been widely studied using dichotomous scale i.e. pleasant/unpleasant or happy/sad. However, emotions elicited through music are complex and highly subjective which might not be captured by such a discrete scale but rather need more diverse and broader degree of freedom [1]. In this paper, using circumplex model i.e. two-dimensional scale of valence and arousal, we acquired continuous rating from participants while they listen to different musical pieces. This subject specific continuous rating was further analyzed using the source separation framework known as Source Power Co-Modulation (SPoC) [2]. Our aim is to extract subject specific valence and arousal weights and identify its association with music reward and personality. The study of how music alter our emotions on subjective level can help us to build personalized musical therapies for patients with emotional disorders.

Material, Methods and Results:

Total 19 subjects (9 females) listened to 30 classical musical excerpts while EEG data was recorded. Each song lasts 40s, during these 40s participants continuously rate their feeling towards a musical piece on two dimensional scale labelled as pleasant - unpleasant (valence) and stimulating - relaxing (arousal). After preprocessing of EEG data using ICA for eye artifact removal and bad epoch rejection, 2s epoch was generated. We used supervised learning framework SPoC to extract brain sources that co-varies with participant's valence and arousal responses.

SPoC utilizes a stimuli related variable such as reaction time, task rating, known as target variable, to extract brain components. In our paradigm target variables are valence (x-axis) and arousal (y-axis) ratings.

Each participant's EEG data with their respective continuous rating gives total 600 epochs. The quantity of epoch might vary after rejection of artifacts related epoch / song. Further, epochs were divided into train (50%), validation (30%) and test (20%) set. Individual weights of valence and arousal were determined on train and validation set. The determined weights were further kept fixed and test accuracy was observed. Fig 1.0 illustrate the process of grid search to determine the subject specific weights of valence (Wv) and arousal (Wa). Once the Wv and Wa are determined, the correlation of these weights were performed with the music reward questionnaire (BMRQ), music listening habits and big five inventory (BFI) test.

Interestingly, we found that participants who listen music to regulate mood have more sensitivity to valence and less to arousal aspect of music listening. Moreover, we found negative correlation of arousal weights with shy and reserved personalities. Participants who are more shy and reserved have less arousal weights in their music listening experience.

Discussion:

We found that arousal and valence weights vary across subjects. This variation is associated with personality and rewarding aspect of music for each participant. Previous research has also proposed the mood regulation as most important reason for music consumption [3]. Since mood are typically described as having either positive or negative valence, our results corroborate that participant who use music to regulate their mood have higher weights for valence comparing to arousal.

Significance:

Individual emotional response towards music varies depending on different factors. These factors might include personality, age or culture. In order to use music for therapeutic purposes we need to first find the brain patterns that causes these individual differences. Using these subject - specific features we can build personalized emotion regulation therapies for people suffering from emotional disorders such as depression or bipolar disorder.

1-F-61 Functional verification of fNIRS probe locations using a generalized SVM classifier model for BCI applications

Michael Lührs[1], Anita Tursic[1], Rainer Goebel[1]

[1]*Maastricht University, Brain Innovation B.V.*

Introduction: With the advancement of brain-computer interfaces (BCIs), an increasing number of applications are becoming available for home use (e.g., P300 speller) . As most of the future users, as well as caregivers, might not be professionally trained, the setup and employed methods, including cap placement and BCI application, should be simplified. In this functional near-infrared spectroscopy (fNIRS) study, we explore a simple localizer task, together with a support vector machine (SVM) classifier model, to verify and, if necessary, correct the positioning of the fNIRS cap to ensure the optimal placement for BCI experiments. Material, Methods and Results: A NIRx fNIRS system (NIRSport) with 8 sources and 8 detectors (standard NIRx motor 8x8 montage) and the acquisition software NIRStar (version 14.2) were used. The setup resulted in 20 channels covering left and right motor cortices. Eight participants (age 26-48, mean age=29.6, 2 male) with the cap applied in accordance with the 10-20 system, underwent three runs of left/right hand squeezing ("make a fist") to train an SVM classifier and create a model. Two additional participants (age 27 and 44, both male) were measured with a suboptimal cap positioning (rotations and translations of up to 3cm). The complete three-run data sets of 5 participants with optimal cap positioning were used to create a model, that would include fatigue effects, participant- and run variability. The second model included the first run of each of the eight participants with optimal cap positioning. Only measurements of oxygenated hemoglobin were used to create and test the models. The SVM was trained to differentiate between the left- and right-hand squeezes. During the experiment, participants were asked to close their eyes and follow the instructions presented through standard computer speakers (alternating a rest condition of 14 seconds and task of 10 seconds). Satori (v0.92) was used for offline analysis and Turbo-Satori (v0.9.8.4) for real-time data inspection, model comparison and BCI interface. Using a leave-one-participant-out splitting procedure, the participants achieved on average a 95.6% single trial decoding accuracy in the first model, 91.7% in the second, using the individual two-class classifier for left- and right-hand squeezing (table 1). The GLM beta-map pattern correlation of the two tasks within the models was -.65 ($p<.01$) for the first model and -.42 ($p<.01$) for the second. Testing the models by a) correlating to separate runs of two participants with the suboptimal cap positioning and b) testing the model-based classifiers showed the feasibility of using a standard model across participants. Finally, the two models were used to test individual runs (n=3) of the two "test" participants (figure 1 upper left). The resulting channels, as shown in figure 1 (upper right), were then used to test example BCI applications shown in figure 1 bottom. These games show the potential of fNIRS to easily train and control up/down regulation paradigms with left/right hand squeezes. Discussion: The first model showed higher decoding accuracies and correlations with single subject data, and stronger hemisphere effects. This implies that the first model either benefited from having more data points (more runs in general) or that fatigue effects and run variability added to the flexibility of the model. We plan to further compare the two models by adding 7 extra single-run measurements to equalize the number of data points in the two models. Moreover, we also plan to additionally investigate the potential use of the models by limiting the channels used in the models to the channels determined as informative. This would allow a reduced number of optodes, which would be beneficial for patients and care-takers in terms of practicality, simplicity, patients' comfort and time that is necessary for cap application and preparation. Additionally, the implemented BCI paradigms further confirm the ease of use in the sense that the necessary information is automatically retrieved and processed from the real-time analysis software to provide it directly to the BCI application. Significance: Functional localization of activity patterns can potentially be used to verify proper fNIRS cap placement for non-clinical and clinical users to apply BCI paradigms using only source/detector positions of interest. Acknowledgements:Funding:FP7 grant n°602450 and 602186

1-F-62 Alterations in cortical connectivity during P300-based BCI use by people with amyotrophic lateral sclerosis

Roohollah Jafari Deligani[1], Charles Carmack[2], Susan M Heckman[2], Lynn M McCane[2], Dennis J McFarland[2], Theresa M Vaughan[2], Jonathan R Wolpaw[2], Debra J Zeiltin[3], Dean Krusienski[4], Yalda Shahriari[5]

[1]Univerity of Rhode Island, [2]National Center for Adaptive Neurotechnologies, Wadsworth Center, [3]Helen Hayes Hospital, [4]Old Dominion University, [5]University of Rhode Island
Introduction: People with amyotrophic lateral sclerosis (ALS) can use a P300-based brain-computer interface (BCI) to operate application software in their homes without expert supervision [Sellers et al., ALS, 2010; Birbaumer et al., Nature, 1999]. Although long-term BCI performance typically remains stable [Krusienski et al., JNM, 2008; Wolpaw et al., Neuroscience Meeting Planner, 2013], home users experience significant day-to-day variability in copy-spelling accuracies that are not explained by device malfunction or signal-to-noise ratio [Shahriari et al., BCI Meeting, 2013]. Prior studies have correlated within-subject variability during supervised BCI use with physiological and cognitive variations [Ahn et al., JNM, 2015; Nijboer et al., Frontier in Neuroscience, 2010]. This study takes initial steps toward understanding how within-subject changes in brain activity might affect BCI performance during unsupervised BCI use. It explores the user contribution to day-to-day performance variability by comparing connectivity in the electroencephalograph (EEG) across different brain regions during successful (≥70% accuracy) and unsuccessful (<70%) copy-spelling runs. Materials and Methods: EEG data were recorded from nine people with ALS over a period of 2-18 months. Each wore an elastic cap with sensors at locations Fz, Cz, P3, Pz, P4, PO7, PO8, and Oz (referenced to right mastoid). EEG activity was amplified, digitized at 256 Hz, and bandpass filtered at 0.5-30 Hz. The BCI was controlled by the P300 application of BCI2000 [Schalk et al., IEEE TBME, 2004]. The participants completed 10-character copy-spelling runs. Electrode impedances were kept below 40 kΩ [Vaughan et al., BCI Meeting, 2016]. Accuracy was defined as the ratio of correct selections made online to total selections. Runs were divided into successful and unsuccessful runs using 70% accuracy as the threshold (chance accuracy was 3%) [Kübler et al., Psychological Bulletin, 2001]. We explored oscillatory relationships in the EEG data using Thomson multitaper method in 1-sec consecutive time windows with no overlap for frequencies of 1-30 Hz with ±1 Hz frequency bandwidth (TW=1, K=2TW-1=3 tapers) [Thomson, Proceedings of IEEE, 1982]. For each run of each subject, coherence between each pair of electrodes was obtained for [1-3 Hz], theta [4-7 Hz], alpha [8-12 Hz], and beta [13-30 Hz] bands. A non-parametric Wilcoxon signed rank test was used to test the statistically significant connectivity alterations across different brain regions and the two different types of runs (i.e., successful and unsuccessful). Results: In initial analyses of the data, the most prominent finding was that successful and unsuccessful runs differed significantly in the correlations at lower frequencies (i.e., delta and theta) between the frontal (Fz) electrode location and other locations. As figure 1 illustrates, unsuccessful runs had higher theta- and/or delta-band coherences between Fz and other locations than did successful runs. Discussion: Previous reports indicate that the decreased theta-band connectivity linked to the frontal parts is associated with task-related attention [Kitaura et al., Clinical Neurophysiology Practice, 2017; Hamilton et al., Biological Psychiatry, 2015], and thus, can affect the BCI performance. The present results indicate a significant increase of delta- and theta-band coherence over frontal-parietal and frontal-central regions in unsuccessful runs. Cooper et al. (2015) found similar increased theta connectivity and attributed it to error and goal conflict [Cooper et al., NeuroImage, 2015]. The Wadsworth BCI home system gives immediate feedback to the BCI user, and thus, the users were aware of an incorrect selection. Further analysis is needed to determine to what extent the differences in coherence reflect inter-electrode differences in amplitude versus differences in phase. Significance: This study is an initial step toward establishing a set of electrophysiological markers that could help to improve the level and consistency of BCI performance for people with ALS or other severe neuromuscular disorders. Acknowledgement: Research reported in this study was supported by the Institutional Development Award (IDeA) Network

for Biomedical Research Excellence from the NIGMS of the NIH (P20GM103430), NIBIB/NIH Grant EB018783 (National Center for Adaptive Neurotechnologies), and NSF 1421948.

1-F-63 Exploring mental state changes during hypnotherapy using adaptive mixture independent component analysis

Sheng-Hsiou Hsu[1], Ying Wu[1], Tzyy-Ping Jung[1]

[1]*University of California San Diego*

Introduction: A significant challenge to brain-state monitoring in clinical or BCI contexts is effective decoding of underlying cognitive or mental states and quantitative assessment of state changes. This study explores new computational tools for decoding brain states from continuous, unlabeled electroencephalogram (EEG) and obtaining insights into source network dynamics that contribute to state changes. In particular, Adaptive Mixture Independent Component Analysis (AMICA) [1] is a general unsupervised-learning approach that solves for a mixture of distinct ICA models - each representing a different set of statistically independent sources - to characterize active brain networks under different cognitive states. Recently, we have successfully modeled brain activities under different sleep stages or alertness levels as separable ICA models [2]. Here, we apply AMICA to EEG data collected from 2 adults during Healing Light Guided Imagery (HLGI). HLGI - and other forms of guided imagery hypnotherapy (GIH) - involve guiding participants through relaxation, then a light, self-induced trance, during which self-affirming imagery is explored. GIH has been implicated in reducing anxiety, stress, and depression [3], as well as fatigue and pain [4]. Our goal is to characterize mental-state changes over the course of an HLGI session, identify active brain sources associated with distinct states, and evaluate the temporal evolution of different brain-state dynamics. Ultimately, we hope to link metrics derived from these approaches to HLGI treatment outcomes. Materials, Methods and Results: A certified hypnotherapist led HLGI for two adults. Sessions began with a brief resting state EEG recording (eyes open), followed by a goal-setting interview with the therapist, a relaxation routine, then guided imagery. Sessions concluded with another resting state recording. 64-channel BioSemi EEG was recorded. Preprocessing steps included removing channels with flat or irregular signals, high-pass filtering (1Hz), and common average re-referencing. Next, 8 ICA models were learned simultaneously on the cleaned but unlabeled EEG data. The figure plots the probabilities - that is, the normalized data likelihood that indicates the degree of activation, of the eight models at various phases of the HLGI session for one subject. Notably, distinct models - which are based on the statistics of channel EEG - characterize distinct hypnotherapy stages. Broadly speaking, brain networks engaged during the pre- and post-session resting state periods and pre-induction goal setting are differentiated from those during the therapy itself, which includes induction and visualization phases. Further, distinct models, or ratios of models, distinguish the induction period and other subcomponents of the visualization. For instance, Model 5 is engaged most actively during the portion of the script associated with motor imagery, including ascent and descent of stairs, and sitting in a chair. Discussion: The preliminary results demonstrate that AMICA can effectively characterize brain-state changes across various phases of a hypnotherapy session. We will explore the source compositions and activities of each ICA model to provide insights into active brain networks associated with different hypnotherapy stages. Also, the temporal dynamics within each stage will be examined at a sub-second resolution to study the state transitions and the precise timing of induced responses. Finally, we will report results across sessions and subjects to address the generalizability of findings. Significance: AMICA is an effective data-driven approach that learns interpretable ICA models for exploring underlying cognitive or mental states changes from continuous, unlabeled EEG data, supporting developments toward brain-state monitoring for clinical applications and passive BCI. Acknowledgements: We thank J. Palmer for the open-source AMICA EEGLAB plug-in, and P. Jackson and T. Thudiyanplackal for HLGI expertise. References: [1] Palmer et al., "Newton method for the ICA mixture model." ICASSP 2008 [2] Hsu et al., "Modeling Brain-State Dynamics Using AMICA." (under review) [3] Sloman R. "Relaxation and imagery for anxiety and depression control in community patients with advanced cancer." Cancer Nurs. 2002 [4] Menzies et al., "Effects of guided imagery on biobehavioral factors in women with fibromyalgia." J Behav. Med. 2014

1-F-64 Modelling causal connectivity from EEG for BCI with multi-direction hand movements

Tushar Chouhan[1], Kai Keng Ang[2], Vinod Prasad[3], Cuntai Guan[1]

[1]Nanyang Technological University, [2]Institute for Infocomm and Research, Agency of Science, Technology and Research, Singapore, [3]Indian Institute of Technology Palakkad

Introduction: In this paper, we attempt to quantify the brain networks involved in the preparation and execution of a relatively complex motor task, for the development of a brain-computer interface. Material and Methods: 7 subjects participated in an experiment in which they performed right hand centre-out movements in 4 directions randomly (North, East, South, West) while high-density EEG was recorded, following a visual cue. We analysed 2 seconds of EEG data which included 1 second of planning (starting at t= -1), visual cue for movement onset (t=0) and 1 second of movement execution (ending at t=1). Raw EEG data was band-pass filtered and preprocessed in EEGLAB to remove ocular and muscle artifacts [1]. The cleaned data was then decomposed into independent components (ICs) using Infomax ICA and fit to equivalent current dipoles using the MNI Colin 27 Boundary Element Method (BEM) head model [2]. Group level analysis was done after clustering the dipoles using K-means (k=15) clustering and obtaining the cluster centroids using the STUDY module in EEGLAB. Subject-specific models of causal connectivity were built using the Adaptive Multivariate Vector Autoregressive (AMVAR) models and analysed using the Source Information Flow Toolbox (SIFT) [1, 3]. Results and Discussion: The group-level average spectral maps of all the dipole clusters for each of the 4 directions were analysed. It was found that clusters including those with centroids on the right Broadmann Area 24,BA24 (Cluster 4) and left BA25 (Cluster 11) showed statistically significant separation among the spectra (3 - 40 Hz) of the 4 directions (Fig.1(a) and 1(b)), determined using a 1x4 ANOVA ($p < 0.05$). Clusters with centroid dipoles located in the sensory-motor pathways (left Thalamus) and right parahippocampal Area (PPA) showed clear alpha band peaks (8 - 12 Hz) (Fig. 1(c) and 1(d)). The spectra showed clear separation of "West" from other directions, although this was not statistically significant. It can be inferred that the areas, right BA24 (located in the Anterior Cingulate Cortex), left Thalamus and PPA, that are activated in decision making, sensory-information and cognitive processing, are involved in preparation period of the tasks after the subject was informed about the movement direction. We investigated the spectro-temporal characteristics of the causal networks modelled using the subject-specific clusters of dipoles, determined using K-means clustering (k=5). Our observations on one subject for the "West" movement direction are presented here. One representative dipole (with minimum residual variance) from each cluster was used for AMVAR modelling (model order 10 with window size of 0.25 seconds, increment step size 0.03 seconds). These dipoles were located on the left BA47 (IC1), right BA9 (IC2), left BA19 (IC3), left BA6 (IC4) and right BA47 (IC5). The flow of information in the preparation interval (centred at t= -0.5s, 9 Hz) is seen from left BA19 to left BA6, as quantified using Direct Directed Transfer Function (dDTF) (Fig. 1(e)). Moreover, peaks can been seen in the preparation interval (between t = -0.6s and t= -0.4s, 8 - 10 Hz) in the information transfer from left BA19 to left BA47, quantified using DTF on the fitted AMVAR model (Fig. 1(f)). Left BA6 is part of the premotor cortex (PMC) and supplementary motor area (SMA), involved in planning of coordinated movement. Left BA19 is a part of the occipital cortex involved in visual feature extraction. Left BA47 is part of the frontal cortex involved in semantics and language processing. The information flow between these brain regions is visible in the alpha band that is consistent with the group-level alpha peaks seen in areas in the visuo-motor cortex. Significance: Quantifying and studying brain networks in a relatively complex motor task showed evidence of information flow in the preparation stage which involved sensory, visuo-motor areas, which emphasizes the importance of studying networks-based BCI for revealing more comprehensive information. In future, we can use similar approaches with more accurate source localization techniques to corroborate our observations above and study more complex hand movements. References: [1] A. Delorme et al., Comput. Intell. Neurosci., 2011 [2] A. J. Bell et al., Neural Comput., 1995. [3] H. Courellis et al., Front. Neurosci., 2017

1-F-65 The cortical encoding of kinematics and kinetics during an object grasp task

Robert Flint[1], Matthew Tate[1], Marc Slutzky[1]

[1]*Northwestern University*

Introduction: Restoration of grasping function is a major priority for paralyzed individuals to achieve increased independence. Brain computer interfaces (BCIs) have the potential to grant this restoration. Previous studies have demonstrated that finger movement and grasp aperture can be decoded in real time from cortical activity in order to control a BCI. Motor cortical signals are capable of exceptionally stable movement representations over long time periods, which is promising for BCI development. However, some aspects of the cortical representation of object grasp are still not well understood. Manipulating objects with one's hands requires transitioning between movement and isometric force. To provide naturalistic interactions between any BCI-controlled hand prosthesis and objects in the environment, it will be necessary to decode both movement and intended level of force. Studies of motor control in both humans and nonhuman primates suggest that separate cortical processes may be responsible for controlling movement and force. Any complete description of the hand motor system, as well as naturalistic BCI control, requires an understanding of how movement and force are encoded in the cortex of healthy individuals. Materials, Methods and Results: We investigated the cortical representation of movement and force in seven human subjects undergoing ECoG placement for treatment of epilepsy or functional mapping of brain tumors. We used high-density electrocorticography (ECoG) arrays positioned over pre- and post-central areas (including primary motor, primary sensory, pre-motor and some pre-frontal cortices) to record the subjects' neural activity. The subjects completed a one-finger precision motor task that required both movement and isometric force application. We decoded continuous isometric force levels, as well as the kinematics of the index finger, using spectral power at individual ECoG electrodes. The ECoG sites' prediction accuracies on each part of the task provided a layout or map that revealed the cortical representation of the behavior. In addition, we investigated the spectral changes that accompanied the transitions from rest to movement and from movement to force. Finally, we quantified the timing of the movement-force transition, using a novel neural vector angle measure. ECoG signals allowed us to decode continuous movement with very high accuracy, with variance accounted for (VAF) of 0.69 ± 0.3 (median ± interquartile range; IQR) across all recordings (7 sessions, 14 runs, approximately 70 minutes of data). Continuous force decoding was slightly higher: 0.7 ± 0.12 (median ± IQR) VAF. Single-electrode decoding maps revealed different representations for movement and force execution within the same cortical region. Spectral analysis indicated that low frequency power modulations (approximately within the 20-50Hz range) were time-locked to movement onset, while higher frequency modulations were time-locked to force onset. Discussion: Everyday examples highlight the importance of controlling both kinematics and kinetics while grasping objects: lifting a paper cup full of liquid, turning a doorknob, social interactions like shaking hands. For BCIs to restore these abilities to individuals living with paralysis, they will need to allow control over both movement and force, and switch between these modes appropriately. The results presented here are being used to inform the design, currently underway, of a real-time, hybrid BCI for practical object grasp combining kinematics and force. Significance: Our findings indicate that practical BCI control of a real-world neuroprosthetic, complete with the ability to interact with objects, is feasible with ECoG signals.

1-F-66 Automatic artifact rejection using the Real-time EEG Source-mapping Toolbox (REST)

Luca Pion-Tonachini[1], Sheng-Hsiou Hsu[1], Chi-Yuan Chang[1], Tzyy-Ping Jung[1], Scott Makeig[1]

[1]*University of California San Diego*

Introduction: Brain computer interfaces (BCI) and other real-time electroencephalogram (EEG) applications often suffer when artifacts are present. Independent component analysis (ICA) has been widely used for separating out stereotyped artifacts from EEG data, such as saccade and eye-blink activities [1], and an online and real-time implementation of ICA is realized by Online recursive ICA (ORICA) [2].Unfortunately, ICA is sensitive to one-off, large-amplitude artifacts that can severely degrade the learned decomposition and requires visual inspection to manually identify artifactual components. Therefore, this study applies artifact subspace reconstruction (ASR) [3] prior to ORICA to remove large-amplitude artifacts and thus stabilize the ICA decomposition for improved artifact separation. ASR is an automatic, real-time artifact rejection (AR) method that is especially effective at detecting atypical, high-variance components such as movement artifacts by comparing against a pre-recorded "clean" dataset. Furthermore, we employ independent component (IC) classifiers, such as EyeCatch [4], to automate recognition and removal of the artifactual components. The full real-time, automatic AR pipeline is available in the open-source Real-time EEG Source-mapping Toolbox (REST) [2]. Materials, Methods, and Results: To evaluate the proposed AR pipeline in REST, we first collected a closed-eye EEG dataset in which a healthy subject performed a series of cued artifact-inducing actions comprised of jaw clenching, electrode tapping, head turning, and jumping.The subject rested for 2 minutes before performing each type of actions for 10 seconds at 5-second interval. Our goal is to evaluate the effects of artifacts on ORICA convergence and whether the proposed method can alleviate these effects. Next, we recorded 1 minute of the subject blinking at 1 second intervals and 1 minute of the subject looking to the left, right, and center of his visual field with saccades occurring at 1 second intervals. The subject rested with eyes closed for 2 minutes before each 1-minute section. Our goal is to characterize the performance of the proposed method in automatic identification and rejection of eye-related components and thus eye activities. We processed both datasets with the proposed pipeline using REST in a simulated real-time setting, which consists of channel rejection, common-average re-referencing, FIR high-pass filtering, ASR, ORICA, IC-classification/rejection, and channel reconstruction. For the first experiment, we processed the data both with and without ASR; for the second experiment, we processed the dataset both with and without ORICA/EyeCatch. The figure shows the combined effect of ASR, ORICA, and EyeCatch during the second experiment. The detected and rejected eye-related components are visible in the bottom left. The upper right panel shows that blink and saccade artifacts are cleanly removed (color traces) as compared to the original data (over-plotted gray traces). Discussion: The preliminary results demonstrate that the proposed automatic real-time AR pipeline, with the combined use of ASR, ORICA, and EyeCatch, can effectively remove various types of artifacts on live-streaming data. We will evaluate the effects of ASR on stabilizing ICA decomposition in the presence of different types of artifacts. We also expect that, with ASR removing large-amplitude artifacts, ORICA and EyeCatch can effectively separate, recognize, and reject eye-related activities. Significance: The proposed real-time, automatic AR pipeline - featuring ASR and ICA-based cleaning - can effectively remove both large-amplitude artifacts and eye activities and is available in an easy-to-use, open-source toolbox (REST), which allows real-time data-cleaning for BCI applications. References: A. Delorme, et al. , "Independent EEG sources are dipolar," in PLoS One, 2012. L. Pion-Tonachini, S.-H. Hsu, S. Makeig, T.-P. Jung, G. Cauwenberghs, "Real-Time EEG Source-Mapping Toolbox (REST): Online ICA and Source Localization," in IEEE EMBS, 2015. C. Kothe, T. P. Jung , "Artifact removal techniques with signal reconstruction," U.S. Patent Publication, 2015. N. Bigdely-Shamlo, et al., "EyeCatch: Data-mining over half a million EEG independent components to construct a fully-automated eye-component detector," in IEEE EMBS, 2013.

G- User Aspect: Experience, Ethics

1-G-67 A revised sensory/cognitive/communication screen for use with communication BCI study participants

Betts Peters[1], Michelle Kinsella[2], Brandon Eddy[3], Aimee Mooney[2], Melanie Fried-Oken[3]

[1]Institute on Development and Disabilities, Oregon Health & Science University, [2]Oregon Health & Science University, [3]Institute on Development and Disabilities, Oregon Health and Science University

Introduction: Use of a visual spelling BCI involves visual acuity, ocular motility to direct gaze to stimuli, and ability to maintain fixation. Cognitive and communication skills for attention to stimuli, understanding and following instructions, literacy, and executive functioning are also required. We previously developed a screening protocol for studies using the RSVP Keyboard? BCI, and reported

successful administration to 12 participants with severe speech and physical impairments (SSPI) [1]. When planning studies with the Shuffle Speller BCI, we realized that different skills were required and revised our screening to better fit the demands of that protocol. We also hoped to streamline and simplify screening administration and include informed consent procedures. Here we describe the revision process and the resulting tool. Material, Methods and Results: Revision began with a task analysis to identify skills and characteristics relevant to use of the Shuffle Speller BCI, including hearing, auditory comprehension, vision, cognition (including executive function for error awareness), letter recognition, spelling, pain, and medications. Our goal was to screen these areas with tasks requiring only yes/no or eye-movement responses. Portions of the original screening used an E-TRAN board, with Velcro-attached stimuli for each item. This was cumbersome and time-consuming. The new design is an 8.5x11" flipbook with one item per page and a hole for viewing eye movements. The examiner sees only number-coded boxes rather than actual response options to reduce the risk of bias when interpreting eye movements. Our original screening included questions for a participant's caregiver. These prolonged the screening visit, and caregivers may have felt uncomfortable giving thorough answers about some topics (e.g. cognition) in front of participants. The revision instead features a pre-screen, completed with a caregiver via telephone, with introductory questions on communication, motor, vision, hearing, and cognitive abilities. The updated screening includes informed consent procedures based on Vansteensel et al [2]. It begins with a hearing screening and a set of yes/no situational orientation and auditory comprehension questions. Respondents with a passing score of ≥19/20 on these sections are read the study consent form and asked 10 yes/no questions related to its content. An initial score ≤18/20 may indicate decisional impairment. Visual skills including fixation, pursuit, saccades, visual field, acuity, and visual perception are screened with items based on standardized assessments, modified for yes/no and eye movement responses. Subsequent items address pain interference, current medications, motor function, and positioning concerns. A modified Trail Making Test [3] screens cognition, followed by novel tasks addressing concepts of print, letter identification, copy-spelling, word completion, and error awareness. The revised screening was piloted with 2 individuals with SSPI, and the pre-screen with 1 caregiver. The pre-screen required ~20 minutes. Not including consent form read-through, the remainder of the screening required ~1 hour. Discussion: The OHSU BCI Sensory/Cognitive/Communication Screen-Revised assesses requisite skills for use of the Shuffle Speller BCI. It is compact, easy to transport and use in participants' homes, and requires a 20 minute caregiver phone call and 1 hour with a participant. Informed consent procedures require additional time. Administration may take 2 sessions, depending on participant endurance. Screening requires only yes/no responses and eye movements, and is thus suitable for people with incomplete and classic LIS. Significance: This screening tool allows for thorough description of the skills and characteristics of BCI study participants, and provides a method for obtaining informed consent from individuals with SSPI. It may also reveal barriers to successful BCI use, leading to identification of modifications and supports to help overcome such barriers. This screening may be a model for the development of screening tools tailored to other BCI systems. More detailed participant description will lead to better sharing and comparison of results within the field. Supported by NIH 2R01DC009834, NIDILRR 90RE5017.
References: 1. DOI: 10.3109/17483107.2013.836684 2. DOI: 10.1056/NEJMoa1608085 3. Trail Making Test, Bowie & Harvey, 2006

1-G-68 Icons are not equal: Considerations for use of icons in BCI systems.

Brandon Eddy[1], Betts Peters[2], Shiran Dudy[3], Tab Memmott[4], Steven Bedrick[4], Melanie Fried-Oken[1]

[1]Institute on Development and Disabilities, Oregon Health and Science University, [2]Institute on Development and Disabilities, Oregon Health & Science University, [3]Oregon Health and Science University, [4]Oregon Health & Science University

Introduction: BCIs for communication have historically been designed for literate adult users [1, 2]. There exist few communication options for potential end-users with limited literacy skills who rely on visual presentation. Previous work has demonstrated proof of concept for an icon-based BCI system for such users [3]. Within an RSVP platform, 7 of 10 literate, healthy adults successfully completed an icon copy-spelling task. Message generation using the alphabet has unlimited word options while messages created with icons rely on a restricted vocabulary. The next step is to identify appropriate icon sets for future testing. Icons for communication can be rated according to features including concreteness, visual complexity, meaningfulness, semantic distance, and familiarity [4-6]. Icon features influence how users process icons and affect selection accuracy, visual search time, reaction time, and accuracy expressing icon meaning [6, 7]. Here we present pilot data from the systematic evaluation of an icon set for use with the RSVP Keyboard? BCI. Material, Methods, and Results: We accessed the SymbolStix symbol set through a contract with News2You (www.n2y.com). Metadata were intersected with Subtlex [8] to develop a list of icons represented in both databases to prepare for development of an icon language model using word-level evidence. Icons were sorted into categories from SymbolStix metadata. Singular-form noun icons were selected from five categories applicable to end-users (health, home, places, nature, general). In total, 476 icons met criteria. Of those, 100 were randomly selected for rating. Two rating forms were created: (1) icon rating for concreteness, visual complexity, and meaningfulness (raters blinded to icon label); (2) semantic distance (icon label present). Familiarity was not rated since volunteers had no prior experience with the icon set. 25 icons were randomly selected for reanalysis at the end of each survey to assess intra-rater agreement. A convenience sample of 12 volunteers rated 125 icons according to icon features (Table 1) on a 5-point, partially labeled Likert scale. Intraclass correlation coefficient was calculated via a mixed-effects regression model to assess intra-rater reliability. Intraclass correlation was 0.69 and Kappa correlation was 0.53. Icon ratings for each feature were averaged across raters. Ratings were plotted using multidimensional scaling. An L-infinity norm was used to calculate distance between icons on multiple dimensions. Icons were paired with the icon with the shortest distance then removed from remaining pairings. Icon pairs were then separated into two equivalent icon sets for use in future experiments. Discussion: BCI systems must present only a limited number of icons to maximize efficiency, and it is critical to understand icon variables that may influence BCI performance. Our pilot demonstrated procedures for controlling icon sets for BCI studies, and resulted in development of two sets of icons for use in future experiments. We focused on singular-form noun icons, though similar procedures may be applied to other grammar classes. Low intra-rater reliability may suggest fatigue or refinement of a schema across ratings; future studies may consider monitoring rater fatigue and providing training examples. Significance: Icon features affect behavioral responses and may affect BCI performance. BCI research teams exploring non-orthographic language representation (e.g. emoji, pictures, icons) should attempt to control for concreteness, semantic distance, meaningfulness, familiarity, and visual complexity as potential confounding variables. Future research is needed to evaluate the effects of icon features on BCI performance, and to assess the effects of systematic training on users' ability to attend to and recognize icons. Acknowledgements: This work was supported by the RERC NIDILRR grant #90RE5017 and NIH grant #2RO1DC009834. References: 1. doi: 10.1109/icassp.2012.6287966 2. doi: 10.1088/1741-2552/aa776b 3. doi: 10.1090/2326263X.2014.996066 4. doi: 10.1037/h0054087 5. doi: 10.1016/S0022-5371(66)80061-0 6. doi: 10.1518/001872007x200102 7. doi: 10.1037//1076-898X.6.4.291 8. doi: 10.3758/s13428-012-0190-4

1-G-69 Towards a user-centred bci design: A survey of preferred mental strategies

Elmar G. M. Pels[1], Mariana Branco[1], Ruben Sars[2], Erik Aarnoutse[1], Mariska Vansteensel[1], Nick Ramsey[1], Femke Nijboer[2]

[1]Brain Center Rudolf Magnus, University Medical Center Utrecht, [2]Faculty of Social and Behavioural Sciences, Leiden University

Introduction: The prevalence of locked-in syndrome (LIS) has been estimated at 0.73 per 100.000 people in the Netherlands1. Brain-Computer Interfaces (BCIs) have been proposed as an assistive technology (AT), to aid people with LIS to use neural signals to spell sentences, control a cursor, or handle a robotic limb. To generate the appropriate neural signals to control these applications, users can adopt different mental strategies. We identified eight mental strategies that are often used for BCI control: visual imagery, hand movement attempt, other body part movement attempt, visual P300, auditory P300, SSVEPs, attempted speech and counting backwards. BCI studies typically investigate how different strategies affect BCI performance and speed. However, the users' opinion about which mental strategies are intuitive to use for BCI control, have hardly been investigated. Yet, a user-centered approach is crucial for an optimal development of daily usable BCIs, especially to reduce the risk of technology abandonment. Here, we present preliminary results of interviews with people with LIS and our investigation on which of the 8 mental strategies they prefer for BCI-control. Material, Methods and Results: So far, eight Dutch participants with LIS (median age 54 years old, range 29 to 64; 2 males), who were contacted through their primary caregiver, enrolled in the study. The institutional review board of the university medical center Utrecht approved the study and, with the participants' assent, the legal responsible signed informed consent. Before consent participants filled out an online screening form, the data of which were used to describe demographics and aspects of the participants' paralysis. The survey on mental strategies for BCI was administered during a 3-hour home visit, and consisted of an introduction video about BCIs followed by questions about the current AT(s) used, and 8 animation videos presented in random order explaining the mental strategies for BCI-control. After each animation the participant was asked to imagine using that particular mental strategy and then rate that strategy on difficulty and enjoyment. Most questions were multiple-choice or an answer could be given on a 5-point rating scale, but participants always had the opportunity to make remarks. The revised ALS functional rating scale was administered to assess LIS severity (scores ranged from 2 to 29 on a scale from 0 to 48). After explaining and rating the individual strategies we asked participants to rank their top 4 preferred mental strategies. The results (table 1), show that attempted movement of the hand or another body-part (mostly foot/toes) were most often picked in the top 4 of our participants. However, attempted speech was given the first rank on most occasions. Although visual P300 was perceived as fun (mean enjoyment score 4 out of 5) and easy (mean 5/5), only once it was picked in a top 4. So far, no relationship was observed with age, duration of paralysis or etiology. Discussion: The preliminary results suggest that attempted speech and movement are preferred over the reactive strategies, such as P300 and SSVEPs. Indicating that people like and find it intuitive to use the action generating part of the brain, the motor cortex, for BCI control. However, this might not apply to everybody. One participant, paralyzed from birth, said she cannot imagine or attempt to make a movement. Additionally, some possible users may have comorbid cognitive problems making it difficult for them to use certain strategies2. The survey expects to include 20 or more participants in total. Significance: Knowing what mental strategies are considered usable by potential BCI users is important. Our survey provides valuable information for stakeholders in BCI and AT development, promoting optimal BCI design and reducing risk of abandonment. Acknowledgment: The authors thank all respondents and their caregivers, and Wesley Sewnundun, Stéphane Tijs and Hanneke de Bruijne for their help with the questionnaire. References: 1: Pels et al. Neurorehabil Neural Repair, 2017 2: Nijboer et al. Brain-Computer Interfaces, 2014

Poster and Exhibitor Demonstrations Session 2

A- BCI Implant- Control

2-A-1 Dexterous control of seven functional hand movements using cortically-controlled transcutaneous muscle stimulation in a person with tetraplegia

Sam Colachis[1], Marcie Bockbrader, Mingming Zhang[2], David Friedenberg[2], Nicholas Annetta[2], Michael Schwemmer[2], Nicholas Skomrock[2], Jerry Mysiw, Ali Rezai, Herbert Bresler[2], Gaurav Sharma[2]

[1]The Ohio State University, [2]Battelle

Introduction: Individuals with tetraplegia identify restoration of hand function as a critical, unmet need to regain their independence and improve quality of life. Brain-Computer Interface (BCI)-controlled Functional Electrical Stimulation (FES) technology addresses this need by reconnecting the brain with paralyzed limbs to restore function. In this study, we quantified performance of an intuitive, cortically-controlled, transcutaneous FES system on standardized object manipulation tasks from the Grasp and Release Test. Using the system, the participant could volitionally select one of seven distinct functional hand states to successfully manipulate six everyday objects in real-time using naturalistic grasps with 12-15 mins of training. Materials, Methods and Results: The investigational system has been demonstrated during an FDA and IRB-approved study. We utilized a chronically-implanted intra-cortical microelectrode array to record multiunit activity from the motor cortex in a study participant with C5 quadriplegia from cervical spinal cord injury. We applied machine-learning algorithms to decode the neuronal activity and control activation of the participant's forearm muscles through a custom-built high-resolution FES system (Fig. 1). The participant's functional improvements were evaluated using the standardized Grasp and Release Test (GRT). With the system, the participant was able to perform seven distinct functional hand movements which allowed the participant to manipulate most objects more efficiently than with his baseline, adaptive grips and provided the ability to manipulate objects he could not grip at baseline. A single Support Vector Machine (SVM)-based decoder was able to reliably decode the seven attempted movements with the individual decoding accuracy of >96% for each movement. During the GRT experiment the participant accurately selected the desired hand movement out of the seven possible trained movements using naturalistic motor intent. Analysis of underlying motor cortex neural representations associated with the seven hand movement states also revealed non-separability in neural activation patterns for grasps required for similarly shaped objects that affected BCI-FES performance. Discussion: The ability to successfully manipulate multiple real-world objects encountered during activities of daily living remains a key challenge limiting the practical applicability of BCI-controlled FES devices for people living with tetraplegia. In this study, we build on prior knowledge by applying standardized tasks developed for neuroprosthetic studies (GRT object manipulation) to the evaluation of system performance. In this way, we allow for comparison between our BCI-FES technology and other neuroprosthetics, and develop a new understanding of the strengths and limitations of the BCI-FES system. We showed that the participant in our study could train to use the BCI-controlled FES system to perform functional tasks that required dynamic integration of FES-enabled paralyzed hand/arm muscles with non-paralyzed shoulder/elbow muscles. The system enabled the participant to select the desired hand movement, out of the seven possible trained movements, as well as a rest state available to him, using motor intent. The BCI-FES also enabled the participant to manipulate objects of different sizes, shapes, and weights with skilled, forceful grasps. In addition, our study revealed insights into the neural representation of hand movements in the motor cortex: we showed that stable representations of different hand movements can form in a very small area of the motor cortex under the implanted MEA; furthermore, we demonstrated that discriminability between these neural representations can affect decoder performance. These results suggest that motor cortex neural representations for functional grips are likely more related to hand shape and force required to hold objects, rather than to the objects themselves. Significance: We demonstrate that a BCI-FES system can enable seven functional, skilled hand functions that can generate adequate force to manipulate everyday objects with high-precision and naturalistic speed, meeting tetraplegic individual's desired priorities. Our results on enabling multiple, naturalistic functional hand movements constitute a further step towards translating BCI-FES technologies from research devices to clinical neuroprosthetics, returning hand function to people with paralysis.

2-A-2 Adaptive deep brain stimulation: Optimization of treatment in essential tremor using electrocorticography data

Benjamin Ferleger[1], Sebastián Castaño-Candamil[2], Andrew Haddock[1], Brady Houston[3], Michael Tangermann[2], Howard Chizeck[1]

[1]University of Washington, [2]University of Freiburg, [3]University of Wasington

Introduction: Deep brain stimulation (DBS) of thalamic and subthalamic structures has become a standard therapy for treating essential tremor (ET). Standard procedure for ET patients receiving DBS therapy is traditionally restricted to implanting and activating the device such that it provides a constant level of stimulation at parameters determined by a clinician. Consistently high stimulation amplitude is known to cause several unpleasant side effects. Closed-loop (CL) DBS seeks to simultaneously reduce unnecessary battery drain and mitigate side effects by modulating stimulation parameters based on the analysis of either external sensor data, e.g. worn inertial measurement units (IMUs) or, more recently, data from implanted sensors (e.g. ECoG arrays). Current CL-DBS methods use binary (on/off) control approaches. Recent research [1, 2] suggests that CL-DBS is at least as effective as constant stimulation. However, ET patients generally experience significant variations in severity of tremor depending on the activity they are engaging in, and even baseline changes day to day. Rather than generating a binary output, presented here is the initial demonstration of a graded CL-DBS system that provides the minimum stimulation amplitude required to suppress tremor. It is hypothesized this approach will reduce side effects and battery drain even further than in binary CL-DBS. Material, Methods and Results: Making use of the Activa PC S (Medtronic) platform, two patients (P1 and P2) were unilaterally implanted with DBS electrodes in the ventral intermediate nuclei and an ECoG strip on M1. Calibration sessions involved 10s relaxed in a chair without speaking (at rest) and 10s while maintaining a tremor-inducing arm posture, each while being stimulated at levels of {0.0; 0.5; 1.0; 1.5; 2.0; 2.5}V. Tremor was assessed by an IMU contained in an LG G smartwatch fastened to the subject's wrist and characterized as the [3 - 7]Hz band power. A regression model for estimating tremor intensity was trained on power-spectral features of the acquired single ECoG channel, preceded by a greedy forward feature selection. The estimator achieved crossvalidated linear correlation of 0.28 for P1 and 0.46 for P2 on calibration data. During each trial of the online phase, patients remained at rest for 20s before taking a tremor inducing arm pose for 30s. Each online block consisted of 6 trials. Two blocks were executed for P2; P1 completed only one due to time constraints. Stimulation was triggered by the tremor estimator: a binary or graded (increase/decrease amplitude) command was issued depending on the executed condition and corresponding to the two competing CL-DBS strategies. Promising results comparing these strategies are summarized in Figure 1. The graded stimulation in P1 worked as expected, i.e., during rest stimulation mostly remained off, whereas stimulation was active during the tremor-inducing arm posture. By P1's report, binary and graded CL-DBS were approximately as effective. Control signals determined for P2 seemed effectively random; this might be explained by P2's highly inconsistent tremor. However, P2 also reported that the treatment itself seemed unchanged across the different conditions. Discussion and Significance: As medicine progresses into more personalized arenas, the declining popular appetite for one-size-fits-all treatments will only accelerate. CL-DBS will assist patients and clinicians by erasing the balancing act between side effect mitigation and effective treatment in patients receiving DBS. The generation and early adoption of nuanced treatments will preempt popular misunderstanding of treatments. Our pilot results suggest that graded CL-DBS is a viable improvement upon binary CL-DBS. Acknowledgements: The authors appreciate support of the German Research Foundation (grant EXC1086 Cluster of Excellence BrainLinks-BrainTools and bwHPC grant INST 39/963-1 FUGG), the National Science Foundation for the Center for Sensorimotor Neural Engineering, and Medtronic for technical and intellectual contributions. References: [1] B. Houston, M. Thompson, J. Ojemann, A. Ko, H. Chizeck, "Classifier Based Closed-Loop Deep Brain Stimulation for Essential Tremor". In: 8th Int'l IEEE/EMBS Conf. on Neural Eng. (2017). [2] B. Houston, M. Thompson, A. Ko, H. Chizeck, "Comparisons of Closed-Loop Deep Brain Stimulation and Clinical Settings for Essential Tremor", (Ongoing).

2-A-3 Control of multiple hand movements using cortically-controlled, non-invasive muscle stimulation in a tetraplegic person

David Friedenberg[1], Sam Colachis[2], Nicholas Annetta[1], Mingming Zhang[1], Nicholas Skomrock[1], Michael Schwemmer[1], W. Jerry Mysiw, Ali Rezai, Herbert Bresler[1], Marcia Bockbrader, Gaurav Sharma[1]

[1]Battelle, [2]The Ohio State University

Introduction: Restoration of hand functionality is recognized as a critical, unmet need that has the potential to significantly increase the independence of patients suffering from tetraplegia. Advances in Brain Computer Interface (BCI)-controlled Functional Electrical Stimulation (FES) devices provide a promising approach towards meeting this need by bypassing the spinal cord injury and directly linking neural activity to a paralyzed limb in order to restore function. Translating these systems from the lab to home use introduces several engineering challenges including hardware ease-of-use, robustness of decoding algorithms, and overall system usability. In this talk we will present several improvements towards translation to home-use of our BCI-FES system since it was originally introduced [1], including increasing the number of movements, enabling continuously graded muscle contraction, developing novel decoding methods that can minimize daily decoder recalibration and training, and a new, wearable FES sleeve. Materials, Methods and Results: The investigational system has been demonstrated during an FDA and IRB-approved study. We utilized an intracortical microelectrode array to record neural activity from the motor cortex in a study participant with C5 tetraplegia from cervical spinal cord injury. We applied machine-learning algorithms to decode the neuronal activity and control activation of the participant's forearm muscles through a custom-built high-resolution FES system (Fig. 1). In one set of experiments, the participant was able to perform multiple distinct functional hand and finger movements, and use them to manipulate multiple objects of varying size, shape and weight. A Support Vector Machine (SVM)-based decoder was able to reliably decode the seven different attempted movements with individual decoding accuracy of >96% for each movement. The participant was able to select accurately the desired hand movement out of the seven possible trained movements available to him using naturalistic movements to manipulate objects by combining FES-enabled evoked hand/wrist movements with residual shoulder/elbow movements. In another study, we demonstrated that with small changes to the system, our participant was able to volitionally grade the contraction of his muscles to achieve targeted movements to which he had not been trained previously, with a success rate of 89.6%. In offline analyses we introduced a new deep learning based decoder paradigm and demonstrated that it is more accurate, does not require explicit daily retraining, could sustain performance for over a year, and can be generalized to additional movements using only a few training data sets. Finally, we will discuss our new high definition wearable FES sleeve, which is more user-friendly. Discussion: Potential BCI users prioritize systems that restore hand function, can enable a large number of functions, are non-invasive, have minimal set-up time, are accurate, responsive and simple to use. Both hardware and software improvements to our original system have advanced our BCI-FES system towards those goals. We have demonstrated improved hand function, using the system for more and diverse grasps as well as the ability to modulate force levels. Our new decoding methods overcome the need for daily retraining of decoders as well as making it easier for users to increase the number of movements. Simultaneously, these decoders demonstrate excellent accuracy and response times. Lastly, our new stimulation sleeve significantly improves usability and can generate more movements to improved electrode layout. Significance: In summary, our BCI-FES neuro-orthotic device meaningfully improves upon the state-of-the-art for assistive devices capable of meeting the desired priorities of restoring multiple, voluntary, and naturalistic hand functions for tetraplegia. We demonstrate that our BCI-FES system can enable functional, skilled hand grasps that can generate adequate force to manipulate everyday objects with high-precision, naturalistic speed, and minimal training requirements. Acknowledgments: This work was funded by Battelle and the Ohio State Wexner Medical Center [1] C. E. Bouton et al., "Restoring cortical control of functional movement in a human with quadriplegia," Nature, vol. 533, no. 7602, pp. 247-250, May 2016.

2-A-4 Population-level changes in primary motor cortex induced by the presence of an object

Angelica Herrera[1], John Downey[2], Delaney Moran[3], Aaron Batista[1], Steven Chase[4], Byron Yu[4], Michael Boninger[1], Robert Gaunt[1], Jennifer Collinger[1]

[1]University of Pittsburgh, [2]University of Chicago, [3]Middlebury College, [4]Carnegie Mellon University

Introduction: Brain computer interfaces (BCIs) can restore lost limb function by using neural signals recorded from primary motor cortex (M1) to control an external effector such as a robotic arm. We previously observed that many neurons in M1 increased their firing rate as the hand approached an object as compared to generating the same movement in empty space. This object-specific change in modulation led to a decrease in BCI performance if not accounted for in the BCI decoding algorithm. Here we extend that analysis to investigate how object presence modulates population-level neural activity during object interaction. Material, Methods and Results: A 28-year old male participant with tetraplegia who had intracortical microelectrode arrays (Blackrock Microsystems, Inc.) implanted in M1 completed this study. Neural data were recorded while the participant used a BCI to move a robotic arm to a specified location and either grasped an object or closed the fingers at that location. Neural firing rates were transformed into a 5-dimensional (5D) velocity control signal for the robotic arm using optimal linear estimation. These dimensions included 3D translation, 1D wrist rotation, and 1D grasp. An audio cue indicated the start of the trial when the subject could begin to reach towards the target. Once the arm was within 5 cm of the target, a second audio cue marked the beginning of the grasp phase. For a trial to be considered successful, the subject had to grasp within 5 seconds of the audio cue and maintain a grasped posture for 2 seconds. Data were recorded over five test sessions (355 trials). Neural spike counts were binned in 40 ms time bins. Successful trials were matched across both conditions and aligned at the beginning of the grasp phase. Data were analyzed for the final 2 seconds of the reach phase and the first 2 seconds of the grasp phase. Factor analysis was used to identify a low dimensional (n=10) representation of the population-level activity measured during reaches to objects and empty space. For each trial, neural data were projected into the latent space and we compared the neural trajectories projected onto each latent dimension for the object and no-object conditions. The participant demonstrated a decrease in performance when an object was present. He had a 92.3% success rate for no-object trials and 61.5% success rate for object trials. Trial-averaged neural trajectories were significantly different between the object and no-object conditions in either the first or the second latent dimensions, those that make up the highest variance in the data ($p< 0.001$ for all test sessions, Wilcoxon rank-sum). Separation between these neural trajectories began at around 386 ms before the grasp cue and the average maximal distance between them occurred at 480 ms after the cue to grasp. The latter time is most likely the actual onset of grasp, delayed due to the reaction time of the participant to the audio cue. Discussion: Our results demonstrate that there is a clear separation between population-level neural activity when reaching to an object. Future analysis will identify the axis of maximal separation between the object and no-object conditions and will determine whether this axis changes over time, suggesting either a constant or dynamic change in co-modulation patterns. We also plan to expand the conditions to determine which task parameters are driving this object-specific modulation of population-level activity. Significance: We previously showed that many neurons increased their firing rate when reaching towards an object as compared to reaching in an empty workspace. Here, by implementing a population-level analysis, we determined that the presence of an object is actually a dominant factor in driving neural co-modulation patterns in motor cortex. This context-dependent modulation in M1 can negatively impact BCI performance, as demonstrated by the drop in success rate when an object was introduced into the workspace. Understanding not only the impact but also the mechanism behind task context changes are thus vital to providing consistent BCI control.

2-A-5 Proposed strategies for simultaneous cognitive and motor state estimation for an intracortical brain-computer interface with sensors in prefrontal and motor cortices

Chadwick Boulay[1], Alireza Rouzitalab[2], Adam Sachs[1]

[1]Ottawa Hospital Research Institute, [2]University of Ottawa

Introduction: Goal-oriented behaviour requires sensory integration, decision-making, motor planning, and motor execution. In the brain, these processes are continually updated, they are interdependent, and each is represented across multiple brain regions. For example, prefrontal cortical neurons exhibit mixed selectivity for context, decision outcomes, and movement-related parameters (Boulay et al. 2016; Stokes et al. 2013; Jia et al. 2017) and kinematic encoding in primary motor cortex is context-dependent (Marsh et al. 2015; Downey et al. 2017). A BCI may be able to provide more natural assistive communication if cognitive and motor information can be demixed and used synergistically to drive an assistive device. Here we describe different decoding strategies that we are testing in a BCI human clinical trial (NCT03100110) with microelectrode arrays in both prefrontal (Brodmann area 8) and motor cortices. Material, Methods and Results: We identified methods for real-time motor or cognitive state estimation in the intracortical BCI literature. Intracortical BCI studies that investigate cognitive state demonstrate discrete goal decoding using linear discriminant analysis on signals in parietal (Aflalo et al. 2015) and prefrontal (Jia et al. 2017) cortices, though the description of the cognitive state is somewhat intangible and does not generalize well outside the experimental task. The most successful motor state estimators are variants of the Kalman filter (KF) that incorporate assumed intention and estimate effector end-point kinematics (Pandarinath et al. 2017). In our clinical trial, we are testing the following decoder strategies: (1) kinematic estimation with a KF and click estimation with a HMM; (2) a two-stage decoder with stage 1 being a discrete context decoder whose result selects among a bank of KFs for stage 2 context-dependent motor state estimation; (3) parallel cognitive and motor state estimation where the decoded goal probabilities constrain the kinematic output and the decoded kinematics constrain the goal selection output. Each strategy will be tested with different combinations of signal sources and dimensionality reduction techniques. We implemented the decoder components in our signal processing pipeline and tested them individually on playback of nonhuman primate data from either motor cortex (Riehle et al. 2013) or PFC (Boulay et al. 2016). While the individual decoder components work as expected, the novel decoder strategies have yet to be tested because we do not yet have simultaneous recordings from PFC and motor cortex. Discussion: BCI translation of a user's intention into action may benefit from novel decoder strategies that use a combination of direct goal decoding and context-aware kinematic decoding. It remains unknown if the proposed decoder strategies will result in improved assistive communication. Experiments performed in the framework of our clinical trial will provide unique insight into the cognitive and motor neuronal activity underlying goal-oriented behaviour. In this framework, rapid iteration of decoder-strategy testing is possible and community input is encouraged. Significance: Cognitive state estimation in isolation or in combination with motor state estimation will enable novel communication applications that are faster and more versatile than trajectory decoders. Novel strategies to translate cortical activity into device function are needed. Here we propose several approaches to combine cognitive state estimation and motor state estimation that we will test in a human clinical trial.

B- BCI Implant- Other

2-B-6 Effects of goal-directed sensory information on intracortical hand representations in human sensorimotor cortex

Dylan Royston[1], Stephen Foldes[2], Jeffrey Weiss[1], Cody Wabiszewski[1], Timothy Verstynen[3], Jennifer Collinger[1]

[1]University of Pittsburgh, [2]Phoenix Children's Hospital, [3]Carnegie Mellon University

Introduction: Intracortical brain-computer interfaces (BCI) can allow people with spinal cord injury (SCI) to control robotic limbs by translating patterns of neural activity recorded from microelectrode arrays in motor cortex (M1) into intended movements(1). Since the primary goal of using these BCI systems is to interact with objects, it is critical that we understand how the context or goal of a movement influences movement encoding; for example, we have observed that M1 activity differs when reaching to an object versus generating the same movement in an empty workspace(2). Here we investigate how goal-related visual, auditory, and somatosensory cues during attempted movements influence motor cortical population activity. Material, Methods and Results: We collected intracortical recordings from two 88-channel microelectrode arrays implanted in the primary motor (M1) cortex of a human participant with a C5-motor/C6-sensory incomplete SCI. Spike counts from each active (>5 spikes/sec) electrode were binned every 20ms while the participant viewed and attempted to perform movement tasks paced at 0.5Hz with their right hand, including hand grasping, finger tapping, and wrist flexion/extension. Each task was presented with 4 levels of multimodal sensory information: Simple (video of basic movement/sensation), Goal (object-directed), Audio (object-directed + auditory timing cue), and Stim (object-directed + auditory cue + vibrotactile timing cue). Data were collected in a single session. For each movement, a nested block design was used with four 10-second repetitions of each enrichment condition. To determine how population-level movement encoding is affected by task context, we performed principal component analysis (PCA) on binned firing rates to define a neural state space for each movement type. We then examined the trajectory of the population's trial-averaged time-series activity through this space during different enrichment conditions of the same task. We found that the general shape and centroid of these trajectories remained largely stable across conditions for each movement, while the volume of neural space traversed during attempted movement varied across conditions. To quantify this change, we computed the "neural distance" between the centroid and the neural trajectory for every time bin for each condition (Figure 1). On the medial array, the distance in the Goal, Audio, and Stim conditions were significantly greater than the Simple baseline for all three movements. Changes on the lateral array were more variable. Neural distances in the Goal and Stim condition were greater than Simple during hand movement, and all conditions were greater than Simple during wrist movement. No significant differences in trajectory distance were observed across enrichment conditions during finger movements. Discussion: We saw significant increases in the volume of neural space traversed by motor cortical neurons with increasing enrichment. This demonstrates that multisensory context information induces changes in the coordinated activity of sensorimotor populations. We also observed different enrichment effects on the two arrays, suggesting that adjacent motor cortical areas may process the same sensory information differently based on the target of their descending connections. Significance: These findings indicate that goal-directed multisensory information modulates population-level neural activity in motor cortex. Sensory enrichments may prove useful for BCI systems for rehabilitative and assistive applications. References: 1. Wodlinger, B. et al. Ten-dimensional anthropomorphic arm control in a human brain-machine interface: difficulties, solutions, and limitations. J. Neural Eng. 12, 16011 (2014). 2. Downey, J. E. et al. Motor cortical activity changes during neuroprosthetic- controlled object interaction. Sci. Rep. 1-16 (2017). doi:10.1038/s41598-017-17222-3 Acknowledgements: This material is based upon work supported by the Department of Veterans Affairs under grant B1464-R and Defense Advanced Research Projects Agency (DARPA) and Space and Naval Warfare Systems Center Pacific (SSC Pacific) under Contract No. N66001-16-C-4051. Any opinions, findings, conclusions, or recommendations expressed in this material are those of the authors and do not necessarily reflect those of the US government. We thank the participant for his time and effort.

2-B-7 Speech synthesis with densely Connected 3D convolutional neural networks from ECoG

Miguel Angrick[1], Christian Herff[1], Emily Mugler[2], Marc Slutzky[2], Dean Krusienski[3], Tanja Schultz[1]

[1]University of Bremen, [2]Northwestern University, [3]Old Dominion University

Introduction: Direct synthesis of neural activity into audible speech would provide an intuitive and natural communication means for mute users. Intracranial recordings of brain activity (ECoG) provide high temporal and spatial resolution and are an ideal candidate for the decoding of speech processes [1], and the recreation of speech from neural signals. Recent studies [2, 3, 4] have shown promising results with statistically- significant correlations between original and reconstructed speech by using mainly linear models. The complex spatio-temporal dynamics of continuous speech and ECoG data implicate that a simple linear mapping from one onto the other might not be sufficient. Convolutional neural networks (CNNs) have recently shown promising results for Brain-Computer Interfaces with limited training data [5]. For the network architecture we used Dense Convolutional Networks (DenseNet) [6] which yield state-of-the art results in computer vision while keeping the number of trainable parameters low compared to alternative architectures. Here, we show that DenseNet can be used to reconstruct a waveform with audible speech characteristics from invasively-measured brain activity. Material, Methods and Results: In our experiment, we presented a sequence of single words visually to three participants and asked them to read the words aloud. Each participant had a square ECoG grid with 8x8 electrodes implanted during awake surgery for glioma removal covering regions of the ventral motor cortex, ventral premotor cortex and the inferior temporal gyrus. Acoustic speech and ECoG activity were recorded simultaneously. Audio data was preprocessed by extracting 40 logarithmic mel-scaled coefficients from the spectrogram. For the ECoG data, logarithmic broadband gamma (70-170Hz) power was extracted for each electrode. This results in an 8x8 grid of high-gamma features for each time interval. To add temporal context dependencies into our reconstruction model, we concatenate neighboring intervals up to 200 ms preceding and following the current interval. DenseNet is a multilayer CNN that operates in a feed-forward fashion but uses feature-maps of preceding convolutions as additional inputs in all subsequent layers. Figure 1 shows the network structure integrated into the synthesis pipeline. We used 3 dense blocks and 20 feature-maps for the first convolution with a growth rate k = 10. To exploit the square shape of the electrode grid and the temporal features simultaneously, we changed the convolution to operate on all three dimensions to find patterns in the spatio-temporal space. The output layer applies a linear transformation to create a continuous output. We used Spearman's rank correlation to compare the reconstructed speech spectrogram with the original. For all three participants, we achieve statistically significant ($p<0.001$) correlations averaged over all spectral bins. Correlation coefficients reach mean scores of $p=0.38$ (std: ±0.12), $p=0.24$ (std: ±0.11) and $p=0.31$ (std: ±0.04) for the three participants, respectively. Discussion: We show that deep convolutional neural networks can reconstruct the speech spectrogram from intracranial activity recordings capturing characteristic aspects of the participant's speech. An audio waveform can be resynthesized from the reconstructed spectrogram [4]. Significance: This is a first step towards synthesizing audible speech with a non-linear model from neural signals measured directly from the cortex by using a deep convolutional neural network during speech production. References [1] Schultz, T., et al. (2017). Biosignal-based spoken communication: a survey. IEEE/ACM Transactions on Audio, Speech and Language Processing. [2] Herff, C., et al. (2016). Towards direct speech synthesis from ECoG: A pilot study. Engineering in Medicine and Biology Society, 38th Annual International Conference of the IEEE. [3] Martin, S., et al. (2014). Decoding spectrotemporal features of overt and covert speech from the human cortex. Frontiers in neuroengineering, 7. [4] Pasley, B., et al. (2012). Reconstructing speech from human auditory cortex. PLoS biology, 10(1). [5] Schirrmeister, R., et al. (2017). Deep learning with convolutional neural networks for EEG decoding and visualization. Human brain mapping. [6] Huang, G., et al. (2016). Densely connected convolutional networks.

2-B-8 The impact of intracortical microstimulation frequency on perceived intensity and its relationship to somatosensory processing in human somatosensory cortex

Christopher Hughes[1], Sharlene Flesher[2], Jeffrey Weiss[1], Michael Boninger[1], Jennifer Collinger[1], Robert

Gaunt[1]

[1]University Of Pittsburgh, [2]Stanford University

Introduction: It is difficult to handle objects without tactile feedback, but prosthesis users typically work with this limitation. To address this challenge, we provide somatosensory feedback via intracortical microstimulation (ICMS) delivered to area 1 of primary somatosensory cortex (S1). We have shown that ICMS evokes spatially selective percepts with a range of perceptual qualities. Here, we aim to better understand the relationship between pulse train parameters and perceptual quality by exploring the relationship between stimulus frequency and perceived intensity. Materials, Methods, and Results: This study was conducted under an Investigational Device Exemption from the U.S. Food and Drug Administration and approved by the Institutional Review Boards at the University of Pittsburgh and the Space and Naval Warfare Systems Center Pacific. We implanted microelectrode arrays (Blackrock Microsystems) in primary motor cortex (M1) and S1 in a person with a C5/C6 spinal cord injury. We conducted the present studies, in which the participant received charge-balanced biphasic ICMS in S1, to better understand how to modulate perceptual quality. To assess the effect of pulse train frequency on perceived intensity, we used a magnitude estimation task. Pulse trains were delivered for 1-s at 60 µA while we varied frequency between 20 and 300 Hz in pseudo-randomized order. The participant reported the perceived intensity on a self-selected numeric scale. We found that the relationship between frequency and perceived intensity was electrode-dependent: on some electrodes, pulse trains with low frequencies were perceived as more intense than stimulus trains at high frequencies, while on other electrodes, the opposite was observed, and still other electrodes were perceived as most intense at intermediate frequencies. We also found that, by lowering the amplitude from our standard amplitude of 60 µA to 30 µA and then to perithreshold levels (typically 10 to 16 µA), the relationships between frequency and perceived intensity transformed gradually such that, at the lowest amplitudes, high frequencies elicited higher intensities on all tested electrodes. We investigated if there was a spatial organization to the frequency-intensity trends by determining the likelihood of co-occurrence of the three frequency categories (low, high, intermediate). We examined electrodes within 800 µm of each tested electrode. If these trends occurred randomly in cortex, the presence of electrodes with similar responses would be approximately 33%. We found, however, that the co-occurrence was 59% for electrodes that showed significant frequency-intensity trends. To probe the mechanisms underlying these trends, we developed a simple computational model based on leaky integrate-and-fire (LIF) neurons. Changes in the stimulation amplitude affected the total recruitment of pre-synaptic neurons and thus activation of post-synaptic neurons. Increases in perceived intensity were assumed to result from increases in the activation of the post-synaptic neurons. We found that the frequency trends could be reproduced by modulating the ratio of excitatory to inhibitory pre-synaptic neurons or by changing the number of neurons recruited assuming a population of pre-synaptic cells where the ratio favors inhibitory neurons. Discussion: Our findings show that frequency impacts the perceived intensity of a stimulus train in an electrode-dependent manner. The effect of amplitude on these frequency-intensity trends may imply that they are an emergent property of larger populations of cells. Smaller amplitudes, and thus smaller populations of recruited cells, consistently produce results in which higher frequencies lead to higher perceived intensities. Further, the spatial clustering implies this is a property of the local networks and not simply a side-effect of ICMS. A simple LIF model can produce similar results based on variations in the ratio of excitatory to inhibitory neurons or the total number of recruited neurons for a network with a higher ratio of inhibitory neurons, which may provide a plausible mechanism for the observed trends. Significance: Understanding the mechanisms by which perceptual qualities are modulated by pulse train parameters will help us understand how sensation is processed in somatosensory cortex. This will ultimately allow for better intentional control of the percepts elicited by ICMS feedback in closed-loop brain computer interfaces.

C- BCI Non-Invasive- Control

2-C-9 3D BCI control through simultaneous overt spatial attentional and motor imagery tasks

Jianjun Meng[1], Taylor Strietz[1], Nicholas Gulachek[1], Bin He[1]

[1]*University of Minnesota*

Introduction: It is of significance and great interest to move the noninvasive electroencephalography (EEG) based brain-computer interface (BCI) beyond the one-dimensional (1D) or two-dimensional (2D) controls. The conventional motor imagery based modulation of brain rhythms provides relatively easy and intuitive way for 1D or 2D controls [1], however, three-dimensional (3D) control or even beyond is challenging based on solely motor imagination. 3D BCI control is vital for an efficient robotic arm or prosthetic control [2]. In this study, we propose a paradigm based on parietal brain rhythm modulation named overt spatial attentional (OSA) orientation and combine this paradigm with the conventional motor imagination (MI) to formulate a novel 3D BCI control based on endogenous EEG modulation. Material, Methods and Results: EEG data were recorded from 16 subjects via a 64-channel NeuroScan Synamps RT amplifier. All subjects signed informed consent according to a protocol approved by the IRB. Subjects were required to focus their attention on the direction of which the yellow bar appeared (i.e. left, right, top or bottom side of the display screen) to enable the control of 1D or 2D cursor movement in the OSA modulation; they were asked to perform hand movement imagination (i.e. left, right, both hands and relax) to enable the control of 1D or 2D cursor movement in the MI modulation, as illustrated in Fig. 1(a). Ultimately, the combination of the most confident and comfortable OSA or MI modulations in three dimensions was customized for each subject and this combination allows subjects to control a cursor moving in 3D simultaneously. Fig. 1(b) showed the experimental scene in a realistic experiment. The subjects were required to move the cursor from the center of the cubic to hit a highlighted target at one edge of the cubic working space. Each subject participated in three sessions of BCI 3D control task of 8 targets. In each session, they finished 7 runs of BCI cursor control and each run consisted of 25 trials. Fig. 1(c) showed a group average percent valid correct (PVC) of 16 subjects. At the first session, the subjects showed a group average of higher than 50% PVC accuracy and later showed a trend of improvement across the three sessions. There is a statistically significant improvement of PVC accuracy from session one to session three which might indicate a learning of a complex brain rhythm modulation happened during the three training sessions. Discussion: With the motivation of moving noninvasive EEG based BCI control to the 3D setting, a combination of OSA modulation and MI modulation was proposed in this study. An endogenous brain modulation named OSA beyond motor imagination was proposed and studied for the first time here. Our promising experimental results supported the hypothesis that

BCI 3D control could be realized through simultaneously modulating spatial attention and motor imagery which had distinct spatial topography. Significance: Moving the noninvasive EEG based BCI towards 3D control is vital for the implementation of assistive technology by BCI such as BCI control of a robotic arm. It might also be useful for the application of stroke rehabilitation which was mostly explored in a 1D setting previously even though our hand or arm movement was much more complex than a movement in a single dimension. Acknowledgment: This work was supported in part by NIH AT009263, MH114233, NIH EB021027, NS096761, and by NSF CBET-1264782. References [1] He B, Gao S, Yuan H, Wolpaw J. Brain-Computer Interface. In He B (Ed): Neural Engineering, Springer, pp. 87-151, 2013. [2] Meng J, Zhang S, Bekyo A, Olsoe J, Baxter B and He B. "Noninvasive Electroencephalogram Based Control of a Robotic Arm for Reach and Grasp Tasks." Scientific Reports 6 (2016).

2-C-10 MoreGrasp - EEG-based non-invasive neuroprosthesis for decoding of multiple natural single limb movements and multipad-electrodes for closed-loop grasp pattern control

Gernot Müller-Putz[1], Andreas Schwarz[1], Joana Pereira[1], Patrick Ofner[1], Andreas Pinegger[1], Matthias Schneiders, Björn Hessing, Andrew Ramsey[2], Roderick Murray-Smith[2], Carlos Escolano[3], Luis Montesano[3], Granit Luzhnica[4], Eduardo Veas[4], Jan Loitz[5], Rüdiger Rupp[6]

[1]Graz University of Technology, [2]University of Glasgow, [3]Bit & Brain Technologies, [4]Know Center, [5]MEDEL, [6]University Hospital Heidelberg

Intoduction Motor neuroprostheses based on functional electrical stimulation (FES) can restore permanently lost functions in people with high spinal cord injury (SCI), specifically of the grasping. Non-invasive FES using surface electrodes represents a less complex, easy-to-apply alterative to invasive approaches [1]. An EEG-based Brain-Computer Interface (BCI) may be used to control grasping by imaginations or attempts of movements [2]. While the feasibility of the combination of BCI with FES was already shown in single case studies [3, 4], intuitive EEG-based BCI-neuroprostheses control is still missing. Due to the fact that the output of non-invasive BCIs is mainly digital, autonomous, closed-loop generation of grasp patterns is needed. Additionally, methods for supporting the end users in electrode placement need to be established. The European MoreGrasp consortium tries to overcome these problems by realization of an individualized, sensorized forearm sleeve with integrated multi-pad electrodes and the implementation of a BCI based on the decoding of single limb movements. Methods Two high-resolution EEG studies with 15 able-bodied subjects each were used to determine the decoding classification accuracy of 6 single joint movements of the same arm and of 3 different grasp types of the same hand. In both studies, motor-related cortical potentials (MRCPs) in a narrow 0.3 to 3 Hz band were investigated [REF1, REF2]. Following the protocol of these 2 studies, 2 subsets of movements were classified in 5 participants with high cervical SCI (Neurological level: C3 - C5). Currently a clinical study is being setup where already eight end users are appointed for screening and FES training. However, first results on this will be ready to be presented at the BCI Meeting. Two sets of multi-pad electrodes were developed: 1) a stackable screening electrode matrix consisting of 15 (5 x 3, HxW, 6.3 x 3.8 cm) electrodes (diameter 7mm, inter electrode distance of 2.5 cm) made of conductive silicone, and 2) a personalized forearm silicone sleeve with 64 electrodes and two inertial measurement units (IMUs) for wrist rotation angle measurement. A tablet computer based software for determination of the most selective and robust electrode positions was developed. Results The 1st BCI-study revealed a classification accuracy of 37% (chance level 16.7%), with classifier sources mainly in premotor and primary motor areas. The 2nd study showed that grasps can be decoded from MRCP features (binary classification of 74% grasp vs. grasp). Experiments with SCI showed a classification accuracy (3 conditions) of 53 % (subset 1) and 57 % (subset 2). The test results of the multi-pad electrodes in 3 able-bodied subjects and 1 end user with SCI reveal that not only a semi-autonomous quantification of the degree of denervation is possible, but also robust electrode positions for palmar or lateral grasps and electrode switching strategies can be defined for generation of a wrist-rotation-angle-independent grasp force. Discussion: The studies show that it is possible to detect single movements of the same arm from the EEG, either single joints or different grasp patterns. The multi-pad concept of the MoreGrasp grasp neuroprosthesis helps to overcome major challenges of noninvasive grasp neuroprostheses for every-day use. The system is currently tested in a proof-of-concept study at end users' homes. Significance: With the restoration of hand function in end users with cervical spinal cord injury the quality of life can be dramatically increased. Acknowledgements: This project is supported by the EU Project H2020-643955 MoreGrasp. References [1] Rupp R. (2017) Neuroprosthetics. In: Weidner N., Rupp R., Tansey K. (eds.), Neurological aspects of spinal cord injury, Springer, Cham, Switzerland, 689-720. [2] Müller-Putz GR et al. (2016) From classic motor imagery to complex movement intention decoding: The noninvasive Graz-BCI approach. Prog.Brain.Res 228. [3] Rupp R et al. (2015) Functional rehabilitation of the paralyzed upper extremity after spinal cord injury by noninvasive hybrid neuroprostheses. Proc. IEEE 103(6). [4] Müller-Putz GR et al. (2005) EEG-based neuroprosthesis control: a step towards clinical practice. NSL 382(1). [5] Schwarz A et al. (2017). Decoding natural reach-and-grasp actions from human EEG, JNE, 2017. [6] Ofner P et al. (2017) Upper limb movements can be decoded from the time-domain low frequency EEG, PlosOne.

2-C-11 Source localization of pediatric Brain-Computer Interface using electroencephalography

Brett Paffrath[1], Adam Kirton[2], Ephrem Zewdie[2]

[1]Alberta Children's Hospital, [2]Cumming School of Medicine, University of Calgary

Introduction: Electroencephalography (EEG) is the most common method of recording brain activations during Brain-Computer Interface (BCI) use. Inverse modeling techniques of EEG for source localization is commonplace in adults, but has not been examined in children. This study examined the EEG source activation patterns of 19 typically developing children between the ages of 6 and 18 using an EMOTIV EPOC 14 electrode BCI system. 17 individuals were surveyed to be right handed and 2 were left handed. Participants were recruited from the Alberta Children's Hospital's HICCUP database of healthy children. All participants had no prior experience using a BCI. Material, Methods and Results: This trial focused on two independent methods of BCI control to perform a single task: using motor imagery (MI) and Goal Oriented Thinking (GO) based BCI to move a remote-controlled (RC) car. During MI testing, participants were instructed to imagine opening and closing both of their hands to move the car forward and to think of nothing in particular ("neutral") to keep the car still. During GO testing, participants were instructed to imagine the car performing the desired task. All participants completed both tests in two discrete sessions with a two week intermission. Participants trained each command for 16 seconds and were subsequently given 10 attempts per command, in a randomized order, to either drive the car forward 2 meters or leave the car stationary. Each attempt lasted 20 seconds, where participants were required to either hold neutral for 5 seconds or move the car within 8 seconds for a successful attempt. Performance for both tests was evaluated using a Cohen's Kappa measure of agreement between command given and action performed. To begin source localization, The EEG recordings for motor imagery and neutral were mapped onto standard brain MRI as a calculated estimate of dipole current; these maps were then averaged over time and per trial to yield average dipole current per participant. Neutral was then subtracted from the motor imagery to create a baseline normalized map. Regions of greatest activation in both tests appeared to be the visual and motor cortices as well as the Frontal Gyrus. The frontal lobes were divided into 6 anatomical regions and a single quantitative measure of the EEG power was calculated from each region. Comparing EEG measures with the performance score shows a significant correlation ($p < 0.05$) between Left Medial Frontal Gyrus ($R=0.571$, $p=0.0168$), Precentral Gyrus ($R=0.526$, $p=0.0303$), and Superior Frontal Gyrus ($R=0.530$, $p=0.0285$) activations with performance during MI control. For the GO tests, a significant correlation between EEG and performance was found across both hemispheres in the Anterior Commissure, Superior Frontal Gyrus and Supplementary Motor Area, in addition to the Right Medial Frontal Gyrus. Discussion: MI results show a significant left side lateralized correlation in line with the majority handedness of participants. This suggests a significant improvement in BCI control by the favouring of the dominant side. GO results show significant bilateral correlation between activation and performance in nearly all regions tested. This shows that for a complex thought involving deep concentration, many brain regions are involved in near equal priority and as such, an increase in the output of any of these regions can lead to greater accuracy by improving the readable signal for the BCI. Significance: By correlating sites of activation with BCI performance, this examination could prove invaluable in the designing of montages that allow for greater user precision and reduced number of electrodes in BCI for children with stroke, ADHD, or other neurological disorders. While the primary motor cortex was not examined extensively due to the limited montage of the Emotiv Epoc, this experiment can be utilized to identify secondary EEG regions of motor initiation and planning.

2-C-12 Effects of extended relaxation and motor coordination training on SMR BCI performance

Andrea Kübler[1], Loic Botrel[1]

[1]University of Würzburg

Introduction: 30 years have passed since the introduction of non-invasive sensorimotor (SMR) based brain-computer interfaces (BCIs), which allow for controlling a device with no muscular input by using electroencephalographic (EEG) brain signals. Psychophysiological variables explaining variations in BCI performance have been reported, such as the ability to concentrate on a task and the proficiency in a two-hand visuomotor coordination [1]. Those two predictors have then been manipulated by Botrel and colleagues for increasing SMR-BCI accuracy [2]. A group of N=154 participants performed either short progressive muscle relaxation (PMR), visuomotor coordination training (VMC) training or reading (CG) prior to a BCI session. SMR BCI performance was not affected by the pre-BCI intervention. Authors suggested that the 23 minutes trainings may have been too short to lead to any substantial effect on BCI accuracy. Thus, in the current study, training durations were extended. Materials, Methods and Results:

N=39 healthy participants, with no prior SMR-BCI experience were recruited at the University of Würzburg (Germany) and received monetary reward or student participation credits. Thirteen participants were pseudo-randomly assigned in each of the three groups, with 23 minutes of either Jacobson's PMR for relaxation, VMC training, and reading a book as control. For VMC training subjects had to steer a cursor with two knobs along a track; the time the cursor was outside the track accumulated to error duration. After the PRE-BCI session on day 1, four training sessions took place on days 1 to 4, followed by a POST-BCI session on day 5. Subjective relaxation level was measured before and after each training and BCI sessions. Error duration was used as a measure of VMC ability. EEG signals were recorded with a 63 electrodes EEG cap (Acticap), digitized at 1000 Hz (two BrainAmp amplifiers), bandpass filtered between 0.016 Hz and 250 Hz. PRE and POST BCI sessions were identical, based on the Berlin BCI [3] including a co-adaptive classification, zero-training approach, automatic band and trial time selection and a combination of predefined Laplacian and common spatial filtering. The BCI design was similar to [2] but without positively biased feedback. BCI accuracy was calculated on 240 four seconds supervised online trials of either left- or right-hand motor imagery. BCI accuracy PRE=67.8%, SD=15.9 and POST=71.2%, SD=16.3. Repeated measures ANOVAs yield a significant effect of time on BCI accuracy $F(1,36)=4.34$, $p=.044$ but no effect of group nor interaction between group and time. Relaxation intervention did not lead to increased relaxation levels prior to BCI sessions $F(2,36)=.251$, $p=.77$. VMC error duration varied over VMC training sessions $F(3,36)=10.17$, $p<.001$, showing a reduction between day 1 and day 4 $M=-.84$, $SD=.76$, $t(12)=3.23$ $p_{adj}=.044$. Discussion: BCI accuracy increased between PRE and POST BCI sessions, independently from any training. Visuomotor coordination proficiency increased with time, but did not lead to a higher BCI accuracy. Subjective relaxation level did neither increase with PMR nor did it improve BCI accuracy. Thus, intensifying the training duration did not yield any effect on BCI accuracy. In contrast, long-term relaxation training studies have shown a positive association between such training and BCI accuracy [4,5] such that e.g., meditation practitioners performed better than non-practitioners. Relaxation methods were different across studies and require proper definition. Significance: More studies that replicate and manipulate potential predicting variables are necessary to substantiate potential predictors. VMC and PMR training do not affect later SMR BCI performance even if the predictor itself is improving. References [1]: Hammer et al. (2014). Frontiers in human neuroscience, 8:574. [2]: Botrel et al. (2017). International Journal of Psychophysiology, 121(Supplement C):29 - 37. [3]: Blankertz et al. (2007). NeuroImage, 37(2):539-550. [4]: Tan et al. (2014). Consciousness and Cognition, 23:12-21. [5]: Cassady et al. (2014). Technology, 2(3):254-260.

2-C-13 Mind body awareness training improves performance with sensorimotor rhythm based brain computer interfaces

James Stieger[1], Christopher Cline[1], Christopher Coogan[1], Bhavani Sai Rohit Murakonda[1], Samantha Sherman[1], Andy Huynh[1], Desirae Hammond, Kit Breshears, Taylor Boyle, Mary Jo Kreitzer[1], Stephen Engel[1], Bin He[1]

[1]University of Minnesota

Introduction: Sensorimotor rhythm (SMR) based brain-computer interfaces (BCIs) can be used to control an external device through motor imagery [1-3]. SMRs are oscillations that can be measured by electroencephalography (EEG) over the sensorimotor cortex. The ability to imagine movements and modulate SMRs is variable across individuals. Previous work has suggested that long-term mind-body awareness training (MBAT) offers merits in improving the performance of SMR based BCIs [4]. However, whether such improved BCI performance results from a natural affinity for mental training or directly from MBAT is not clear. The aim of this study was to test the hypothesis that short-term MBAT can exert an influence over BCI control in a random assignment design. Material, Methods, and Results: To assess the effects of MBAT on BCI control, 41 subjects attended an 8-week mindfulness-based stress reduction (MBSR) class. BCI learning was compared between these MBAT subjects and 34 wait-listed controls, across several days of SMR based BCI training sessions. Subjects performed motor imagery of hand movements while EEG mu rhythms were extracted and used to decode subjects' intention to move a computer cursor [1-3]. Subjects were instructed to imagine left (right) hand movement to move the cursor left (right), movement in both hands to move the cursor up, and a voluntary rest to move the cursor down. In separate blocks of trials, subjects attempted to steer the cursor to a target that required left/right (LR) movement only, up/down (UD) only, and combined 2D movement (2D), performing 150 trials of each per session. Accuracy was quantified by a percent valid correct (PVC) metric, calculated as the number of hits divided by the total number of non-timeout trials. Overall, MBAT subjects outperformed control subjects in all paradigms. MBAT subjects improved more during training in the UD and 2D paradigms compared to controls (PVC differences from baseline of 14% vs. 9% in UD and 10% vs. 6% in 2D). MBAT subjects reduced their average number of error trials per session by a significantly greater extent during the early learning phase (first 5 sessions) of BCI training in the UD and 2D paradigms (reduction of 12.6 errors vs. 4.7 errors in UD and 9.5 errors vs. 1.9 errors in 2D). While final statistical analysis is ongoing, preliminary results reveal multiple trends for improved performance following MBSR. Discussion: MBAT subjects demonstrated enhanced learning in our study, suggesting short-term mindfulness meditation training can improve the efficiency of SMR based BCI training. Our past work showed an advantage for subjects with years of MBAT training; the present work extends this finding to 2 months of training. Work is ongoing to examine whether cognitive, behavioral, or electrophysiological measures can explain the observed results. Significance: The major challenge facing the widespread adoption of non-invasive BCIs is variable user proficiency. Our work demonstrates that errors can be reduced through MBAT. Determining whether the observed changes result from stable attention or more distinguishable motor rhythms could lead to standardized BCI training protocols including targeted MBAT practices. While work so far have focused on basic tasks such as computer cursor movement, it will also be interesting to test whether MBAT can enhance learning of more complicated BCI tasks [5]. Acknowledgment: This work was supported in part by NIH AT009263, MH114233, EB008389, and by NSF CBET-1264782, DGE-1069104. REFERNECES: [1]He B, Gao S, Yuan H, Wolpaw J: "Brain-Computer Interface," In He B (Ed): Neural Engineering, Springer, pp. 87-151, 2013. [2]H. Yuan and B. He, "Brain Computer Interfaces Using Sensorimotor Rhythms: Current State and Future Perspectives," IEEE Transactions on Biomedical Engineering, vol. 61, no. 5, pp. 1425-1435, May 2014. [3]He B, Baxter B, Edelman B, Cline C, Ye W: "Sensorimotor Rhythms based Noninvasive Brain-Computer Interfaces," Proceedings of the IEEE, 103(6): 907-925, 2015. [4]K. Cassady, A. You, A. Doud, and B. He, "The impact of mind-body awareness training on the early learning of a brain-computer interface," Technology, vol. 02, no. 03, pp. 254-260, Sep. 2014. [5]LaFleur K, Cassady K, Doud A, Shades K, Rogin E, He B: "Quadcopter control in three-dimensional space using a noninvasive motor imagery based brain-computer interface,"Journal of Neural Engineering,10:2013

2-C-14 Transferring shared responses across electrode montages for an SSVEP-based BCI

Masaki Nakanishi[1], Yu-Te Wang[1], Tzyy-Ping Jung[2]

[1]*University of California San Diego,* [2]*University of California, San Diego*

Introduction: The performance of steady-state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs) has been drastically improved in the past decade [1]. Recent advances in SSVEP-based BCI attribute to 1) an effective multiple stimulus modulation and 2) efficient target identification algorithms. For example, an SSVEP-based BCI combining 40 visual flickers coded by a joint frequency-phase modulation (JFPM) method [1] and task-related component analysis (TRCA) achieved an unprecedented ITR of 325.33 ± 38.17 bits/min [2]. Although the study results showed that optimizing template signals for each session and individual would lead to best performance, collecting template (or training) data might be time-consuming. To facilitate the training procedure, this study aims to explore the feasibility of transferring template signals from different sessions with the same or different EEG montages (or headsets). Material, Methods, and Results: In conventional template-based SSVEP detection methods, the templates can be obtained by averaging training data across trials [1, 2]. The proposed method transfers the templates in shared feature spaces between training and test data by applying linear projection coefficients. In the training phase, canonical correlation analysis (CCA) and TRCA [2] were employed to find the coefficients. In the testing phase, projection coefficients are computed for every single trial so as to minimize the mean squared errors between the test data after projection and the transferred templates. Final feature values are calculated by combining 1) canonical correlations between the multichannel test data and the computer-generated reference signals, and 2) Pearson's correlation coefficients between the projected test data and transferred templates into a shared feature space. The visual stimulus corresponding to the maximal final feature value is selected as the target stimulus. The proposed algorithm was evaluated using a 40-class SSVEP dataset [1]. Eight subjects participated in BCI experiments on two different days, in which they performed six blocks of a simulated online BCI task with 40 visual stimuli modulated by the JFPM. The EEG data were recorded by nine electrodes over the parietal and occipital areas (Pz, PO5, PO3, POz, PO4, PO6, O1, Oz, and O2). As shown in Figure 1(a), different subsets of electrodes were extracted from each day to simulate the non-overlapped montages of different EEG headsets. Figure 1(b) depicts the correlation matrices of SSVEPs between two days after projecting them onto the shared feature space, showing higher correlations along the diagonal elements than in others. Figure 1(c) shows the classification accuracy as a function of stimulation length using three algorithms including the unsupervised standard CCA, the proposed method with CCA- and TRCA-based transferred templates. The proposed methods outperformed the standard CCA-based method with all the data lengths. Two-way repeated measures analysis of variance (ANOVA) showed significant main effects of target identification algorithms (From Day 1 to 2: $F(2,14) = 16.48$, $p < 0.001$; From Day 2 to 1: $F(2,14) = 8.56$, $p = 0.004$). Discussion: The spatial filtering techniques used in the conventional template-based SSVEP detection algorithms generally require consistent electrode placements between training and test data, which causes difficulty in transferring SSVEPs across sessions and/or electrode montages [1, 2]. The proposed method made it possible to transfer templates across different domains by finding their shared feature space. This approach is ideal for detecting SSVEPs coded by JFPM because the transfer templates contain both frequency and phase information embedded in the SSVEPs. Furthermore, this approach might also be applicable to other reactive BCI paradigms such as P300 or rapid serial visual presentation. Significance: The proposed template-transfer approach has great potentials to facilitate training procedures required toward high-speed BCI systems by desterilizing previously recorded datasets collected on different days or by different headsets. [1] Chen X, et al., High-speed spelling with a noninvasive brain-computer interface. Proc. Natl. Acad. Sci. U.S.A., 112(44): E6058-6067, 2015. [2] Nakanishi M, et al., Enhancing detection of SSVEPs for a high-speed brain speller using task-related component analysis, IEEE Trans. Biomed. Eng., 65(1): 104-112, 2018.

2-C-15 Phase-locked visual stimulation for precise modulation of the amplitude of alpha wave based on real-time decoding of alpha phase

Jia Liu[1], Gan Huang[1], Qianqian Lin[1], Linling Li[1], Chunqi Chang[1], Chuang Lin[2], Zhiguo Zhang[1]

[1]Health Science Center, Shenzhen University, [2]Shenzhen Institutes of Advanced Technology Chinese Academy of Sciences

Introduction: Growing evidence has shown that the visual stimuli delivered at different phases of alpha wave evoke different alpha dynamic behaviors [1, 2]. It inspires us to develop a new neural modulation system which can deliver visual stimuli continuously at a specific alpha phase based on real-time decoding of the dynamic evolution of alpha wave. With the new system, the amplitude of alpha wave can be more precisely tuned, providing a more precise and reliable means for modulating brain states. Material, Methods and Results: The schema for the proposed real-time decoded neural modulation technique is shown in Fig. 1. The online alpha wave decoding module and visual stimuli feedback module were developed based on BrainAmp SDK and Arduino Uno. Raw EEG was recorded by BrainAmp from Oz (referenced to FCz). Four types of the alpha wave phases ($0, \pi/2, \pi, 3\pi/2$) were estimated, which corresponded to the upward zero-crossing, local maximum, downward zero-crossing and the local minimum of the filtered signal (10-10.5 Hz). Visual stimuli with the four types of alpha phases were randomly arranged in one session of 2 minutes (0.5 minutes for each phase). Visual stimuli at seven different light intensities were delivered and each intensity was repeated for 3 times. Four healthy volunteers (all males, 23.25±0.96 years) participated in the experiment. The Welch's method was used for estimating EEG spectra. Repeated measure one-way ANOVA with cluster based permutation test [3] was performed at each frequency bin (frequency resolution is 1000 Hz) to examine the modulation effect of the visual stimuli delivered at specific decoded alpha phases on the amplitude of alpha wave. The statistical analysis was used separately for each subject. Fig. 2 shows that the amplitude of alpha wave was remarkably different in response to visual stimuli delivered at different alpha phases for subject 1, 3 and 4. However, for subject 2, the modulation effect of the proposed system is not significant, which may be because this subject did not have a prominent alpha wave. Discussion: In this study, we built a proof-of-concept real-time phase-decoded neural modulation system and showed it could effectively modulate the amplitude of the alpha wave if one individual has a prominent alpha wave. The proposed system would be potentially used for augmentation of sensory, cognitive and motor functions. However, the cross-subject variability in using this system should be further studied in future. Significance: Ideally, BCI provides a direct communication pathway for the bidirectional information flow between brain and machine. Currently, the noninvasive BCI, like motor imaginary, P300 and SSVEP,

focuses more on decoding brain states from EEG, but less on neural modulation. On the other hand, brain modulation techniques, like neurofeedback and brain stimulation, do not place emphasis on the neural decoding. The proposed decoded neurofeedback system combines the merits of BCI and neurofeedback. 1.Compared with the traditional BCI techniques, the proposed system decodes phase of the alpha wave and directly uses this information in feedback to modulate the alpha wave in a more precise and adaptive manner. 2.Compared with the traditional EEG-based neurofeedback technique, this novel phase-decoded neural modulation technique requires no training and can be achieved a millisecond scale. 3.Compared with the traditional TMS, tDCS-based neural modulation method, the LED light is used as the visual stimuli, which is more convenient, lower-priced and less harmful. 4.More importantly, the proposed technique is subject-specific and -adaptive, which could achieve optimized modulation performance. Acknowledgments This work was supported by National Natural Science Foundation of China, No. 61701316, Research Project of State Key Laboratory of Mechanical System and Vibration MSV201710. None of the authors have potential conflicts of interest to be disclosed.
Reference [1] Ritter, P., & Becker, R. (2009), 'Detecting alpha rhythm phase reset by phase sorting: caveats to consider', Neuroimage, vol.47, no.1, pp.1-4 [2] Mazaheri, A., & Jensen, O. (2006), 'Posterior α activity is not phase-reset by visual stimuli', Proceedings of the National Academy of Sciences of the United States of America, vol.103, no.8, pp.2948-2952 [3] Maris, E., & Oostenveld, R. (2007), 'Nonparametric statistical testing of EEG-and MEG-data', Journal of neuroscience methods, vol.164, no.1, pp.177-190

2-C-16 A comparison of oddball and deterministic paradigms for ERP-based brain computer interfaces

Bruna Girvent[1], Paula Gonzalez -Navarro[1], Mohammad Moghadamfalahi[1], Lama Nachman[2], Deniz Erdogmus[1]

[1]Northeastern University, [2]Intel Corporation

Introduction: The P300 matrix speller [1] enables users with speech and physical impairments to communicate with others. Typically, an oddball paradigm is used to elicit the P300 event-related potential (ERP) and detect user intent. Several variations have been presented by changing the shape, color and duration among other characteristics of the visual stimuli [2]. However, all the variations rely on an oddball paradigm where the rows and columns are highlighted in a pseudo-random order to elicit the P300 ERP. In this study, we investigate whether a matrix speller is ultimately dependent on an oddball paradigm. We address this question by comparing it with a deterministic paradigm, where the rows are highlighted from the top to the bottom and the columns from left to right. In this way, the user can predict where their intended target will be highlighted. We think this paradigm relies on other ERPs (e.g visual evoked potentials) instead of the established P300 component. Material: We used the RSVP Keyboard [3], a BCI typing interface developed in our lab. This system can employ rapid serial visual presentation (RSVP) and matrix-based presentations [4]. Data was collected using the g.USBamp amplifier with 16 electrodes. Method: We implemented the two paradigms in the matrix-based presentation of the RSVP Keyboard [4]. The oddball paradigm highlights the rows and columns of the matrix in a pseudo-random order. In contrast, the deterministic highlights them in order from top to bottom and left to right. 10 users participated in the study which consisted of two sessions to evaluate the two paradigms. Each session started with a calibration task to collect supervised data for training the classifier. Then the user had to copy 8 words containing a total of 37 characters. After completing both sessions, the user rated the difficulty of each paradigm and indicated which one they preferred. For character prediction, the EEG data was first pre-processed and then windowed from 0 to 500ms to capture the ERPs of each visual stimuli. PCA was used for dimensional reduction and regularized discriminant analysis (RDA) for feature extraction. A maximum a-posteriori (MAP) classifier combined the EEG features with a 6-gram language model and predicted users' intended target. Results: 100% accuracy was achieved when predicting each character for most of the participants in both paradigms. This is because multiple repetitions were used for prediction. To better compare both paradigms, we compared the AUCs for single-trial ERP detection obtained after 10-fold crossvalidation as shown in the figure. An average of 0.88 was achieved for both paradigms. The figure also compares the rating of difficulty given by each user. Overall, users found the deterministic paradigm easier. Discussion: Similar results were obtained for both paradigms. Some users performed slightly better with the oddball paradigm, whereas others performed better with the deterministic. Statistical analysis does not show significant differences in performance between the two paradigms. However, most of the users preferred the deterministic paradigm and found it easier as the highlighting of each row or column is predictable. Significance: In this study we have shown that the widely used matrix-based spellers are not ultimately dependent on an oddball paradigm. A deterministic paradigm can be used instead. This paradigm is easier to use according to our participants, potentially causing less fatigue and making it more suitable for long usage. Although, this needs further investigation, we think it has potential to be used with people with disabilities. Acknowledge: Our work is supported by NSF (IIS-1149570, CNS-1544895, IIS-1717654), NIDLRR (90RE5017-02-01), and NIH (R01DC009834). References: [1] L. A. Farwell and E. Donchin, "Talking off the top of your head: toward a mental prosthesis utilizing event-related brainpotentials", 1988, DOI:10.1016/0013-4694(88)90149-6. [2] M. Akcakaya et al., "Noninvasive brain-computer interfaces for augmentative and alternative communication", 2014, DOI:10.1109/RBME.2013.2295097. [3] U. Orhan et al., "Rsvp keyboard: An eeg based typing interface", 2012, DOI:10.1109/ICASSP.2012.6287966. [4] M. Moghadamfalahi et al., "Language-model assisted brain computer interface for typing: A comparison of matrix and rapid serial visual presentation" 2015, DOI:10.1109/TNSRE.2015.2411574.

2-C-17 Semiautomatic physiologically-driven feature selection improves the usability of a brain computer interface system in post-stroke motor rehabilitation

Emma Colamarino[1], Floriana Pichiorri[2], Donatella Mattia[3], Febo Cincotti[1]

[1]Sapienza University of Rome; Second affiliation: NeuroElectrical Imaging and BCI Lab, Fondazione San, [2]Fondazione Santa Lucia- IRCCS, [3]Fondazione Santa Lucia IRCCS

Introduction: Sensorimotor Brain-Computer Interface (BCI) systems can be beneficial for post-stroke functional motor recovery. In a randomized controlled clinical trial, it was demonstrated that an electroencephalogram (EEG)-based BCI-assisted Motor Imagery (MI) training improved the outcome of motor rehabilitation of the upper limbs with functional and neurophysiological relevant benefits in subacute stroke patients [1]. In this context, the reinforcement of a specific EEG pattern elicited by correct MI required that expert neurophysiologists with knowledge of BCI technology identified the optimal control features for each single patient. As such, this procedure is highly dependent on the operator and is currently restricted to researchers with experience in the BCI field and specific neurophysiological knowledge. To overcome these limitations, we developed a semiautomatic method to select control features that by combining both physiological and statistical approaches could ultimately increase the usability of BCI technology and thus, foster its use in clinical routine. Here, we present a preliminary validation of performance accuracy based on a comparison between classification performances obtained using BCI control features selected by expert professional users (manual procedure) and those obtained by semiautomatic method (guided procedure). Material, Methods and Results: EEG dataset previously acquired from 13 first ever, unilateral, subacute stroke patients [1] were analysed to compare manual vs guided procedure in terms of classification performance. In [1] all patients were trained to perform motor imagination of the affected hand movements. EEG data from the initial screening session [1], collected from 61 electrodes according to an extension of the 10-20 International System, were analysed to identify the control features. For the performance evaluation step, EEG data collected in the first training session [2] were considered. EEG data (sampled at 200 Hz) were re-referenced to the common average reference and divided into epochs of 1 second. Spectral features (spectral amplitude at each bin for each EEG channel) were extracted using the Maximum Entropy Method (2 Hz resolution). Two types of features selection were considered: i) the manual selection in which expert professional users (neurophysiologist, BCI researchers) identified the control features and assigned them weights based on visual inspection of the EEG pattern as in [1]; ii) the guided selection in which experts imposed some constraints(e.g., topographical, that is involving only the stroke hemisphere) and the semiautomatic method which was implemented as a stepwise regression algorithm would then operate the feature selection and the weight evaluation. For each procedure, the linear combination of the selected features and weights was the score value used for the offline performance assessment evaluated by means of the Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) curve. A paired-samples t-test was applied to compare AUC values relative to manual vs guided procedure (statistical significance threshold $p < 0.05$). Figure 1 shows for each dataset and each procedure the AUC values. No significant differences were found between two procedures ($p=0.13$). Discussion: The improvement of the BCI system's reliability is substantially based on an optimization of BCI system control features. When dealing with BCI application in post-stroke rehabilitation to promote motor function recovery (and plasticity related phenomena) control feature selection requires specific knowledge and expertise. The application of a guided procedure based on a method that combines both physiological and statistical feature selection approaches on real data sets showed performances comparable to those obtained with manual procedure. This suggests that it is feasible to successfully support the professional end-users such as therapist/clinicians who are not necessarily expert in BCI field, in the EEG feature selection yet according to evidence-based rehabilitation principles. Significance: The provision of BCI control feature selection with the semiautomatic physiologically-driven method allows for the reproducibility of the selection (and thus, reliability) and facilitates it, promoting the transferability of BCI technology to post-stroke rehabilitation routine. References: [1] Pichiorri et al., Ann Neur 2015 [2] Morone et al., Arch Phys Med Rehabil 2015

2-C-18 Post-stroke rehabilitation training with a Brain-Computer Interface: Clinical and neuropsychological study

Guzel Aziatskaya[1], Roman Lyukmanov[1], Olesya Mokienko[1], Nataliya Varako[1], Alexander Frolov[2], Lyudmila

Chernikova[1], Natalya Suponeva[1], Michael Piradov[1]

[1]Research Center of Neurology, [2]Institute of Higher Nervous Activity and Neurophysiology of RAS (IHNA&NPh RAS)

Introduction. According to the recent Guidelines for adult stroke rehabilitation and recovery (Hatem et al. 2016), mental practice is reasonable to consider as an adjunct to upper extremity rehabilitation services (A level of evidence). Repeated use of brain-computer interfaces (BCIs) providing contingent sensory feedback of brain activity was recently proposed as a rehabilitation approach to restore motor function after stroke. Little is known about limitations of neuropsychological deficit on mental practice. The aim of this study was to evaluate clinical efficacy of BCI-supported mental practice and to reveal specific cognitive impairment which determines mental practice ineffectiveness and inability to perform MI. Material, Methods and Results. Fifty five hemiplegic patients after first-time stroke (median age was 54, 0 [44, 0; 61, 0], time from onset 6, 0 [3, 0; 13, 0] month) were randomized into two groups - BCI and sham-controlled. Severity of arm paresis was measured by Fugl-Meyer Assessment of Motor Recovery after Stroke (FMA) and Action Research Arm Test (ARAT). Twelve of them were examined using Luria method in a form of interview performed by certified neuropsychologist. After assessment patients were trained to imagine kinesthetically a movement under control of BCI with the feedback presented via an exoskeleton. Patients underwent 12 training sessions lasting up to 40 min. BCI classifier recognition rate was analyzed as an indirect indicator of motor imagery quality. Significant correlation was revealed between particular neuropsychological tests (Taylor Figure test, choice reaction test, Head test) and online accuracy rate. Evaluation of the UL clinical assessments indicated that both groups improved, but only the BCI group showed an improvement in the ARAT's grasp score from 0,0 [0,0; 14,0] to 3,0 [0,0; 15,0] points ($p<0{,}01$) and pinch scores from 0,0 [0,0; 7,0] to 1,0 [0,0; 12,0] points ($p<0{,}01$). Upon training completion, 21.8% and 36.4% of the patients in the BCI group improved their ARAT and FMA scores respectively. The corresponding numbers for the control group were 5.1% (ARAT) and 15.8% (FMA). Discussion. These results suggest that adding BCI control to exoskeleton-assisted physical therapy can improve post-stroke rehabilitation outcomes. Both maximum and mean values of the percentage of successfully decoded imagery-related EEG activity were higher than chance level. A correlation between the classification accuracy and the improvement in the upper extremity function was found. An improvement of motor function was found for patients with different duration, severity and location of the stroke. Significance. It seems to be promising that the detailed neuropsychological approach can shed light into process of mental imagery and its transformation in damaged brain and might be used as a screening before mental practice admission as well as neurophysiological data obtained from BCI can probably predict to some extend clinical outcomes in post stroke patients.

2-C-19 Can the MIQ-RS questionnaire be used to estimate the performance of a MI-based BCI?

Sébastien Rimbert[1], Nathalie Gayraud[2], Maureen Clerc[2], Stéphanie Fleck[3], Laurent Bougrain[4]

[1]Inria Nancy, [2]Inria Sophia Antipolis-Méditerranée and Université Côte d'Azur, [3]Université de Lorraine - PErSEUs EA 7312, [4]Université de Lorraine, LORIA, UMR 7503

Introduction: Predicting a subject's ability to use the interface with good accuracy is one of the major issues in the motor Brain-Computer interface (BCI) domain. A few recent studies show that subjective questionnaires could be used to predict the performance of motor imagery (MI) based BCI. Indeed, the Kinesthetic and Visual Imagery Questionnaire (KVIQ), could allow a better predictability of BCI-illiterate cases [1]. Another more recent questionnaire called the Motor Imagery Questionnaire Revised-Second Edition (MIQ-RS) is a suitable option for examining MI ability [2]. In 2016, Marchesotti et al. found that the representation of subjective behaviour, calculated using the MIQ-RS questionnaire, and the control of the BCI were intimately linked [3]. However, in these studies [1, 3], the performance of the classifier was calculated for a right-hand MI versus a left-hand MI task. In this abstract, we classify between resting state and imagined movement, which is a relevant classification task in BCI research [4]. The aim of this study is to answer the following question for a resting state versus MI classification task: can the MIQ-RS be used to estimate the performance of an MI-based BCI? Material, Methods and Results: 36 right-handed healthy subjects (12 females; aged 31.3 years ± 14.4) were tested for their perception level of their visual and kinesthetic MI ability via the MIQ-RS questionnaire. EEG signals were recorded with a Biosemi Active Two 32-channel EEG system during a MI task (i.e. a single closing of the right hand) in one session of 40 trials. The EEG signal was bandpassed using a Butterworth filter between 8 and 30 Hz and segmented into 3.5 second trials. A Riemannian-based Tangent Space classification method [5] coupled with a Logistic Regression classifier was used to generate classification results in a 4-fold cross validation scheme. We computed the correlation between the classification results and both the kinesthetic (K) and the visual scores (V). The recovered Pearson correlation coefficient was equal to $\rho = 0.02$, (p-value = 0.87) in the first comparison, and $\rho = -0.12$ (p-value = 0.47) in the second. Moreover, we performed a Principal Component Analysis over the aforementioned three features (Figure 1A) whose analysis produced no indication of any correlation between them. Finally, we observed 3 different profiles according to users' MIQ-RS values (identified K+ and/or V+ if their score is over 70%, K- and/or V- otherwise). We computed the average accuracy of each class (Figure 1B) and performed Welch's t-test to verify the statistical significance of the differences between the average classification results. We obtained the following p-values: 0.118 between K+V+ and K-V+; 0.714 between K+V+ and K-V-; and 0.048 between K-V- and K-V+. Finally, we computed the Event-Related Spectral Perturbation (ERSP) between 5-30 Hz within each group using the EEGlab toolbox and we again compared the differences between groups. The obtained p-values were all superior to 0.01. Discussion: Our results revealed no correlation between the classification results and the MIQ-RS scores, contrary to those suggested by [1, 3]. While the classification results and ERSPs differ upon grouping the subjects according to their MIQ-RS profiles, we found no statistical significance (p-value < 0.01). Significance: Our results demonstrate that the MIQ-RS questionnaire cannot be used to estimate the performance of a MI-BCI based on distinguishing between resting state and right-hand MI tasks. References: [1] A. Vuckovic, BA. Osuagwu, "Using a motor imagery questionnaire to estimate the performance of a Brain-Computer Interface based on object oriented motor imagery", Clinical Neurophysiology, Vol 124, pp 1586-1595. 2013. [2] A. J. Butler et al. "The Movement Imagery Questionnaire-Revised, Second Edition (MIQ-RS) Is a Reliable and Valid Tool for Evaluating Motor Imagery in Stroke Populations", eCAM. 2012 [3] S. Marchesotti et al. "Quantifying the role of motor imagery in brain-machine interfaces", Sci. Rep. 6. 2016. [4] G. Townsend, B. Graimann, and G. Pfurtscheller, "Continuous EEG classification during motor imagery-simulation of an asynchronous BCI. IEEE Transactions on Neural Systems and Rehabilitation Engineering," 12(2), 258-265. 2004 [5] A. Barachant, S. Bonnet, M. Congedo and C. Jutten, "Riemannian geometry applied to BCI classification" in LVA ICA. Springer, Berlin, Heidelberg, pp. 629-636. 2010.

2-C-20 BCI-based control of pre-movement sensorimotor rhythm amplitude may improve motor performance after stroke

Sumner Norman[1], Dennis J McFarland[2], Alex Miner[1], Steven Cramer[1], Eric Wolbrecht[3], Jonathan R Wolpaw[2], David Reinkensmeyer[1]

[1]University of California Irvine, [2]National Center for Adaptive Neurotechnologies, Wadsworth Center, [3]University of Idaho

Introduction: Robotic devices, including exoskeletons and brain-computer interface (BCI) technology, are attracting increasing interest as tools for enhancing movement training after stroke [1]. To the extent that poor motor preparation limits motor function, using a BCI to train pre-movement sensorimotor rhythms (SMR) might improve the ensuing motor action. Here, we studied the immediate and therapeutic effects of BCI-based training to control pre-movement SMR on robot-assisted finger extension in people with moderate-to-severe hand impairment after chronic stroke. Material, Methods, and Results: Seven participants who had a chronic stroke completed a 4-week 3-phase protocol during which they practiced finger extension with assistance from the FINGER robotic exoskeleton [2] while we digitized EEG (at 256 Hz) from 16 scalp locations. In Phase 1 (week 1), we identified for each person SMR spatiospectral features in the pre-movement period that correlated with the intent to extend the index and/or middle finger(s). In Phase 2 (weeks 2 & 3), participants learned to increase or decrease those SMR features given visual feedback, without finger movement. In Phase 3 (week 4), we cued the participants to increase or decrease their SMR features, and when they were successful, we cued them to immediately attempt to extend the finger(s) with robot assistance. Robot assistance was only triggered after participants reached a small threshold of finger extension force against the robot. In Phase 1, movement intention correlated with a decrease in SMR power in person-specific spatiospectral locations. In Phase 2, four of seven participants achieved SMR control (binomial test, $p<0.001$). In Phase 3, SMR condition had a significant effect on movement latency (two-way ANOVA, $p=0.012$). Three of the four participants with SMR control initiated finger extensions faster (t-test, $p<0.05$), and two extended at least one of their fingers more forcefully ($p<0.05$), after decreasing (vs. increasing) pre-movement SMR amplitude. Across the course of training, hand function, measured by the BBT, improved 7.3 +/- 7.5 blocks in the participants with SMR control and 2.0 +/- 1.0 in those who did not gain SMR control. Higher BBT scores at baseline correlated with larger changes in BBT score (ordinary least squares, R2=0.925, $p=0.038$; SMR control group only, R2=0.99, $p=0.005$). Discussion: In previous work in people without movement impairment, movements preceded by reduced SMR power (vs. increased) had significantly shorter latency [3]. Here, we set out to explore for the first time the effect of controlling pre-movement SMR in people with motor impairment due to stroke. These results suggest that decreasing SMR power before a finger extension reduces movement latency and improves force. Participants also experienced a therapeutic benefit to hand function following the four weeks of BCI-enhanced robotic training, especially if they had more hand function at baseline. These encouraging results merit further investigation in a larger study with an appropriate control group. Significance: This study showed for the first time in people with stroke that learning to decrease SMR amplitude before movement may allow people to produce faster and more forceful ensuing finger extension movements. Distinctive features of the approach presented here are: 1) Identifying subject-specific SMR features associated with the intent

to move; 2) Using the BCI to train people to modulate these personalized features to improve movement preparation (instead of using the BCI to directly assist movement or to modify the brain state during movement); and 3) Training individuated finger extensions. Acknowledgements: This work was supported by NIH grants R01HD062744 (NCMRR/NICHD), EB00856 (NIBIB), and 1P41EB018783 (NIBIB).
References: [1] J. J. Daly and J. R. Wolpaw, "Brain-computer interfaces in neurological rehabilitation," The Lancet Neurology, vol. 7, pp. 1032-1043, 2008. [2] H. Taheri, J. B. Rowe, D. Gardner, V. Chan, K. Gray, C. Bower, et al., "Design and preliminary evaluation of the FINGER rehabilitation robot: controlling challenge and quantifying finger individuation during musical computer game play," Journal of neuroengineering and rehabilitation, vol. 11, p. 10, 2014. [3] D. J. McFarland, W. A. Sarnacki, and J. R. Wolpaw, "Effects of training pre-movement sensorimotor rhythms on behavioral performance," Journal of neural engineering, vol. 12, p. 066021, 2015.

2-C-21 An affordable BCI design for robot and wheelchair navigation

Yih-Choung Yu[1], Brandon Smith[1], Ashley Goreshnik[1], Lisa Gabel[1]

[1]Lafayette College

Introduction: Brain-Computer Interfaces (BCIs) offer an alternate means of motor control and communication, especially for those with severe motor impairments and disabilities. BCIs bypass the peripheral nervous system by using neural activity to control an external device. By way of a neuro-feedback loop, users learn to modulate their neural signals to control a specific computerized paradigm. Ultimately these devices enable individuals who suffer from motor impairment to regain some degree of autonomy, possibly enhancing their quality of life. In this study, we present a hybrid BCI device, which employs a wireless EEG headset with a gyroscope function for a low-cost, easy-to-use design, to control two ground-based devices (a small robot and a full-size wheelchair) through a host computer. Material, Methods and Results: The design of the Hybrid BCI consists of a signal acquisition device, controlled device, and feature extraction and control scheme. The Emotiv Epoc EEG wireless headset (Emotiv Systems) was used to acquire signals from the occipital lobe (O1 and O2), frontal lobe (AF3 and AF4), and gyroscope associated with head rotation at a rate of 128 Hz. The ability to navigate two devices was examined in this study: a Lego Mindstorms NXT robot and an electric wheelchair. The electric wheelchair was designed specifically for this application: a pair of dc motors controlled via Victor 884 motor controllers by an Arduino Uno microcontroller. The microcontroller receives the commands, forward, backward, turning left/right, and stop, from the BCI control scheme and sends pulse-width modulation signals to the motor controllers to accomplish the task. The Lego NXT robot serves as a model of the wheelchair for user training. The BCI detects specific features of a user's neural signals that are associated with their specific intentions, and then sends the appropriate commands to move the robot or wheelchair. The design relies on signal processing and feature extraction implemented in a Java program. This asynchronous BCI paradigm uses alpha waves, neuromuscular artifacts, and head rotation to control both the NXT robot and wheelchair. In this study, eye closure increases the alpha wave activity detected over O1 & O2, and is used to start and stop movement of the robot or wheelchair. High frequency blinking (5 blinks within 2 seconds) detected over the AF3 & AF4 is used to reverse the device's current direction, allowing users to toggle between forward and backward movement. Head rotation detected by the horizontal axis gyroscope controls navigation of turns. Accuracy of wheelchair operation was determined by the number of true positives (the system responds when asked) to the total number of operational commands given to the wheelchair ratio. After properly calibrating the detection thresholds, wheelchair operations resulted in 90% accuracy on reverse operation, 85% on start/stop, and 100% on rotation left/right, respectively. The ability of participants (n=20) to navigate an obstacle course using the hybrid BCI and the possibility of performance improvement with repeated training were evaluated over a two-day procedure. Following training, participants were asked to navigate the robot through an obstacle course, mimicking a real-world scenario (e.g. traversing a ramp, navigating within a bathroom stall). Results from this study demonstrate that participants perform as well on the first day of testing as they do on the second day of testing, occurred at least 24 hours later. All participants were able to successfully navigate through the obstacle course following a brief training period. Discussion: Accuracy of the BCI operations relies on proper calibration of the detection thresholds. An automated graphical user interface would make the calibration more user-friendly. Results from this study demonstrated that participants perform equivalently on both days of test, although they did report their ability to use the BCI was better on day two comparing to day one. Significance: This study demonstrated the feasibility of a BCI-controlled wheelchair by training participants to navigate a BCI robot using straightforward controls, testing their BCI abilities, and then comparing their performance from two separate days of training and testing. High user success rates and short training times suggest that this low-cost, wireless BCI device has potential to reach a broader population for use with a variety of applications.

2-C-22 Evaluation of a congruent auditory feedback for motor imagery BCI

Emmanuel Christophe[1], Jérémy Frey[2], Richard Kronland-Martinet[1], Jean-Arthur Micoulaud-Franchi[3], Jelena Mladenovic[4], Gaelle Mougin[5], Jean Vion-Dury[6], Solvi Ystad[1], Mitsuko Aramaki[1]

[1]PRISM laboratory - CNRS - Aix Marseille Université, [2]Ullo, [3]Clinique du Sommeil - CHU de Bordeaux - Univ. Bordeaux - CNRS, [4]Potioc Inria, and CRNL Inserm, [5]CNRS, ENS, Pays germaniques - Archives Husserl, [6]PRISM laboratory - CNRS - Aix Marseille University

Introduction: Designing a feedback that helps participants to achieve higher performances is an important concern in BCI research. Various congruent (task-related) visual feedback have been examined and showed promising results, e.g. using body ownership illusions in VR [1]. The use of congruent sound in combination with the visual modality demonstrated to increase performances in Motor Imagery (MI) BCI [2]. However, evaluating solely auditory feedback is often neglected, even though it could be a valuable alternative modality. We investigate the relevance of congruent versus non-congruent (abstract) auditory feedback in assisting the user to imagine feet movement in an EEG-based MI BCI. Material, Methods and Results: Users task was either to imagine moving their feet or to rest. The instructions consisted of 4-taps of sticks for MI of feet, and a relaxing sound for the resting state (figure A). There were two conditions: "non-congruent", during which the feedback provided was abstract and not related to any task (harmonic sounds with a different pitch) and "congruent", during which the MI feedback reflected the sound of one's footsteps on gravel, and the rest feedback a relaxing sound of water. The choice of such sound for the congruent MI task was motivated by the fact that

rhythmical sounds relate to motor cortex [3]. For the same reason, both tasks in the non-congruent condition were as non-rhythmic as possible. Moreover, such congruent sounds were chosen to increase sense of ownership. The influence of the feedback was evaluated within-subjects. Non-congruent and congruent feedback were generated in real-time, the former with Max-MSP and the latter with a dedicated synthesizer of environmental sounds. [4]. Ten participants were recruited (2 women, mean age: 24.8, SD: 4.98, all BCI naives). They were seated in front of a single speaker. 7 passive gold cup electrodes were placed over Cz, C1, C2, FCz, CPz, CP1 and CP2 in the 10-20 system and connected to an OpenBCI Cyton amplifier. Before the experiment participants heard an example of each sound to get accustomed to the task. In order not to reveal the outcome of the experiment, the feedback was simply introduced as "environmental sounds" or "musical sounds". A run of calibration was followed by two runs with one feedback and then two runs with the other (conditions' order was counterbalanced across participants). A run contained 30 trials of 13 seconds, 15 for each class (rest or MI) in random order. A session lasted ~45m. Using OpenViBE, signals were filtered in the alpha (8-13 Hz) and beta (13-30 Hz) bands, passed to a Filter Bank Common Spatial Pattern filter and classified using linear discriminant analysis. We tested for significance using Wilcoxon signed-rank tests. There was no difference in online performance between the two feedback (Figure B). An offline analysis revealed a significant difference ($p < 0.05$) in classification accuracy when a classifier was trained separately on the "congruent" and "non-congruent" runs (respectively 66.1%, SD: 7.45 and 63.9% SD: 7.8, 10-fold cross-validation, Figure C). There were also changes in EEG spectral power, with more activation in the "congruent" condition within the beta band during rest and within both alpha and beta bands during MI (Figure D and E). Discussion: While the online performance remained unchanged with a congruent feedback, an offline classifier could benefit from increased differences between rest and MI signals. Additionally, post-hoc interviews revealed that participants felt assisted by a congruent feedback. Significance: In a pilot study, we demonstrate how a congruent auditory feedback could improve classification in a EEG MI BCI, a promising result for creating alternate feedback modality. This prompts for further investigations on a larger sample and with more channels to better assess the underlying change in brain activity.
References: [1] Alimardani et al. Effect of biased feedback on motor imagery learning in BCI-teleoperation system. Front sys neurosci 8 (2014). [2] Tidoni, et al. "Audio-visual feedback improves the BCI performance in the navigational control of a humanoid robot." Front neurorobotics 8 (2014). [3] Bengtsson et al. Listening to rhythms activates motor and premotor cortices. Cortex 45 (2009) [4] Verron et al. A 3-D immersive synthesizer for environmental sounds. IEEE Trans on Audio, Speech, and Language Proc 18.6 (2010)

2-C-23 BCI-based operation of Microsoft Active Accessibility (MSAA) compatible TOBII Dynavox Communicator 5

Theresa M Vaughan[1], Kamilya Gosmanova[2], Charles Carmack[1], David Goldberg[3], Kelly Fitspatrick[2], Bart Zoltan[4], Debra Zeitlin[4], Jonathan R Wolpaw[1]

[1]National Center for Adaptive Neurotechnologies, Wadsworth Center, [2]Wadsworth Center, New York State Department of Health, [3]Tobii Dynavox, [4]Helen Hayes Hospital, New York State Department of Health

Introduction The Wadsworth P300-based brain-computer interface (BCI) home system allows Users with ALS to choose among items in a matrix to communicate with others and to control other functions independently in their own homes [1,2]. This study seeks to establish the Wadsworth P300-based BCI as an effective access method for highly-configurable Tobii Dynavox Communicator 5 (TD-C5) software. TD-C5 is a highly configurable and widely used software package for communication and computer access using eye-tracking and other conventional switches [3]. Materials, Methods and Results Six people (3 women) took part in this study, one had advanced ALS (average age 37 + 19, range 17-63). The study had been reviewed and approved by the NYS Department of Health IRB; and all subjects gave informed consent. We recorded eight EEG channels (locations Fz, Cz, P3, Pz, P4, Po7, Po8, Oz), referenced to the right and grounded to the left mastoid, respectively. Signals were amplified by a Guger Technologies g.USBamp biosignal amplifier, sampled at a rate of 256 Hz, high- and low-pass filtered at 0.1 Hz and 60 Hz, and notch filtered between 58-62 Hz. All aspects of the BCI were controlled by BCI2000 [4]. The dynamic screens were presented as a Field-Programmable Gate Array (FPGA) overlay using an NeTV device via a Perl script and the program was accessed using the Microsoft Active Accessibility (MSAA) software development kit. The BCI User sat in a comfortable chair or upright in bed at a comfortable viewing distance from a 50-cm screen for a single approximately one-hour session. The screen showed a set of items that could be selected (Fig 1). To make a selection, the person attended to the desired item while pictures of faces [5] flashed over groups of 4-6 items four times/sec [6]. The experiment, including consent, instructions, cap application and removal, and data collection took 75-90 min, and included ~65 min of data collection. Each session comprised three tasks. In the calibration task (T1), the User was given 21 characters to copy-spell without feedback as to the result. In the validation task (T2), feedback was provided while the User copy-spelled "JULY" and free-spelled one 3-letter word of his or her own choosing. In the matching task (T3), the User played a nine-set matching game. Completing a set required the User to: 1) Enter a set (1-9) sequentially from the main menu; 2) view and make decisions about three pairs of pictures by selecting match or no match (where only one pair matched); and 3) return to the main menu to select the next of the nine sets. All six Users completed T1 and validated the weights by successfully completing T2; they then completed T3. Average online performance for the six subjects during the T3 session was 98.4%(+4.9)%. There were no significant changes in performance between any two sets, including Sets 1 and 9. Discussion The results indicate that the TD-C5 software can be readily accessed with our P300-based BCI system. Furthermore, accuracy is very high and remains stable for at least an hour. Future work will seek to streamline system setup and use, and develop an integrated system that can use eye-tracking control and BCI control alone or in combination. Significance BCI access to MSAA-compliant Tobii Dynavox Communicator 5 software introduces new opportunities for restoring communication and control capacities to people with ALS or other severe neuromuscular disorders. It further incorporates BCI technology into the spectrum of clinically useful assistive communication devices. References [1] Sellers, EW, Vaughan, TM, Wolpaw, JR. (2010) Amyotrophic Lateral Sclerosis 11: 449-55. [2] Wolpaw, JR, Bedlack, RS, Ringer, RJ, Reda, DJ. Hill, KJ, et al. (2013) Program number J45.55 2013 Neuroscience Meeting Planner. San Diego, CA: Society for Neuroscience, Online. [3] Tobii Dynavox. (2016). Communicator 5. Retrieved from http:// www. tobiidynavox.com/communicator5/ [4] Schalk, G, McFarland, DJ, Hinterberger, T, Birbaumer, N, Wolpaw, JR (2004) IEEE Transactions Biomedical Engineering. 51(6):1034-43. [5] Kaufmann, T, Schulz, SM, Grünzinger, C, Kübler A (2011) Journal of Neural Engineering 8(5):056016. doi: 10.1088/1741-2560/8/5/056016. [6] Townsend, G, LaPallo, BK, Boulay, CB, Krusienski, DJ, Frye, GE, et al. (2010) Clinical

Neurophysiology. 121(7):1109-20. Disclosures None Support NCMRR, NICHD, NIH (HD30146); NIBIB/NINDS, NIH (EB00856); The James S. McDonnell, Altran; ALS Hope; NEC

D- BCI Non-Invasive- Other

2-D-24 EEG predictors for upper limb motor recovery of stroke patients undergoing BCI and tDCS rehabilitation

Ravikiran Mane[1], Effie Chew[2], Kok Soon Phua[3], Kai Keng Ang[3], Cuntai Guan[1]

[1]Nanyang Technological University, [2]National University Hospital, [3]Institute for Infocomm and Research, Agency of Science, Technology and Research, Singapore

Introduction & Purpose: Stroke survivors often require rehabilitation in the chronic state. Since different rehabilitation paradigms promote recovery of lost motor functions in a unique manner; we hypothesized that the distinct sets of biomarkers might exist for different treatments, which are capable of predicting the clinical efficacy of the treatment. Additionally, we expected that the predictive capabilities of the biomarkers would vary with the timespan of prediction. To test this hypothesis, we explored the predictive capabilities of the resting-state EEG (eyes open) features in 19 hemiplegic chronic stroke patients for two-week (ten 1hr sessions) tDCS-BCI (tDCS-Group (n=10)) and sham-BCI (BCI-group (n=9)) interventions for upper limb motor recovery.Methods & Materials:All the patients underwent rehabilitative intervention involving motor imagery of a reaching task followed by an online robotic feedback upon successful detection of MI by MIT-Manus robot. In addition to the MI-BCI training, tDCS group received a bi-hemispheric tDCS for 20 minutes preceding the training. The total FMA score (range, 0-66) on the stroke-impaired upper extremity was measured at three time-points (wk-0, wk-2, wk-4) to access the motor improvements. The details of the trial are reported elsewhere[1].As the prognostic abilities of EEG biomarkers are of interest, EEG data from the first rehabilitation session was analyzed. The data was thoroughly preprocessed and cleaned for artifacts by the expert user with the help of PREP, FASTER and, ADJUST toolbox. Post-cleaning, each subject had minimum 140 trials and first 2s resting state EEG from each trial was extracted for analysis. Trial-averaged PSD at every channel was calculated using Welch's periodogram and was used to calculate the relative band power ($r\delta$, $r\theta$, $r\alpha$, $r\beta$) averaged over the scalp. The trial averaged PSD was also used to compute global delta-alpha ratio (DAR)[2], theta-alpha ratio (TAR), theta-beta ratio (TBR), theta-beta-alpha ratio (TBAR), and Power ratio index (PRI)[2]. Interhemispheric brain asymmetry was quantified and calculated using pairwise derived brain symmetry index (pdBSI)[2] and revised brain symmetry index (rBSI)[3] resulting in total 11 EEG features. The relationship between EEG features and FMA improvement over two (ΔFMA(0,2)) and four (ΔFMA(0,4)) weeks was assessed using Spearman's rank correlation coefficient.Results & Discussion:Demographic variables (age, time post-stroke & FMA(wk-0)) displayed no correlation with FMA improvements. The correlation analysis between EEG features and FMA improvements resulted in a statistically significant negative correlation of FMA improvements with $r\delta$, PRI, DAR, TBR, pdBSI, rBSI and positive trend with $r\beta$. The complete results are presented in table 1. The results are in accordance with the reported literature with an indication that better motor recovery comes from the brain activity in higher frequency bands and from reduced interhemispheric asymmetry. Along with this, it can be observed that the functional outcomes for tDCS group can be better predicted by band power features (rδ, PRI, DAR, TAR) whereas interhemispheric asymmetry indices (pdBSI, rBSI) are best suitable for predicting motor recovery post BCI rehabilitation. Moreover, the set of EEG features that display predictive capabilities in two interventions are mutually exclusive. Interestingly, the similar contrast in predictive capabilities can be observed by comparing the results of [2] & [3]. These results suggest that functional outcomes of different rehabilitation protocols might be predicted by a unique set of biomarkers specific to the intervention. Additionally, PRI displayed an excellent correlation with ΔFMA(0,2) whereas ΔFMA(0,2) can be better predicted using rδ, pdBSI and DAR. This indicates that the predictive capabilities of EEG features might be distinct to the timeframe of prediction.Significance:This study reports and compares the predictive capabilities of various EEG features for prognosis of motor function improvement caused by two different rehabilitation interventions over two timeframes. Also, to our knowledge, this is the first study reporting the predictive potential of EEG band power and interhemispheric asymmetry features for tDCS-BCI rehabilitation in a chronic state. References:[1]:Ang at el, Arch. Phys. Med. Rehabil,2015, [2]:Trujillo at el, Neural Syst. Rehabil. Eng.,2017, [3]:Ang at el, Clin. EEG Neurosci,2014

2-D-25 BCI-based language training induces changes in ERP responses in chronic post-stroke aphasia patients

David Hübner[1], Sarah Schwarzkopf[2], Mariacristina Musso[2], Michael Tangermann[3]

[1]University Freiburg, [2]University Medical Center Freiburg, [3]University of Freiburg

*The authors MM and MT contributed equally.

 Introduction: Event-related potentials (ERPs) are brain responses elicited upon an event, e.g., when hearing a word. They are used for controlling brain-computer interfaces (BCIs) and are hypothesized to be associated with different neuronal computations such as executive functions [1] and language functions [2]. Several studies have investigated the effect of user training on ERP responses with controversial results. Baykara et al. found no significant changes in P300 amplitudes and latencies for 16 healthy subjects using an auditory BCI over 5 sessions [3] and stable ERPs were reported by Nijboer and colleagues for 6 ALS patients even after 40 weeks of visual BCI usage [4]. Conversely, a study by Halder et al. reported increased ERP amplitudes and classification accuracies for 5 motor-impaired end-users in an auditory BCI over 5 sessions [5]. EEG recordings with post-stroke aphasia patients also showed changed ERP responses before and after a (non-BCI) high-intensity language training [6]. Importantly, this study also reported a correlation between ERP changes and language gains. Following these diverse results, we examine the changes in ERP responses to word stimuli for a BCI-based training protocol in chronic stroke patients with language deficits (aphasia) as proposed in [7].

 Material, Methods and Results: Eight chronic (>6 months) aphasia patients underwent high-intensity (4x per week) EEG-based language training for around 30h of effective training time. In the training, they received feedback based on their ERP responses in a fast auditory BCI (AMUSE [8]) with bisyllabic words as stimuli. Sessions without feedback were conducted before and after the training. In these sessions, we compared the ERP responses of attended (target) and non-attended (non-target) word stimuli (length=300ms) played in a rapid sequence with stimulus onset asynchrony of 250ms, and the ability to classify these events as such. For the P300, we observed a drastic increase in amplitudes and an earlier separation of target and non-target responses (cf. Figure A vs B). The early negativity also showed an increase in amplitude. Additionally, a significant increase in target vs. non-target classification accuracy was observed (see Figure C and D).

 Discussion: Contrary to some previous studies, we observed strong training-induced ERP changes. Proving associations between ERP responses and cognitive functions is very difficult. Previously, Kleih et al. hypothesized that BCI-based visual attention training may result in improved language functions via P300 enhancement [9]. A more direct indication was reported by Nolfe et al. showing delayed and decreased P300 responses for aphasic patients compared to controls [10]. Our hypothesis is that the earlier separation of target and non-target ERP responses indicates faster language processing, and that increased P300 responses indicate a stronger activation of language-related networks. Both effects should be beneficial for aphasic patients.

 Significance: Our findings add significant evidence that a high-intensity training with an auditory BCI can induce changes in word ERP responses for chronic aphasia patients. Enhanced ERP responses improve the usability of BCI-based training approaches for aphasia.

 Acknowledgement: We thank for the support by the BrainLinks-BrainTools Cluster of Excellence funded by the German Research Foundation (DFG), grant number EXC 1086.

 References: [1] Polich, Clin. Neurophysiol. 118 (2007) 2128-2148.
 [2] Kaan, Lang. Linguist. Compass 1 (2007) 571-591.
 [3] Baykara, Ruf, Fioravanti et al., Clin. Neurophysiol. 127 (2016) 379-387.
 [4] Nijboer, Sellers, Mellinger et al., Clin. Neurophysiol. 119 (2008) 1909-1916.
 [5] Halder, Käthner, Kübler, Clin. Neurophysiol. 127 (2016) 1288-1296.
 [6] Barbancho, Berthier, Navas-Sánchez et al., Brain Lang. 145-146 (2015) 1-10.
 [7] Tangermann, Schnorr, Musso, in Proc. of the 6th Int.l BCI Conf., Verlag der TU Graz
 [8] Schreuder, Blankertz, Tangermann, PLoS One 5 (2010) e9813.
 [9] Kleih, Gottschalt, Teichlein, Weilbach, Front. Hum. Neurosci. 10 (2016) 547.
 [10] G. Nolfe, A. Cobianchi, L. Mossuto-Agatiello, S. Giaquinto, Eur. J. Neurol. 13 (2006) 377-384.

2-D-26 Augmenting group decision making accuracy in a realistic environment using collaborative brain-computer interfaces based on error-related potentials

Davide Valeriani[1], Saugat Bhattacharyya[1], Caterina Cinel[1], Luca Citi[1], Riccardo Poli[1]

[1]*University of Essex*

Introduction: In many circumstances, groups make better decisions than individuals [1]. In previous research we have shown that collaborative Brain-Computer Interfaces (BCIs) could be used to estimate the decision confidence of isolated users and improve group decision making in visual tasks involving static images [2][3]. The goals of this study are (a) to test whether such a collaborative BCI could improve group performance when users are exposed to video feeds from a realistic environment, and (b) to significantly reduce the number of EEG electrodes required to estimate the decision confidence. Material, Methods and Results: 10 healthy participants (six females, four left-handed, mean age=35.4 years, SD=2.6) took part in an experiment split into 12 blocks of 28 trials. In each block (Figure 1(a)), a video sequence was presented (frame rate=4 Hz) representing the viewpoint of a user walking along a corridor, where individuals can appear from side doorways. Participants had to decide, within 2.5 s, whether the individual was wearing a helmet (left mouse button) or a cap (right mouse button). After the decision, participants were asked to indicate, within 2 s, the degree of confidence in their decision (0-100%) using the mouse wheel. Neural data were recorded at 2048 Hz using a BioSemi ActiveTwo EEG system with 64 electrodes and were referenced to the mean of the electrodes placed on the earlobes. Each channel was band-pass filtered between 0.15 and 40 Hz and ocular artefacts were removed with a standard subtraction algorithm. For each trial, response-locked epochs lasting 1.5 s and starting 1 s before the response were extracted from the EEG data, detrended, baseline corrected, and downsampled to 32 Hz. The error-related negativity (ERN) of each epoch was computed as the difference between the maximum voltage value recorded in the 150 ms preceding the response and the minimum voltage value recorded in the 150 ms following it at electrode FCz [4]. A logistic regressor was trained for each participant to predict whether a decision was correct or incorrect from the neural feature [3]. The confidence scores produced by the regressor were then used to weigh individual responses when making group decisions. We also tested the possibility of complementing the neural feature with the confidence value reported by the participant after each decision, as well as using those confidence values as weights directly. The results obtained using 8-fold cross-validation are shown in Figure 1(b). The collaborative BCI based only on the neural feature (orange) achieves significantly better performance than majority-based groups (black) for all group sizes 2-9 (one-tailed Wilcoxon signed-rank test $p<0.007$). When using the reported confidence to weigh decisions (blue), groups were significantly more accurate than groups not using it ($p<0.003$), with the best performance obtained by groups using both reported confidence and ERN (green, $p<0.003$). Discussion: We found that our collaborative BCI improves group performance even with this realistic task using video feeds and by using only one neural feature extracted from FCz. Moreover, a hybrid BCI based on both neural and behavioural features achieved significantly better group performance than decision-making systems based on each feature individually. Significance: Collaborative BCIs could augment group performance also in decision making in a realistic environment. The use of ERN features only requires EEG data gathered from one electrode to augment group performance, hence improving the practicality of the BCI. Acknowledgements: The authors acknowledge support of the UK Defence Science and Technology Laboratory (Dstl) and Engineering and Physical Research Council (EPSRC) under grant EP/P009204/1. This is part of the collaboration between US DOD, UK MOD and UK EPSRC under the Multidisciplinary University Research Initiative. References: [1] Surowiecki (2005). The Wisdom of Crowds. [2] Valeriani et al. (2016). Enhancement of Group Perception via a Collaborative Brain-Computer Interface. IEEE Trans. Biomed. Eng., 64(6). [3] Valeriani et al. (2017). Group Augmentation in Realistic Visual-Search Decisions via a Hybrid Brain-Computer Interface. Scientific Reports, 7(7772). [4] Nieuwenhuis et al. (2001). Error-related brain potentials are differentially related to awareness of response errors: evidence from an antisaccade task. Psychophysiology, 38(5).

2-D-27 Closed-loop stimulus parameter optimization framework for event-related potential paradigms

Jan Sosulski[1], David Hübner[1], Michael Tangermann[2]

[1]University Freiburg, [2]University of Freiburg

Introduction: Although stimulus parameters impact the usability of event-related potential (ERP) based brain-computer interfaces (BCIs), only a few studies have investigated their adaption to individual users. The influence of the stimulus onset asynchrony (SOA) upon classification accuracy has been studied in ERP spellers of both the auditory [1] and the visual domain [2,3]. These studies used a time-consuming grid search on few predefined SOA candidate values -- a constrained search strategy. Nevertheless, a significant classification performance gain was reported for individually optimized SOAs [1]. In this work, we propose the use of a closed-loop framework for the online evaluation of SOA optimization strategies. We face non-stationary behavior, high noise and the unavailability of a ground truth about the globally optimal SOA as major challenges. Additionally, in clinical BCI applications it is important to optimize the SOA fast. Material, Methods, Results: Our framework utilizes an auditory oddball paradigm. We present the participant with a low-pitched frequent non-target tone and a rare high-pitched target tone. One trial consists of 15 targets and 75 non-targets. Subjects are instructed to ignore non-targets and attend targets. We expect ERP responses in the measured EEG to differ between targets and non-targets. While arbitrary amplitude features derived from ERP responses could be used to obtain an optimization metric, it is unclear, whether the manipulated stimulus parameter influences this metric. In a pilot experiment, we attempted to increase the non-target amplitude at t=160 ms post stimulus onset, a feature which corresponds to the N2 ERP position in auditory paradigms. As non-targets generally show a weaker negativity, this feature value is smaller in targets compared to non-targets [1]. The SOAs that were detected by two online search strategies were compared to a fixed SOA of 175 ms reported optimal for spelling performance for the grand average of subjects [1]. The first search strategy used Bayesian optimization [4] as implemented in the RoBO toolbox [5]. It was compared to a random search strategy, which has advantages compared to a grid search strategy [6]. Each trial delivered one noisy estimate of the N2 amplitude for one SOA. The experimental session conducted with one subject consisted of two parts. First, online SOA optimization within an interval of 60 to 600 ms was performed. We alternated between strategies until their respective time budgets (20 minutes each) were depleted. The final best SOA was estimated using Gaussian process regression [7]. For validation, 2250 non-target responses each were collected for the SOA determined by the Bayesian strategy (380 ms), the random strategy (123 ms) and the fixed SOA (175 ms). The SOA found by the Bayesian optimization strategy delivered an average non-target N2 amplitude of +0.134 µV, which significantly exceeded amplitudes of the random search (-0.186 µV) and the fixed SOA (-0.261 µV). Discussion: The pilot experiment proved the feasibility of the online optimization framework, and the chosen stimulation parameter did influence the chosen optimization metric. The developed framework allows for an evaluation of fast online stimulus parameter optimization methods in the BCI domain and alleviates the influence of non-stationarity. In an upcoming study with further subjects, the promising Bayesian parameter optimization strategy will be investigated. Significance: The developed framework facilitates research aiming to find optimization strategies for stimulation parameters in BCI. Acknowledgments: This work was supported by the BrainLinks-BrainTools Cluster of Excellence funded by the German Research Foundation (DFG), grant number EXC 1086, and the DFG project SuitAble (TA 1258/1-1). References: [1] J. Höhne, M. Tangermann, in: 2012 IEEE EMBC, 2012. [2] B.Z. Allison, J.A. Pineda, Int. J. Psychophys. 59 (2006) 127-140. [3] E.W. Sellers, D.J. Krusienski, D.J. McFarland, T.M. Vaughan, J.R. Wolpaw, Biol. Psychol. 73 (2006) 242-252. [4] J. Snoek, H. Larochelle, R.P. Adams, in: Adv. in Neural Inf. Proc. Systems, 2012, pp. 2951-2959. [5] A. Klein, S. Falkner, N. Mansur, F. Hutter, in: NIPS 2017 Bayesian Optimization Workshop, 2017. [6] J. Bergstra, Y. Bengio, J. Mach. Learn. Res. 13 (2012) 281-305. [7] C.E. Rasmussen, C.K.I. Williams, Gaussian Processes for Machine Learning, MIT Press, 2006.

2-D-28 Effects on language ability induced by bci-based training of patients with aphasia

Michael Tangermann[1], David Hübner[2], Sarah Schwarzkopf[3], Cornelius Weiller[3], Mariacristina Musso[3]

[1]University of Freiburg, [2]University Freiburg, [3]University Medical Center Freiburg

Introduction: Aphasia refers to an impairment of language abilities mainly due to a left-hemispheric stroke. In Germany alone, there are 60.000-80.000 new aphasic patients every year. Regarding aphasia recovery, there is moderate evidence only for the efficacy of open-loop speech therapy approaches which are very intense and guided by an external person, the speech therapist [1]. However, there is strong evidence that closed-loop approaches such as computer-based interventions guided and controlled by the patients themselves can improve specific language deficits, but only with limited generalization to functional communication [2]. Even after logopedic treatment, about 20% of all stroke patients keep a persistent, chronic communicative impairment with large impact on their quality of life [3]. While BCI systems can tap into ongoing brain activity in single-trial and are investigated as tools for the recovery of motor deficits after stroke [4], we pioneered by implementing and validating a BCI-based closed-loop training protocol proposed in [5] for chronic aphasia patients after stroke. While a patient attends word stimuli the BCI system analyzes his/her electroencephalogram (EEG) signals and provides feedback about the strength of task-relevant EEG features. Material and Methods: The proposed new BCI-supported language training was conducted in 8 patients with a left fronto-temporal-parietal infarct and chronic aphasia. In an online BCI session, auditory event-related potential (ERP) responses evoked by words were measured in an adapted AMUSE paradigm using 32 passive Ag/AgCl EEG electrodes with nose reference [6]. Each trial started with the auditory presentation of a cueing sentence and continued with the repeated presentation of six bisyllabic words. Patients were asked to focus their attention on the one word correctly finishing the sentence. Per trial the word stimuli were repeated 15 times in a pseudo-randomized order with a stimulus onset asynchrony (SOA) below 500 ms. After each trial, patients received feedback based on whether the attended word - as predicted by the ERP responses - did match the target word or not. Each patient took part in an intensive training of about 30 hours that was to be conducted within one month. In order to measure the training effect on language abilities, participants underwent a clinical test battery for language assessment (Aachener Aphasie Test, AAT [7]). Results: The patients accepted the training procedure and showed sufficiently discriminative ERP responses to realize an online BCI training. All patients showed language improvements in a pre-post training AAT assessment (for details see Figure), with strongest and highly significant improvements in the naming test. Discussion & Significance: BCIs can estimate brain states - a virtue whose practical benefit for rehabilitation should not be limited to the training of motor function. For the first time, an effective BCI-based language training has been realized. The obtained preliminary results for chronic stroke patients are promising, and the therapeutic approach generalizes to functional communication. Understanding the training's exact mode of operation, however, and a better characterization of target users requires further investigation. Acknowledgements: This work was partly supported by BrainLinks-BrainTools, funded by the DFG (grant number EXC 1086) and by the Wissenschaftliche Gesellschaft Freiburg i. B. References: [1] Heuschmann et al., Schlaganfallhäufigkeit und Versorgung von Schlaganfallpatienten in Deutschland, Akt. Neurol. 37 (2010) 333-340. [2] Brady et al., Speech and language therapy for aphasia following stroke, Cochrane Database Syst. Rev. (2016) CD000425. [3] Dijkerman et al., Long-term outcome after discharge from a stroke rehabilitation unit, J. Royal College

Physicians London. 30 (1996) 538-546. [4] Remsik et al., A review of the progression and future implications of brain-computer interface therapies for restoration of distal upper extremity motor function after stroke, Expert Rev. Med. Devices. 13 (2016) 445-454. [5] Tangermann et al., Towards Aphasia Rehabilitation with BCI, Proc. 6th Int. BCI Conf., pp. 65-68, Graz. (2014). [6] Schreuder et al., A new auditory multi-class brain-computer interface paradigm: Spatial hearing as an informative cue, PLoS One. 5 (2010) e9813. [7] Huber, Aachener Aphasie-Test: (AAT), Hogrefe Verlag, 1983.

2-D-29 Brain-Computer Interfaces for post-stroke motor rehabilitation: A meta-analysis

María Cervera[1], Surjo Soekadar[2], Junichi Ushiba[3], José del Millán[1], Meigen Liu[4], Niels Birbaumer[5], Gangadhar Garipelli[6]

[1]Ecole Polytechnique Fédérale de Lausanne (EPFL), [2]University Hospital of Tübingen,, [3]Keio University, [4]Keio University School of Medicine, [5]WYSS Center for Bio and Neuroengineering, [6]MindMaze SA

<p>Introduction Brain-computer interfaces (BCIs) can provide sensory feedback of ongoing brain oscillations enabling stroke survivors to modulate their sensorimotor rhythms purposefully. A number of recent clinical studies indicate that repeated use of such BCIs might trigger neurological recovery and hence improvement in motor function. Here we provide a first meta-analysis evaluating the clinical effectiveness of BCI-based post-stroke motor rehabilitation [1]. Materials, Methods and Results Trials were identified using MEDLINE, CENTRAL, PEDro and by inspection of references in several review articles. We follow the PRISMA guidelines[2]. We selected randomised controlled trials that used BCIs for post-stroke motor rehabilitation and provided motor impairment scores before and after the intervention. A random-effects inverse variance method was used to calculate the summary effect size. All the analyses presented in this report were performed using the mais software package of StataIC 14 [3]. We initially identified 524 articles and, after removing duplicates, we screened titles and abstracts of 473 articles. We found 26 articles corresponding to BCI clinical trials, of these, nine studies involved a total of 235 post-stroke survivors fulfilling the inclusion criterion (randomised controlled trials that examined motor performance as an outcome measure) for the meta-analysis. Motor improvements, mostly quantified by the upper limb Fugl-Meyer Assessment (FMA-UE), exceeded the minimal clinically important difference (=5.25) in six BCI studies, while such improvement was reached only in three control groups. The most effective therapy was reported by Kim et al. (2016), where a standardised mean difference (SMD) of 1.86 was found between BCI and control groups. In five studies, the lower bound for the 95% CI lies above the no-effect (SMD=0) vertical line. The only result not favouring BCI was presented in Ang et al. with an SMD of -0.26. Overall, the BCI training was associated with an SMD of 0.79 (95% CI: 0.37 to 1.20) in FMA-UE compared to control conditions, which is in the range of medium to large summary effect size. Also, several studies indicated BCI-induced functional and structural neuroplasticity at a sub-clinical level. We also observed an Higgins' I 2 coefficient of 51.1%, reflecting considerable heterogeneity in the intervention effect [4]. The 95% prediction interval (PI) ranged from -0.39 to 1.97, showing that most new studies are likely to fall on the positive side, and only a few are expected to report negative results. We found no evidence of publication bias (Egger's test [5], p=0.353) Discussion BCI-based neurorehabilitation shows a medium to large effect size on upper-limb motor function and could improve FMA-UE scores more than conventional therapies. Besides motor

outcomes, a number of studies also reported BCI-induced functional and structural neuroplasticity at a sub-clinical level, some of which also correlated with improved motor outcomes. More studies with larger sample size are required to increase the reliability of these results. Significance This suggests that BCI technology might be an effective intervention for post-stroke upper limb rehabilitation and further studies should help increase the reliability of these results. Figure Intervention effect measured as changes in upper-extremity FMA-UE scores between pre- and post- intervention(SMD; random effects)[1]. The mean effect is represented as a diamond in the forest plot, whose width corresponds to the 95% confidence interval, whereas the prediction interval is shown as a bar superposed to the diamond. Box sizes reflect the contribution of the study towards the total intervention effect. References [1] Cervera, Maria A., et al. "Brain-Computer Interfaces for Post-Stroke Motor Rehabilitation: A Meta-Analysis." bioRxiv 2017 [2] Moher D, Liberati A, Tetzlaff J, Altman DG, Group P. Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. PLoS Med. 2009 [3] Hedges LV. Distribution theory for Glass's estimator of effect size and related estimators. J Educ Stat. 1981 [4] Higgins J, Thompson SG. Quantifying heterogeneity in a meta-analysis. Stat Med. 2002 [5] Egger M, Smith GD, Schneider M, Minder C. Bias in meta-analysis detected by a simple, graphical test. Bmj. 1997 </p>

2-D-30 Mirror-therapy as a way to start BCI robot-assisted rehabilitation: a single case longitudinal study of a patient with hemiparesis

Roman Rosipal[1], Natália Porubcová[2], Barbora Cimrová[3], Igor Farka[3]

[1]Institute of Measurment Sciences,Slovak Academy of Sciences, [2]Institute of Measurment Sciences, Slovak Academy of Sciences, [3]Faculty of Mathematics, Physics and Informatics, Comenius University in Bratislava

Introduction: To improve upper-limb rehabilitation in chronic stroke patients we introduce a new training protocol consisting of mirror therapy (MT) followed by the brain-computer interface (BCI) robot-assisted training. MT represents a mental process by which an individual rehearses a limb movement by reflected movements of the non-paretic side in a mirror. A link between motor imagery and passive action observation was found and associated with the concept of mirror neurons [1]. Since the MT process has not a direct feedback loop it evokes changes in movement-related oscillatory EEG rhythms, which can be detected and subsequently used in BCI. Importantly, MT does not require a specific motor imagery strategy produced by a subject. First, in this work we report results of a unique longitudinal 9-month-long study of MT on oscillatory electroencephalogram (EEG) rhythms of a patient with hemiparesis. Second, we describe methods used to identify and validate subject's narrow band oscillatory EEG "atoms", i.e. specific spatio-temporal patterns associated with movement. Finally, we describe our design and experimental results with a BCI-based robotic splint controlled using the time scores of the identified atoms. Material, Methods and Results: The subject is a 58-years-old man who had a right-hand hemiplegia due to an ischemic stroke that had occurred to him two years before he entered the study. Neurological assessment before starting the study exhibited spastic hemiparesis on the right side, more seriously on the hand, which was plegic. MT was designed following the patient's actual level of movement abilities and took the period of 9-months (Fig 1, left). During MT training blocks, the EEG signal was recorded using 12 active EEG electrodes. After standard preprocessing of EEG, the irregular-resampling auto-spectral analysis method was used to separate fractal and oscillatory components in the power spectrum density (PSD) of EEG segments [2]. In addition, a three-way parallel factor analysis (PARAFAC) model was applied to PSD segments [3]. Using this approach five distinct movement-related atoms were identified. Longitudinal PSD changes of oscillatory rhythms as well as changes in time-scores of the PARAFAC atoms were carefully statistically analyzed. Significant short-term effects of a slower mu rhythm and four faster sensorimotor rhythms were identified. Consistent long-term increase of the mu rhythm in both hemispheres and the decrease of the faster beta rhythm in the affected hemisphere were observed. The analysis also revealed a very stable spatial and frequency pattern of the atoms, suggesting the use of time-scores of the atoms to control the robotic splint (Fig 1, right). This BCI design allows to simply and efficiently vary the difficulty of controlling the splint by setting different time-scores threshold levels as well as the training protocols. The system was validated in a longitudinal series of rehabilitation trainings and observed findings and results will be reported. During the whole MT as well as training with the robotic splint, quantitative clinical evaluation of the subject's movement abilities was carried out. Overall, a mild increase of clinical scores for upper extremity were observed. The spasticity of the upper extremity was surprisingly released. A mild improvement of active movement of the right arm, elbow and forearm was also observed. However, the wrist and fingers remained plegic. Discussion: To our knowledge, this is the first longitudinal MT showing the effects on the modulation of sensorimotor EEG oscillatory rhythms. We observed significant short as well as longer term EEG effects. Analysis of the EEG data recorded during the MT sessions reveals stable day-to-day space and frequency atomic EEG representation of dominant sensorimotor oscillatory rhythms and therefore time scores of the atoms can be used for BCI control. Significance: The study results suggest that MT can be used not only to change movement-related EEG oscillatory rhythms, but also as a simple training procedure allowing to identify these rhythms without the need of applying a specific motor imagery strategy by a subject. Acknowledgments: Work was supported by APVV-0668-12, APVV-16-0202. References: [1] Mulder, T. (2007). Journal of Neural Tran., 114:1265-1278. [2] Wen, H., Liu, Z. (2016). Brain Topog. 29:13-26. [3] Bro, R. (1997). Chem. and Intell. Lab. Syst. 38:149-171.

2-D-31 Sensory threshold electrical stimulation a novel feedback modality for BMIs

Tiffany Corbet[1], Iñaki Iturrate[1], José del Millán[1]

[1]*Ecole Polytechnique Fédérale de Lausanne (EPFL)*

Introduction: Although kinesthetic motor imagery (MI) can enhance corticospinal tract (CST) excitability, only few studies showed that BMI training also has the potential to foster motor evoked potential (MEP) peak-to-peak amplitude [1]. Previously, we have demonstrated that sensory threshold electrical stimulation (St-NMES) enhanced MI performance [2]. Here, we tested St-NMES as an online feedback for BMI system, in order to probe the influence of BMI training on CST excitability. Material and Methods: In this cross-over experiment, we recruited 4 right-handed subjects naïve to MI. Every subject performed two blocks of BMI training associated to visual or St-NMES feedback. The BMI decoder had to differentiate MI of right wrist extension vs. right hand at rest. There was a break of two weeks between blocks. Each block was composed of three consecutive days. Session 0 was the offline calibration to build an individual classifier for the feedback modality. Sessions 1 and 2 were online BMI use. Every session was composed of 4 runs of 15 MI trials and 5 trials of intentional non control (INC). With St-NMES feedback subjects received sensory threshold stimulation at the proximal part of the arm only when probabilistic output of the BMI associated to MI increased. Successful decoding was indicated by a distal stimulation. No stimulation was triggered when the probabilities decreased. With visual feedback a bar on the screen moved up or down according to the probability dynamics. The final success or failure of the trial was indicated on the screen. The threshold to define a success was adjusted for every session in order to obtain a performance of 70% of MI decoding across sessions and feedback modalities. MI features stability and similarity were assessed by computing Fisher score of MI features distributions from session 0 and session 2. Before and after sessions 1 and 2 we recorded 24 (MEP) of wrist extensor muscle with transcranial magnetic stimulation (TMS). The intensity of TMS and the position of the coil were similar across sessions. Statistical analyses were performed using a Friedman test comparing MEP peak-to-peak amplitude difference among the two feedback conditions (St-NMES vs. visual), and Wilcoxon paired tests for post-hoc analyses. Results:The averaged MEP peak-to-peak amplitude difference was significantly different among conditions ($\chi^2(2)=6.00$, $p=0.046$). The post hoc analyses (Fig 1a) shows that MEP difference tend to be significantly larger for St-NMES (0.43 mV) compared to visual (0.08 mV) condition ($Z=-1.83$, $p=0.07$). Importantly, the observed increase MEP peak-to-peak amplitude after St-NMES condition was similar for both sessions (for session 1: 0.47mV and session 2: 0.38mV, $F=-1.83$, $p=0.07$). Regarding the BMI system, it is worth noticing three crucial points. First, subjects indeed achieved 70% MI success for both sessions in the two feedback conditions. Second, despite receiving St-NMES, subjects were able to succeed 60% of INC trials. Finally, MI features were more stable for St-NMES compared to visual (Fisher score St-NMES=0.34, visual=0.41). Discussion: St-NMES is a promising feedback for BMI applications. Indeed, results suggest that the combination of MI training with a somatosensory feedback had the potential to enhance CST excitability. Despite it will be necessary to control in the future the impact of St-NMES only on MEP changes, no study has shown an impact of St-NMES on CST excitability. Moreover, St-NMES is a reliable feedback for BMI systems since subjects were also able to perform INC and features were more stable across days. We hypothesize that this new feedback is more suitable and natural for practising motor learning and particularly MI-based BCI. Significance: Our study showcases that a closed loop between efferent motor imagery command and congruent rich afferent feedback can effectively enhance CST excitability. Our new feedback modality has the potential to enlarge the impact of BMI system for motor rehabilitation by facilitating plasticity in the central nervous system. References: [1] Pichiorri et al. Sensorimotor rhythm-based brain-computer interface training: the impact on motor cortical responsiveness. J Neural Eng, 8:1-9 2011. [2] Corbet et al Sensory threshold neuromuscular electrical stimulation fosters motor imagery performance. NeuroImage, in review.

2-D-32 Application of mental state detection in the context of motor stroke rehabilitation with virtual reality based games

Robert Leeb[1], Claire Lugrin[1], Andrea Serino[1], José del Millán[2]

[1]MindMaze, [2]Ecole Polytechnique Fédérale de Lausanne (EPFL)

INTRODUCTION: Virtual reality (VR) and interactive video gaming are increasingly used in stroke rehabilitation, as they allow for motivating gamified therapies in well-controlled environments [1]. However adjustments of the complexity of such games to the patients' needs mostly rely on external and behavioral measures. Especially, since therapists have no insight into the patient's inner mental states. Decoding mental processes of patients undergoing rehabilitation could allow an improved and personalized adaptation of the gaming environment and increase the patient's engagement into the therapy. The objective of this work is to identify electroencephalographic (EEG) measures of the patient's task engagement and cognitive workload to adjust the rehabilitation paradigms in real time. As an initial step, we conduct a feasibility study on decoding these processes in twenty healthy participants while they are performing rehabilitation exercises with VR.
 MATERIAL, METHODS AND RESULTS: Objective measures reflecting different levels of engagement and workload were first computed from EEG recorded during well-established psychology tasks: (i) a vigilance task to elicit varying levels of engagement, (ii) N-back and Sternberg memory tasks to elicit various workload levels. Secondly, these EEG measures were used to decode the mental state of participants playing two interactive wrist rehabilitation games such as the MindMotionTMGO (MindMaze SA, Lausanne, Switzerland). The contexts and difficulty levels of these games were designed to elicit various degrees of engagement and workload (Figure 1.A). Furthermore, participants self-assessed their workload using NASA-TLX rating scales. NASA-TLX revealed that significantly different degrees of intensity of the aforementioned mental processes were elicited by the different games and levels employed (Figure 1.B). Thirty EEG channels were recorded with a TMSI Porti device (Twente Medical Systems International B.V.) using a sampling rate of 2kHz, and wrist movements were tracked with a Leap Motion sensor (Leap Motion, San Francisco, CA, United States). An EEG engagement index ($Ei=\beta/(\alpha+\theta)$ [2]), computed for channels F3, F4, O1 and O2 with EEG power bands θ=4-7, α=8-12 and β=13-30 Hz, was significantly higher during the vigilance task than during rest periods ($p< 1e-3$), and varied between the rehabilitation game contexts. Moreover, a subject specific linear discriminant analysis (LDA) vigilance classifier, reliably detected higher levels of engagement during the vigilance task compared to resting state (remarkably, with 95% average accuracy for vigilance classification). The EEG engagement measures applied to the wrist rehabilitation games showed a decrease in engagement as people habituated to the games, in accordance with the measured behavioral results.
 DISCUSSION: The described measures provide the means to monitor the participants' engagement during rehabilitation tasks. However, tasks borrowed from psychological research had to be used first, in order to provide the ground truth for setting up subject-specific classification methods. This limitation should be addressed in the future by replacing them by rehabilitation-like tasks eliciting the different mental states and loads. Furthermore, the methods described here need to be adjusted and validated with stroke patients, for whom the elicited brain patterns might differ from those of healthy individuals.
 SIGNIFICANCE: This study shows first steps towards the possibility of creating adaptive and personalized gaming in VR-mediated rehabilitation settings, relying on EEG-based decoding of the user's cognitive states, which we believe should increase the therapeutic efficacy.
 REFERENCES: [1] Laver KE, Lange B, George S, Deutsch JE, Saposnik G, Crotty M, Virtual reality for stroke rehabilitation. Cochrane Database Syst. Rev. CD008349, 2015. [2] Mikulka PJ, Scerbo MW, Freeman FG, Effects of a biocybernetic system on vigilance performance, Hum. Factors 44(4), 654-664, 2002.
 FIGURE 1: (A) Experimental setup of the rehabilitation games based on wrist movements with MindMotionGoTM flying car game. (B) Nasa TLX self-ratings (mean ± SE) for the different tasks/games and levels: cognitive workload tasks: N-back and Sternberg tasks on the left, rehabilitation tasks: moving ball and flying car game on the right.

2-D-33 Zero-calibration C-Vep BCI using wprd prediction: A proof of concept

Federica Turi[1], Nathalie Gayraud[2], Maureen Clerc[2]

[1]Inria Sophia Antipolis Mediterranee, [2]Inria Sophia Antipolis-Méditerranée and Université Côte d'Azur

Introduction: Brain Computer Interfaces (BCIs) based on visual evoked potentials (VEP) [1] allow for spelling from a keyboard of flashing characters. Among VEP BCIs, code-modulated visual evoked potentials (c-VEPs) are designed for high-speed communication [2]. In c-VEPs, all characters flash simultaneously. In particular, each character flashes according to a predefined 63-bit binary sequence (m-sequence), circular-shifted by a different time lag. For a given character, the m-sequence evokes a VEP in the electroencephalogram (EEG) of the subject [3], which can be used as a template. This template is obtained during a calibration phase at the beginning of each session. Then, the system outputs the desired character after a predefined number of repetitions by estimating its time lag with respect to the template. Our work avoids the calibration phase, by extracting from the VEP relative lags between successive characters, and predicting the full word using a dictionary. Material, Methods and Results: Using the time-windowed EEG generated while the user is gazing at the first character, we compute the average response Xa over N repetitions. Since the system has not been calibrated, the first character cannot be displayed. For the second character, we again compute the average response, and shift it by l·s time samples where s is the time lag between two consecutive characters. This produces L shifted averages Xl, l = {0 , ... , L-1}, where L is the number of characters on the keyboard. Using the lag l = argmaxl{corr(Xa,Xl)} which produces the maximum correlation to the initial average response, we compute the relative position of this character with respect to the first. Finally, we generate all valid pairs of characters separated by l, and only retain those corresponding to the beginning of valid words within a dictionary. These word beginnings are displayed on the screen as feedback. We repeat this procedure for the following characters, until we are left with a single word (Fig. 1a). At that moment, we will have recovered the original letter, and the absolute position of Xa can be thereafter used during the computation of the time lag. We conducted offline experiments using the database presented in [3], composed of 9 subjects, 2 sessions per subject, and 640 trials per session. The signals were pre-processed using a Butterworth filter between 1 and 15 Hz. Each experiment consisted of spelling a 3-letter word and was parameterized by the number of repetitions. We repeated the experiment 100 times by simulating the spelling of 3-letter words that we randomly selected among 1014 3-letter English words. We compared our results to a calibrated experiment (Fig. 1b and 1c), where we used N repetitions of three characters to compute an average absolute response Xa, and performed the same pre-processing as in [3]. Discussion: Our zero-calibration method achieves good accuracy, even with only 8 repetitions. In comparison, the experiments preceded by calibration reach a good accuracy after 12 repetitions of the m-code flashes. On Fig. 1b we distinguish two groups of subjects: in green, those that perform well, reaching on average an accuracy that exceeds 75% after 12 repetitions; in red, those whose performance does not produce an accuracy higher than 50%. This trend is also seen in the results of [3]. We keep the same color coding on Fig. 1c. While some subjects reach accuracy values equal to 100% after the calibration, others perform poorly, even compared to the zero-calibration method. Significance: Zero-calibration BCIs are widely researched as their use is more natural. We have shown that a word prediction-based zero-calibration method in c-VEP BCIs can be efficient. Since this method relies on the correct detection of relative time lags, online experiments will be conducted to further determine the efficiency of our method. References: [1] G. Bin, X. Gao, Y. Wang, S. Gao, "VEP-based brain-computer interfaces: Time, frequency, and code modulations", IEEE CIM, 2009. [2] G. Bin, X. Gao, Y. Wang, S. Gao, "A high-speed BCI based on code modulation VEP", Journal of Neural Engineering, 2011. [3] M. Spüler, W. Rosenstiel, M. Bogdan, "Online adaptation of a c-VEP brain-computer interface (BCI) based on error-related potentials and unsupervised learning", PloS one, 2012.

2-D-34 New Correlates of Motor imagery BCI performance - eye-open and eye-closed states

Moonyoung Kwon[1], Hohyun Cho[2], Sunghan Lee[1], Kyungho Won[1], Jongmin Lee[3], Minkyu Ahn[3], Sung Chan Jun[1]

[1]Gwangju Institute of Science and Technology, [2]Wadsworth Center, New York State Department of Health, [3]Handong Global University

Introduction: Brain-computer interface (BCI) is a technology that translates brain signals into user's command to control external devices. However, about 15-30 % of subjects cannot handle motor imagery BCI applications, which is called BCI-illiterate [1]. To understand this phenomenon, various neurophysiological correlates have been reported and proposed as a predictor for estimating the BCI-illiterate. Blankertz et al. (2010) proposed a SMR-based predictor using alpha powers of eye-open state at C3 and C4 channels [2]. Ahn et al. (2013) reported another predictor which is called performance potential factor (PP factor) as combining theta, alpha, beta and gamma frequency bands at C3 and C4 channels [3]. In this study, we proposed new motor imagery BCI performance prediction using five frequency bands (over the whole head) of eye-open and eye-closed states. Material, Methods and Results: Ten healthy right-handed volunteers (age 26.6 ± 2.1 years; 2 females) participated in this study; each of subjects joined in multiple sessions on different days. Brain signal was recorded using 64 EEG channels with 512 sampling rate during resting (eye-opened, eye-closed) states and motor imagery task (offline, online task). In offline task, subjects imagined three different pairs (left /right hand, left hand/foot, right hand/foot) of limb movements and the offline classification accuracy of each pair was estimated using cross-validation and signal processing methods; invariant common spatio spectral pattern (iCSSP) and Fisher's linear discriminant analysis (FLDA) [4]. Then the pair with the highest accuracy was chosen and conducted as online task. Two participants' data were excluded due to bad signal quality, total of 20 sessions were used in this work. Resting state signals were band-pass filtered with 1-50 Hz; then the relative powers to the total power were estimated at each frequency range - delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and low gamma (30-50 Hz) - because of minimizing subject variation. Finally, ratio between eye-closed and eye-open was estimated and Pearson's correlation coefficient between online accuracy and the ratio was computed per each frequency range. We observed that in theta oscillation, central and frontal regions have positive correlations, especially, C1 channel yielded the highest correlation of $r=0.52$ ($p<0.05$). Also, for the BCI-literate, power of eye-closed state is more likely higher than that of eye-open state, even if power difference between eye-closed and eye-open states is not notable. In addition, parietal and parieto-occipital channels have negative correlation in low gamma, that is, POz channel yielded negative correlation of $r=-0.51$ ($p<0.05$). Delta and beta bands had no significant correlations over the whole head, and alpha band was similar to delta and beta waves, except for P1 and P2 channels. Discussion: Our results showed that theta and low gamma waves were related to motor imagery task, however, it was not that revealed how theta and low gamma waves are related with motor task, compared to mu and beta waves. Some researchers reported that theta power of fronto-central area is involved in recall of haptic information [5] since most subjects answered, imagined pressing keyboard or mouse, or playing the musical instruments. Also, Cruikshank et al. (2012) insisted that sensorimotor area is relevant to theta activity during movement [6]. In addition, parietal gamma rhythms were associated with attention, working and long-term memory [7]. Significance: We found that classification accuracy and resting state power ratio (eye-closed/eye-open) have positive correlation in theta wave on central and frontal areas and negative correlation in low gamma wave on parieto-occipital lobe. This finding may be useful in predicting BCI performance for the purpose of pre-screening of BCI-illiteracy. Acknowledgements: This work was supported by IITP grant funded by the Korea government (No. 2017-0-00451). References 1. Vidaurre C. and Blankertz B. (2010) Brain Topography 2. Blankertz, B. et al. (2010) NeuroImage 3. Ahn M. et al. (2013) PLoS ONE 4. Cho H. et al. (2013) The 5th International BCI Meeting 5. Grunwalda M. et al. (1999) Neuroscience Letters 6. Cruikshank L.C. et al. (2012) Journal of Neurophysiology 7. Jenson O. et al. (2007) Trend in Neurosciences

2-D-35 Probing for information: Towards a BCI that infers semantic content

Karen Dijkstra[1], Jason Farquhar[2], Peter Desain[3]

[1]Radboud University, Donders Institute for Brain, Cognition and Behaviour, Nijmegen, The Netherlands., [2]Radboud University; Donders Institute for Brain, Cognition and Behaviour, [3]Radboud university, Donders Center for Cognition

Introduction: The N400 is an Event Related Potential (ERP) that is sensitive to the semantic content of a stimulus in its relation to a previously established context [1]. It can for instance be elicited in a word-pair context, in which a probe word is preceded by either a related or unrelated prime. With the ability to measure how presented stimuli relate to the mental context of a user, we can create a BCI that infers the concept on a user's mind by repeatedly presenting probes (i.e. stimulus words) and accumulating information across brain responses elicited from such a sequence of stimuli: a semantic BCI. Existing research has established that the N400 can be used to predict the relatedness of a word-pair with a target and a single probe [2]. Now we want to know whether the N400 is suited for the proposed BCI, in which multiple probes are presented consecutively, as intervening words might distract from the established context (i.e. the target word). Material, Methods and Results: We recorded EEG from 20 participants. Each completed 212 trials where a target word was followed by one to ten probe words, related or unrelated to this target (see figure (a)). Participants were instructed to mentally evaluate the relatedness of each probe to that trial's target. Stimuli were Dutch words: target words and up to 5 related probe words per target, were selected from the Leuven Association Database [3]; the remaining unrelated probes were selected from Celex [4]. To compare a single probe approach to our suggested multiple probing paradigm, we compute a Grand Average difference ERP (unrelated - related) across all participants, for two subsets of probes (see figure (b)): First: the first probe from each sequence; Final: the 9th and 10th probes in a sequence (only 50% of trials are full length). Note: to mitigate overlapping responses we only looked at stimuli that were preceded by an unrelated probe. To determine if there was a significant difference between these two conditions a cluster permutation test was performed on the interval from 0 to 1 s. No significant clusters were identified. Additionally, we performed an offline analysis, training a subject specific relatedness-classifier using k-fold crossvalidation (k:= # full length trials = 105). Individual classification rates vary between 50% (indistinguishable from chance) and 72% (μ = 58%). We use these classifiers to illustrate how this paradigm can be adapted to a BCI: Using the sequence of relatedness-predictions for the probes in a given trial, we rank all the possible trials by the similarity between their true and predicted relatedness. The location of the true presented trial in this list determines its performance (i.e., its percentile rank). In figure (c) we show the results of this analysis, taking into account an increasing number of probes from a trial (compared against random predictions). We see that performance increases when predictions from more probes are considered, with the correct trial being ranked in higher percentiles. How well this is possible varies across subjects; for some subjects, even when 10 probes are considered, results cannot be distinguished from chance. Discussion: Our results show no attenuation of the N400 when going from a single target-probe pair to a longer sequence of probes. Furthermore, we can predict relatedness of probes with up to 72% accuracy and show how accumulating evidence across multiple consecutive probes goes toward the identification of a target. The ten probes used here are insufficient to identify which trial a set of probes belonged to, but this can be overcome in a future BCI by, for instance, (1) using more probes, and (2) intelligently selecting probes words such that the response is most informative given the already acquired evidence. Significance: We looked at the effect of the number of consecutively presented probes on the strength of the N400. Finding no evidence of attenuation, and with an illustration of how evidence from multiple consecutive probes can be accumulated to identify an initial target, we see a clear path toward a semantic BCI that can infer the concept on a user's mind. [1] M. Kutas, K.D. Federmeier, Annual Review of Psychology 62 (2011) 621-647. [2] J. Geuze, M.A.J. van Gerven, J. Farquhar, P. Desain, PLoS ONE 8 (2013) e60377. [3] S.D. Deyne, G. Storms, Behav Res 40 (2008) 198-205. [4] celex.mpi.nl, Max Planck Institute for Psycholinguistics, 2001

2-D-36 Classification of attention types in EEG signals

Léa Pillette[1], Aurélien Appriou[1], Andrzej Cichocki[2], Bernard N'Kaoua[3], Fabien Lotte[1]

[1]Inria, LaBRI (Univ. Bordeaux, CNRS, Bordeaux-INP), France / RIKEN BSI, Wakoshi, Japan, [2]RIKEN BSI, Wakoshi, Japan / SKOLTECH, Moscow, Russia, [3]Handicap, Activity, Cognition, Health, Univ. Bordeaux, France

Introduction: Zomeren and Brouwer led researches on attentional deficits and found the existence of at least four attention domains. Alertness and sustained attentions refer to the intensity of attention (i.e., its strength) whereas selective and divided attentions refer to its selectivity (i.e., the amount of information that are monitored) [14]. The BCI literature has already shown that both some stable attentional capacities of subjects and the fluctuant attentional resources dedicated to the task by the latter are related to MI-BCI performances [8]. Indeed, it was shown that results from attentional tests, such as the digit span, are correlated with MI-BCI performances [3,7]. Furthermore, both spectral (i.e., alpha and theta) and spatial (i.e. attentional networks) neural correlates were correlated with MI-BCI [1,5,6,13]. This study aims at investigating whether we can classify the EEG signatures of the different attention types using EEG, with the future goal to apply this classification to MI-BCI. Material, Methods and Results: We asked 16 participants (5 women; mean age= 32,4 y.o.) to perform different tests related to the different types of attention presented in the previous section. During each task, participants had to react as fast as possible -by pressing a keyboard space bar- to the appearance of target stimuli while we recorded their EEG. The tasks and types of attention were differentiated by the type of sensorial modality of the stimuli, number of distractors, presence of a warning before the stimuli and the length of the task. The characteristics of the different tasks were chosen based on the literature [4,10,11,12]. For each attention task, 80 targets stimuli were presented. We only selected the ones that were at least one second apart from a motor response and used one second prior target presentation as analysis window. The subject-specific discriminability of the EEG patterns between each pair of attention tasks was then assessed using Common Spatial Pattern filtering in the alpha range (8-12Hz) and a Linear Discriminant Analysis classifier, with 5-fold cross-validation using the tool described in [2]. Results are promising and range from 83% accuracy (sd=0.09) to discriminate Alertness (Tonic) from Sustained attention (see Figure) to 74% accuracy (sd=0.13) to discriminate Selective and Divided attention. From the topography representing the mean inter-subject differences from t-tests of the Power Spectral Density in alpha range between the Alertness (Tonic) and Sustained attention we distinguish an influence of the temporal brain region which has already by shown in previous studies [9,11]. Discussion: These results tend to validate the model of Zomeren and Brouwer and indicate that the four types of attention from the model are distinguishable from one another. Current work focused on the alpha frequency range because literature indicates that it is both related to attention and MI-BCI performances [13]. We will also explore the characteristics of the types of attention, the influence of other frequency bands as well as the influence of the performance of the subjects (i.e. reaction time, accuracy) on their EEG. Significance: The literature indicates an influence of attention on MI-BCI performances [7,1] though it would be interesting to test if a feedback related to attention(s) could improve MI-BCI performances. Given the literature it seems that the feedback should focus on selective attention though it would be interesting to test this hypothesis by using the results of this article and classifying the EEG data from someone performing a BCI task. We acknowledge support from the Japanese Society for the Promotion of Science, the European Research Council (grant ERC-2016-STG-714567) and the French National Research Agency (grant ANR-15-CE23-0013-01). References: 1. Ahn et al, PloS one, 2013. 2. Appriou et al, BCI meeting, submitted 3. Daum et al, J. Neurol. Neurosur. PS., 1993. 4. Francis, Atten., Percept., & Psychophy., 2010. 5. Grosse-Wentrup, Int. J. Bioelectromagnetism, 2011. 6. Grosse-Wentrup et al, J. Neural Eng., 2012. 7. Hammer et al, J. Biol. Psychol., 2012. 8. Jeunet, Doctoral dissert., Bdx Univ., 2016. 9. Nobre et al, Brain: a journal of neurology, 1997. 10. Schmidt, Psychol. bulletin, 1968. 11. Sturm et al, Neuropsych. Rehab., 1997. 12. Van Leeuwen et al, Atten., Percept., & Psychophy., 2004. 13. Zhang et al, Neuroimage, 2016. 14. Zomeren et al, Oxford Univ. Press, 1994.

2-D-37 Can we predict when you want to move? An educational BCI game for a general public

Anne Gerrits[1], Ceci Verbaarschot[2], Jason Farquhar[2]

[1]Radboud University Nijmegen, Donders Institute for Brain, Cognition and Behaviour, [2]Radboud University; Donders Institute for Brain, Cognition and Behaviour

Introduction: When we perform self-paced voluntary movements, we typically see a readiness potential

(RP) and event-related desynchronization (ERD) in the alpha and beta bands over the motor cortex [1]. These electrophysiological activities typically build up around 1.5 to 2 seconds prior to movement onset [2]. Both the RP and alpha/beta ERD have been used to predict movement onset on a single-trial level [3] . Using BCI techniques, we developed a computer game that will be used to educate a general public. In the game, players try to beat the computer (see figure 1). At the start of each trial, a balloon will be displayed. The balloon will grow bigger over time. The bigger it gets, the more money is inside the balloon. Whoever pops the balloon first gets the money. In order to win, the computer opponent tries to predict when the human player will move and beat them to it. As soon as a movement is predicted, the computer will act and pop the balloon. The computer can use one of three ways to predict the player's movements: 1. The consecutive timing of previous moves 2. The muscle activity related to the preparation and execution of a movement 3. The pre-movement brain activity (i.e. the RP and alpha/beta ERD) The game will serve as a thought-provoking means to explain how movement intent travels from the brain to the muscles in order to perform a voluntary movement. Materials, methods and results: Five healthy volunteers participated in a simplified pilot version of the game. The game was designed in MATLAB (MathWorks Inc., USA). EEG was recorded using the Biosemi ActiveTwo system with 64 Ag/AgCl active electrodes. EMG electrodes were placed on the arm and the wrist bone to record muscular activity from finger movements. The game consisted of 3 blocks of 50 trials. Each trial, a circle would appear on the screen which grew bigger over time. Players were instructed that the computer learns when they move and tries to take the points just before the player does. Whoever "pressed" space first won the current amount of points. In this pilot, the computer made predictions based on the history of move times only. Specifically, the human was predicted to move at the mean of their previous move times. The computer predictions were made just before the player's mean move time and were calculated as follows: Computer prediction = (mean -1.5s) + (random value between 0 and 1)*SD , where mean refers to the player's mean movement time and SD refers to the standard deviation of the movement times. Preliminary results indicate that players exhibit the desired behaviour; they move randomly, adopt a strategy of waiting to maximise points, and (most importantly) find the game fun. Further, offline analysis of the pre-processed EEG data shows a clear ERD and RP up to 1.5s - 1s prior to movement onset. Finally, classifying 1.5s pre-movement versus 1.5s baseline data gave an average of 74% correct for the RP and 68% for the ERD based on electrodes over the motor cortex. Discussion: The next steps are to use the EEG and EMG datasets to develop classifier algorithms that are able to predict when someone intends to move in real-time. We expect that the history of movement times will provide the least accurate predictions. However, since humans are known to be bad random generators, we do expect that the accuracy will be above chance. Predictions based on muscle activity are expected to be the most accurate, but will also occur quite close (or even during) movement onset. Predictions based on brain activity are expected to be earliest and with above chance accuracy. Significance: We believe that this game will serve as an intuitive and appealing means to explain a neuroscience topic to a general public. Players get a chance to experience real-time feedback on their neural preparatory activity. Moreover, with this game the general public can be informed about the different techniques and steps of EEG and BCI. <I>Acknowledgements: This research was supported by StITPro. References: [1] H. Shibasaki, Clin. Neurophysiol. 123 (2012) 229-243. [2] C. Verbaarschot, P. Haselager, J. Farquhar, Exp. Brain Res. 234 (2016) 1945-1956. [3] O. Bai, V. Rathi, P. Lin, D. Huang, H. Battapady, D.Y. Fei, L. Schneider, E. Houdayer, X. Chen, M. Hallett, Clin. Neurophysiol. 122 (2011) 364-372.

2-D-38 N-back to the future: Estimating cognitive workload in a virtual reality environment using EEG signals

Christoph Tremmel[1], Christian Herff[2], Yusuke Yamani[1], Hector Garcia[1], Srdjan Lesaja[1], Krzysztof Rechowicz[1], Saikou Diallo[1], Dean Krusienski[1]

[1]Old Dominion University, [2]University of Bremen

Introduction: With the recent boom of affordable, high-performance virtual reality (VR) headsets, there is unlimited potential for applications ranging from entertainment, to education, to training, to fitness and beyond. As interfaces to VR applications continue to evolve, passive brain-state monitoring can play a key role in expanding the immersive VR experience, and tracking activity for user wellbeing. By recording physiological signals such as EEG during use of a VR device, the user's interactions in the virtual environment could be adapted in real-time based on brain-state such as cognitive workload level. Current VR headsets provide a logical, convenient, and unobtrusive framework for mounting EEG sensors. Recent advances in dry EEG electrodes and motion artifact suppression further increase the practicality of integrating EEG into VR headsets. The proposed work aims to demonstrate that EEG-based estimates of cognitive workload can be reliably obtained during use of VR. Material, Methods and Results: The classical N-back task [1] is selected to modulate cognitive workload and incorporated into a virtual environment using a HTC VIVE VR headset. The HTC VIVE hardware system consists of a headset, two controllers, and base stations that support 6 Degree of Freedom (6DOF) tracking. Stimuli are a series of colored balls presented in the virtual environment. Following McMillan et al. [2], each ball is colored red, blue, purple, or green. A ball receptacle is placed to the right and left of the participant. Participants complete a 5-minute practice block to familiarize themselves with the VR system and the N-back task. Following the practice block, participants perform a series of four experimental blocks in randomized order: 0-back, 1-back, and 2-back blocks with 6 trials each. In the N-back task, participants are required to report whether current stimulus matches the one presented N trials previously. In the 0-back task, participants simply determine whether each ball is red or not. In each block, participants receive a specific instruction regarding the task, followed by 6 experimental trials. Each experimental trial consists of a sequence of 22 balls, each of them remaining visible for 2.5 seconds, immediately followed by the onset of the next ball. Only a single ball is displayed at any given time and an auditory tone is presented with the appearance of each new ball. The participant's task is to pick up a ball in front of them and move it to the designated receptacle if it matches the one presented N trials before and to the opposite receptacle otherwise. To encourage participants, their performance (percent correct) is displayed after each trial. Figure 1 shows four sample states of the task. The order of the experimental trials and target receptacle locations are presented in a counterbalanced order across participants, and the order of the blocks is random for each participant. EEG is recorded using a g.USBamp amplifier (Guger Technologies, Austria) with 16 active electrodes at a 256 Hz sampling rate. Communication between the VR software and the BCI2000 EEG recording software is performed via UDP communication using BCI2000's application connector. Spectral EEG features in the classical EEG bands are used to estimate the cognitive workload for comparison to prior EEG-based N-back studies, not using VR [3]. [Figure 1 and caption] Discussion: This work will be extended to provide continuous user feedback to the VR environment/interactions based on the estimates of cognitive workload from EEG. Additionally, other cognitive measures such as engagement, fatigue, vigilance, etc. will be explored. Significance: This study demonstrates the viability of passively monitoring cognitive workload using EEG in a room-scale, semi-unconstrained virtual environment. Extending this work to closed-loop brain-state monitoring is envisioned to greatly increase the level of immersion of the VR experience. References: [1] Brouwer, AM et al. (2012) Estimating workload using EEG spectral power and ERPs in the n-back task. Journal of neural engineering, 9(4), 045008. [2] McMillan, K. M., et al. (2007). Self-paced working memory: validation of verbal variations of the n-back paradigm. Brain Research, 1139, 133-142. [3] Palomaki J. et al. (2012). Brain oscillatory 4-35 Hz EEG responses during an n-back task with complex visual stimuli. Neurosci. Lett. 516 141-145.

2-D-39 Clinician awareness of brain computer interfaces and eligible populations.

Sasha Létourneau[1], Ephrem Zewdie[2], Lee Burkholder[3], John Andersen[4], Adam Kirton[2]

[1]School of Medicine, Queen's University, [2]Cumming School of Medicine, University of Calgary, [3]Cummings School of Medicine, University of Calgary, [4]Faculty of Medicine and Dentistry, University of Alberta

Introduction: Few circumstances are more tragic than an intellectually capable individual being trapped inside a body that cannot move. Unfortunately, multiple adult and pediatric neurological conditions can create such locked-in syndromes. Brain-computer interfaces (BCI) are a relatively inexpensive, user-friendly technology which may be able to improve the ability for such patients to interact with their environment. Modern, external, wireless, EEG-based systems can allow locked-in patients to communicate or control electronic devices, such as robotic arms, computers or environmental control systems (e.g. lights). Additional BCI applications are increasingly realized including other forms of neurorehabilitation. Despite this considerable potential, translation of BCI technologies to clinical populations has been difficult. One limitation preventing more widespread trials of BCI technology may be lack of physician and healthcare team awareness. A national survey of relevant experts to assess BCI awareness and patient populations might advance this promising approach but has not been completed to our knowledge. Aims: 1) Assess physicians' knowledge of BCI technology and, in doing so, increase physician's awareness of BCI 2) Estimate the number of patients in Canada who might be able to benefit from this technology and determine what aspects of BCI might benefit them most Material, Methods and Results: This was a cross-sectional survey of Canadian neurologists and physical medicine and rehabilitation specialists (physiatrists). An initial survey based on BCI literature and previous experience working with BCI in pediatric and adult populations was reviewed by a practicing neurologist, a practicing developmental pediatrician, a practicing physiatrist and a biomedical engineer scientist specializing in BCI. The final survey included questions about demographics, baseline BCI knowledge and estimation of relevant clinical populations. REDCap, a secure web-based survey software, was used for survey development and distribution. 664 valid emails for neurologists, 253 valid emails for physiatrists and 4 valid emails of developmental pediatricians were found online. Participants were sent a public survey link via email with a follow up email within 10 days. Participation was incentivized with a 300$ Chapters-Indigo or Amazon gift card. Descriptive statistics were used to describe patient demographics, responses to baseline BCI knowledge questions; subspecialty distributions; patient demographics; rating of BCI applications and utility; and average and median estimates of patient population sizes by condition. One-way ANOVA was used to compare physician BCI knowledge across specialties and subspecialties. A total of 137 physicians (14.9% response rate) completed the survey: 68 neurologists, 39 pediatric neurologists, 23 physiatrists, 4 developmental pediatricians and 3 pediatricians. All respondents were actively involved in clinical work. Nearly one in four respondents (22.6%) reported that >50% of their patients had a severe neurological disorder while 15.3% of physicians estimated that >50% of their patients had both severe neurological disability and the preserved cognition necessary to operate a BCI device. Current knowledge and awareness of BCI was poor with 40% reporting basic knowledge between "no knowledge" and "vaguely aware." Between specialties, there was no significant difference in baseline BCI knowledge (p=0.51). 6 respondents (4.4%) had at least one patient currently using a BCI. The reported number of patients using BCI was 17. BCI communication devices, wheelchair control and then computer usage were considered to have the highest potential to improve patient quality of life. 70% of participants rated BCI as having high utility in clinical practice while 81% believe BCI has high potential to improve patient quality of life. A conservative estimate of the number of patients who could benefit from BCI based on survey responses was >15000 in Canada (population 36 million). Discussion: BCI awareness by the clinicians who serve the primary patient populations is limited despite a large number of patients who could benefit. Significance: Advancing knowledge and engaging these specialists may facilitate program development, research funding options, industry interest, and public awareness to accelerate translation toward improved patient outcomes.

2-D-40 Towards passive BCI based neuoadaptive technology

Laurens Krol[1], Klaus Gramann[2]

[1]Technical University of Berlin, [2]TU Berlin

Parts of this work were already published (1). Introduction: Today's interaction with technology is asymmetrical in the sense that the operator has access to any and all details concerning the machine's internal state, while the machine only has access to the few commands explicitly communicated to it by the human (2), and while the human user is capable of dealing with and working around errors and inconsistencies in the communication, the machine is not (3). We investigate whether a cognitive model (4) can be build and refined continuously by giving agency to the technological system to probe its operator's mind by means of a Passive Brain-Computer Interface (pBCI). Effectively, the machine can pose a question directly to a person's brain and immediately receive an answer, potentially even without the person being aware of this happening. This cognitive probing allows for the generation of a more fine-grained user model. It can be used to fully replace any direct input to the machine, establishing effective, goal-oriented implicit control of a computer system (5). Material, Methods and Results: We have shown that a cursor could be guided discretely over the nodes of a grid in two dimensions (up to eight possible directions: horizontal, vertical, and diagonal) (1). One of the corners of the grid was designated the target. Each automatic cursor movement additionally served as a cognitive probe: the cursor would autonomously move into one direction, the system would evaluate the subsequent neuronal response of the observing participant by a passive BCI, and would then adjust the user model underlying the cursor's movement. In this case, the user model consisted of the participant's preferences for certain directions, and the better-preferred a direction was, the higher was the chance that the cursor would move into that direction. Each cursor movement elicited an automatic, specific neuronal response depending on whether or not the participant felt this was an appropriate move or not. For example, if the cursor moved south-west while the target was towards the north-east, the system would detect this as an inappropriate move based on related EEG activity. After a few such implicit interaction cycles, the model strongly weighted the correct direction towards the target. This scenario describes the online application of the paradigm--before that, the classifier was calibrated on data gathered from a simply randomly moving cursor. During online application the cursor reached its target significantly faster than the randomly moving cursor, and bridged the gap between a mathematically perfect reinforcement and no reinforcement by over 80%. Discussion: The used paradigm shows some similarities to that in (6). Here, participants were though completely unaware that they could affect the cursors behavior over the whole duration of the experiment, showing that implicit direct control is feasible. The machine learned autonomously from human brain activity. Significance: This approach fuses human and machine information processing, introduce fundamentally new notions of 'interaction', and allows completely new neuroadaptive technology to be developed. This technology bears specific relevance to auto-adaptive experimental designs, but opens up paradigm shifting possibilities for technology in general, addressing the issue of asymmetry and widening the above-mentioned communication bottleneck (see figure 1) providing a first step in solving this fundamental problem. 1.Zander, T. O., Krol, L. R., Birbaumer, N. P., & Gramann, K. (2016). Neuroadaptive technology enables implicit cursor control based on medial prefrontal cortex activity. Proceedings of the National Academy of Sciences, 201605155. 2.Tufte E.R., (1990) Envisioning Information (Graphics Press, Cheshire, CT). 3.Suchman L.A. (1987) Plans and Situated Actions: The Problem of Human-Machine Communication(Cambridge Univ Press). 4.Fischer G. (2001) User modeling in human-computer interaction. User Model. User-Adap. 11(1-2):65-86. 5.Zander, T. O., Brönstrup, J., Lorenz, R., & Krol, L. R. (2014). Towards BCI-based implicit control in human-computer interaction. In Advances in Physiological Computing (pp. 67-90). Springer London. 6.Iturrate, I., Chavarriaga, R., Montesano, L., Minguez, J., & Millán, J. D. R. (2015). Teaching brain-machine interfaces as an alternative paradigm to neuroprosthetics control. Scientific reports, 5. Fig. 1: Neuroadaptive Technology

2-D-41 Classifying confidence from single-trial EEG in memory retrieval tasks

Kueida Liao[1], Eunho Noh[1], Matthew Mollison[2], Tim Curran[2], Virginia de Sa[3]

[1]UC San Diego, [2]University of Colorado Boulder, [3]University of California, San Diego

Introduction: In this study, we used dimensionality reduction and two-class pattern classifiers to extract features related to subjects' confidence in their answer on recognition memory retrieval tasks from the temporal information in the EEG data. Based on single-trial scalp EEG activity recorded during the retrieval phase of 4 separate memory experiments, we trained the classifiers to discriminate the confidence level of subjects for both correct rejections and correctly remembered items. We show that it is possible to predict successfully the high vs. low confidence level of subjects. We also reveal the spatiotemporal patterns underlying the classification. Material, Methods and Results: The four datasets were recorded in 3 separate visual memory task experiments, and the description can be found in Mollison and Curran (Neuropsychologia, 2012). Two-class classification was conducted on the confidence level of correct judgement trials (correct item retrieval [i.e., hits] and correct item rejection trials) separately for each subject and each task. The spatiotemporal structure of the single-trial data was extracted for evaluation based on the six channel groups and five 100 ms windows used in previous episodic memory studies (Noh et al, NeuroImage, 2014; Noh and de Sa, Proc. Annu. Meet. Cogn. Sci. Soc., 2014). The features were concatenated to a 30-dimensional feature vector for each trial. A binary classifier using automatic shrinkage linear discriminant analysis (Ledoit and Wolf, J. Multivar. Anal., 2003; Friedman, JASA, 1989) was trained to classify these feature vectors. The feature vectors were projected onto the discriminant vector and calibrated to give values between 0 and 1, referred to as classifier scores. The classifier score is the probability of a given example being a high confidence trial. Leave-two-out (one from each class) cross-validation was performed during the training of the classifier to avoid overfitting to the training data and classes were balanced during training. The average classifier scores across all subjects were compared across all different behavioral conditions. The EEG features utilized by the classifiers were visualized by analyzing the classifier activation patterns representing which channel groups and time periods were important for classification (Haufe et al., Neuroimage, 2014) . In order to identify the consistency of features across all subjects, a cluster-based correction (Maris and Oostenveld, J. Neurosci. Methods, 2007) for multiple comparisons was used. The performance of the classifiers was evaluated by using the area under the ROC curves. Overall, the average accuracy of confidence classification across four datasets is 0.5484, and the average AUC is 0.5721. The spatiotemporal activation patterns utilized by the classifiers are shown in Fig 1 (a). The consistent ($p < 0.05$) activation patterns across subjects identified by the cluster-based correction method are shown in Fig 1 (b). Misses and False Alarm error trials were also classified consistently (though they were not used for training) with confident misses and false alarms receiving intermediate classifier scores and less-confident misses and false alarms receiving on average lower classifier scores. Discussion and Significance: The AUC of the confidence classifiers suggested that the trained classifier could successfully discriminate the confidence level of the subject on a single-trial basis. The activation patterns of the classifier showed the difference in spatiotemporal features in the EEG data that distinguish the different confidence levels. Most of the features utilized were consistent across subjects between 600-800 ms in the four different experiments. The activation patterns of our classifier are generally consistent with previous findings from trial-averaged event-related potentials (Curran, Neuropsychologia, 2004; Woodruff et al, Brain Res., 2006). This work could be useful for automated systems for improving memory (Noh et al., Proc. 6th Int. BCI Conf., 2014). Acknowledgements: This work was supported by NSF IIS 1528214, IIS 1219200, SMA 1041755, KIBM, NIH MH64812, IBM.

2-D-42 Toward a hemicraniectomy-EEG based BMI therapy for the rehabilitation of patients with traumatic brain injury

Mukta Vaidya[1], Robert Flint[1], Po Wang[2], Alex Barry[3], Goran Tomic[1], Emily Mugler[1], Sarah Gallick[3], Sangeeta Driver[3], Nenad Brkic[3], David Ripley[3], Charles Liu[2], An Do[2], Marc Slutzky[1]

[1]Northwestern University, [2]University of California, Irvine, [3]Shirley Ryan Ability Lab

M Vaidya1*, RD Flint1, PT Wang4, A Barry5, G Tomic1, EM Mugler1, S Gallick5, S Driver3,5, N Brkic3,5, D Ripley3,5, C Liu6,7, A Do4,7,, and MW Slutzky1,2,3,5 1Department of Neurology; 2Physiology; 3Physical Medicine & Rehabilitation; Northwestern University, Chicago IL USA 4Department of Neurology, University of California, Irvine CA USA 5Shirley Ryan Ability Lab, Chicago IL USA 6Department of Neurosurgery, University of Southern California, Los Angeles, CA USA 7Rancho Los Amigos National

Center for Rehabilitation, Los Angeles, CA Introduction: Brain-machine interfaces (BMIs) can be controlled with signals obtained with either noninvasive or invasive methods. Invasive recordings, such as electrocorticography (ECoG) or intracortical signals are more informative, higher bandwidth, and have higher spatiotemporal resolution than noninvasive signals such electroencephalography (EEG) or magnetoencephalography (MEG). However, rehabilitative BMIs, which ultimately aim to restore function by driving plasticity, rather than replace function, have largely relied on non-invasive methods. Since plasticity depends on synchronous pre- and post-synaptic activity, invasive BMIs may enable more enhanced plasticity than noninvasive BMIs. However, before implanting a BMI into patients with stroke or traumatic brain injury (TBI), which would involve some risk, we have developed a noninvasive way to test these ideas in patients with traumatic brain injury that have undergone decompressive hemicraniectomies as part of their treatment. This represents a new way to obtain high gamma frequency range noninvasively for a rehabilitative BMI. Materials, Methods and Results: We recorded from six subjects that had undergone decompressive hemicraniectomies after suffering traumatic brain injuries and were undergoing inpatient rehabilitation. We recorded from the electrodes over the hemicraniectomy (hEEG) as well as the rest of the electrodes on the cap (64-channel EEG in one subject, 128-channel EEG in the rest), while the subjects performed a 1-dimensional, continuous force-matching task with their hand contralateral to the hemicraniectomy. To remove artifacts from muscle and eye movements, we developed a novel, automated method, termed Annular Component Removal (ACR), which uses independent component analysis to identify signals coming from the periphery of the head. We then decomposed the neural data in the local motor potential (LMP), and four spectral features: delta (<4Hz), mu (7Hz to 12Hz), beta (12Hz to 30Hz), and high gamma (65Hz to 115Hz). We found the channels above the hemicraniectomy contained high-gamma information, and that we could decode the continuously generated finger flexion force from these signals using a Wiener cascade filter with accuracy approaching that of epidural signals (vaf = 0.1896 +/- 0.1174). We did not observe significant improvement in performance when using all four spectral features and the LMP in our decoder as compared to just using high gamma (t-test, p= 0.0852). Moreover, decoding performance was higher when using electrodes over the craniectomy than homologous electrodes on the contralateral hemisphere (paired t-test, p= 0.0249). We are about to begin using these hEEG signals in a real-time BMI-based therapy for the rehabilitation of TBI patients with hemicraniectomies. Discussion: We have demonstrated the ability to record informative high-gamma activity reliably in hEEG. We decode finger flexion force with reasonably high accuracy using continuous high gamma power. In addition, we designed a novel, automated method, Annular Component Removal (ACR), to reduce muscle and eye artifact-related information from the scalp potentials recorded from the hemicraniectomy patients. These results indicate that the hEEG paradigm is a useful platform for developing BMI based therapies for rehabilitative treatment of this patient population. We plan to start testing our closed-loop rehabilitative BMI. Significance: The primary advantages of hEEG are that it enables non-invasive recording of high-bandwidth signals and that it does so in a potential end-user population (TBI patients). Our hEEG-based paradigm would allow for concurrent research and development of rehabilitative BMIs in TBI patients, providing the ability to test feasibility and design and optimize both to benefit patients. This platform can thus enable prototyping of invasive BMI paradigms (e.g., ECoG) without significant risk to patients.

2-D-43 Mixed results with affective classification of frontal alpha asymmetry and hjorth parameters

David Thompson[1], Rachael Cano[1], Katie Dhuyvetter[1], Md Rakibul Mowla[1]

[1]*Kansas State University*

Introduction: Affective BCIs, which attempt to measure the emotional state of the user, have been of considerable research interest. Many groups have published results based on EEG measurements, focusing on feature selection and classification techniques. Several emotion-elicitation paradigms are in common use, including videos and the International Affective Picture System (IAPS) [1]. This abstract summarizes early findings from an experiment attempting to replicate prior studies with the IAPS. Material, Methods and Results: The experiment was performed in a single session for each participant. We recorded EEG signals from each participant while they viewed pictures from the IAPS and rated each image according to the 3-D Self-Assessment Manikin [2]. Only the answers for Valence and Arousal were used in this study. The pictures were presented using BCI2000. In all, 244 pictures were presented. Within each set of images, the order was randomized. Eight neurotypical people participated in the study, though the data for two has been excluded. One did not have valid emotion labels for the first set of images; the other viewed several images more than one time due to a battery failure. The remaining six participants were college-age (21-22). EEG recordings were performed with a 64-channel Cognionics Mobile-72 wireless EEG system. EEG was recorded at 600 Hz and bandpass filtered from 4 to 30 Hz. Features were selected based on prior publications. These features included frontal alpha asymmetry [3], and the Hjorth parameters of complexity and mobility [4]. Each of these features has been used in several published papers. In our data, several features were found to be well-correlated with either arousal or valence for particular individuals. Two individuals demonstrated strong correlations with Arousal ($p < 0.05$ even after Bonferroni correction for number of features and participants) for five and two of the features, respectively. However, the two sets of features have no intersection. Only one feature, a frontal alpha asymmetry, was correlated at this level with valence, and only for one participant. Without Bonferroni correction, more features were correlated with both labels. However, no single feature was correlated below $p = 0.05$ for more than four participants. Classification, regardless of method used, did not perform well for these participants. Use of MATLAB's neural network toolbox and Classification Learner app allowed quick assessment of 24 classification methods including variants of LDA, SVM, k-NN, Trees, and Neural Networks. Participants achieved maximum three-class arousal accuracies of 66, 54, 45, 42, 80, and 51%. However, only three of these (the second, third and last) are significantly different from the response biases for each participant, and just barely. For valence, accuracy was lower. Discussion: Overall, even features previously shown to be correlated with emotional responses performed poorly in this experiment. Classification was at chance or near-chance levels for six of six subjects, if label bias is taken into account. This despite having a relatively large number of pictures and EEG channels compared to prior work. Significance: This is an early investigation and is not yet a formal failure-to-replicate finding. However, with zero of six participants showing acceptable performance, we are concerned that the IAPS may not be producing sufficient emotional response. Additionally, this study should serve as a reminder that unbalanced datasets can easily produce significant-seeming results, and that reporting data bias should be standard procedure.
References: [1] P. J. Lang, M. M. Bradley, and B. N. Cuthbert, "International affective picture system (IAPS): Instruction manual and affective ratings," Cent. Res. Psychophysiol. Univ. Fla., 1999. [2] M. M.

Bradley and P. J. Lang, "Measuring emotion: the self-assessment manikin and the semantic differential," J. Behav. Ther. Exp. Psychiatry, vol. 25, no. 1, pp. 49-59, 1994. [3] J. A. Coan and J. J. Allen, "Frontal EEG asymmetry as a moderator and mediator of emotion," Biol. Psychol., vol. 67, no. 1, pp. 7-50, 2004. [4] R. Horlings, D. Datcu, and L. J. Rothkrantz, "Emotion recognition using brain activity," in Proceedings of the 9th international conference on computer systems and technologies and workshop for PhD students in computing, 2008, p. 6.

2-D-44 Recovery of hand function in spinal cord injury patients augmented by BCI-driven afferent nerve stimulation

Sarah Thomas[1], Christopher Schildt[1], Elizabeth Powell[1], Yuvaraj Rajamanickam[1], Matthew Ballard[1], Sara Salles[1], Lumy Sawaki[1], Sridhar Sunderam[1]

[1]*University of Kentucky*

Introduction: Development of effective rehabilitation techniques is important for helping patients with spinal cord injury (SCI) recover lost or impaired motor function. Techniques such as peripheral nerve stimulation (PNS) and functional electrical stimulation (FES) have been found to improve function through passive activation of sensory and motor pathways, respectively. However, these techniques do not require the subject's conscious effort, which might limit the potential gains in functional recovery. In contrast, when afferent PNS is applied synchronously with transcranial magnetic stimulation (TMS) to evoke movement, it can induce greater and more sustained cortical excitability than passive activation alone.2 The primary objective of this study is to determine the potential benefit of applying afferent PNS synchronously with volitional movement in a cue-driven motor task performed by individuals with cervical SCI. Materials, Methods, and Results: In this feasibility study conducted with IRB approval, patients with cervical SCI (level C4-C7), at least 10 months removed from the injury, participated in 4 weeks of PNS application to the median nerve (except for one, who dropped out after 2 weeks) while engaged in an interactive cue-driven hand grip task. A brain-computer interface (BCI) system was developed to trigger PNS in real time based on motor intent-related changes in the electroencephalogram (EEG). One group of subjects (n = 8) received BCI-driven closed-loop PNS while the other (n = 12) received PNS uncorrelated with movement initiation. TMS determined cortical muscle representations and maximum voluntary contraction (MVC) force were assessed before and after each session. PNS timing accuracy was calculated based on the system's ability to apply PNS within 500 ms of movement initiation as detected using a hand dynamometer or forearm electromyogram (EMG). Results of this research indicate PNS timing-dependent outcomes that are of direct relevance to clinical practice. Subjects receiving volition-dependent PNS (n = 8) had PNS timing accuracies of 81.6±1.3% and 81.3±1.4%, mean MVC changes of 54.9±4.3% and 63.7±6.4%, and mean TMS motor map volume changes of -0.8±0.3 and 3.2±0.3 units for the left and right hands, respectively. In contrast, subjects with PNS uncorrelated with movement initiation (n = 12) had PNS timing accuracies of 30.3±2.1% and 29.4±2.1%, mean MVC changes of 2.2±6.9% and 23.5±6.7%, and mean TMS motor map volume changes of -1.1±0.4 and 0.2±0.3 for the left and right hands, respectively. Subjects with volition-dependent PNS showed greater increases in MVC force in both hands (significant only for the left hand, $p<0.05$) compared to the other group. Discussion: While these results come from a relatively small cohort, they suggest that BCI-driven closed-loop protocols with fine control of PNS timing could be a valuable adjunct to physiotherapy in the rehabilitation of patients with SCI. A larger sample will allow for a more comprehensive characterization of the correlation between PNS timing and outcome metrics. This research has the potential to produce a more effective rehabilitation technique than current approaches. Significance: SCI is a debilitating physical condition that affects all aspects of an individual's life. Analysis of the National SCI Database has shown that employment status fell to 12.1% one year after injury but then increased to 27.7% and 34.9% at years ten and twenty, respectively.1 Hence, many SCI patients are able to rehabilitate to a level that allows them to re-enter the workforce, but over a long period of time. Research towards advancing motor rehabilitation techniques is crucial for reducing the time required to rehabilitate and increase rehabilitation potential. To the best of our knowledge, this is the first study in which BCI-driven PNS has been successfully applied over several weeks in patients with SCI. Acknowledgements: This work was supported in part by National Institute of Child Health and Human Development grant 1R21HD079747 and by National Science Foundation grant 1539068. References: 1. National SCI Statistical Center. "Spinal cord injury facts and figures at a glance". Univ of Alabama at Birmingham. (2013). 2. Stefan, K., et al. "Induction of plasticity in the human motor cortex by paired associative stimulation." Brain (2000) 123 (3): 572-584.

2-D-45 Multi-paradigm EEG classification using deep neural networks

Gabriel Ibagon[1], Christian Kothe[1], Nima Bigdely-Shamlo[1], Tim Mullen[1]

[1]Intheon

Introduction: The classification of time-locked events using machine learning is an essential component of many EEG-based brain-computer interface (BCI) systems. However, most current BCIs use highly-specialized machine learning models that are trained to perform well on only a single experimental paradigm. An alternative approach would be to combine data from multiple BCI paradigms in order to train a stronger, more general classifier. A multitask learning strategy would allow the model to take advantage of information that is shared across paradigms, thus reducing the amount of task-specific data needed to learn effective internal representations. In this work, we sought to improve event classification accuracy by training a single deep neural network on a large, multi-paradigm corpus of EEG data. By concurrently training the network on multiple tasks, we expect the model will learn to extract information that is common to a range of BCI paradigms, while also building a set of task-specific representations for each paradigm. Material, Methods and Results: We demonstrate the multi-paradigm learning approach by using data from two different paradigms: a Rapid Serial Visual Presentation (RSVP) task and a Visual Oddball (VOB) task. The data from each paradigm went through a common preprocessing pipeline, which consisted of detrending, line-noise removal, eye blink removal, and bad-trial removal. Our deep learning model is based on a convolutional neural network architecture, using a series of spatio-temporal convolutions to extract features from the raw EEG signal in order to classify a sample. We established a baseline by first individually testing each paradigm through the model, using a leave-one-subject-out procedure. We then combined all of the paradigms into a large training set and tested the model's performance on classifying on an unseen subject. When training on a single paradigm, the model achieves a cross-validated test accuracy of 81.66+/-2.3% on the VOB task and

82.74+/-2.2% on the RSVP task. When combining data from both paradigms, test accuracies improved slightly to 84.07+/-1.4% for the VOB task and 83.24+/-2.3% for the RSVP task. Discussion: While the results of this analysis show only slight improvements in accuracy, they suggest that information extracted using a deep learning model may be shared between multiple BCI paradigms, increasing overall classifier performance on new subjects from any of the included paradigms. In a given EEG recording, there exists a high amount of noise and other features that may obscure information relevant to the classification of an event. Given access to more training examples, the network may more effectively learn to distinguish relevant signal from noise in the EEG. The network may also avoid overfitting on paradigm-specific variations that may not contribute to accurate classification of event. Furthermore, given several datasets of related tasks, such as the visual-based VOB and RSVP tasks, the network may learn to extract common neurophysiological components of visually-evoked potentials across tasks. Significance: Learning robust, generalizable classification models is a key step towards establishing accurate BCIs for use in the real world. As large corpuses of heterogeneous data become more prevalent for use with training BCI models, we see increased opportunities to leverage deep learning methods that exploit shared information across paradigms and subjects, increasing classification accuracy when little or no data from an individual is available. Future directions of research will progress these techniques further with the goal of generalizing BCIs to a wider variety of contexts.

E- Signal Acquisition

2-E-46 Development of a portable intracortical BCI system

Jeffrey Weiss[1], Robert Gaunt[1], Michael Boninger[1], Robert Franklin[2], Jennifer Collinger[1]

[1]University of Pittsburgh, [2]Blackrock Microsystems

Introduction: While recent advances have demonstrated the potential of using intracortical BCI to control computers, robotic arms, or functional electrical stimulation systems, numerous challenges remain before intracortical BCI can be used for a clinical take-home system. One important issue is the size and portability of the complete BCI system. A typical laboratory BCI system involves bulky patient cables and amplifiers, rack-mounted neural signal processors, and multiple computer towers and displays. While there has been much attention on wireless transmitters and headstages, including tests with human participants (Nuyujukian 2015, Saab 2017), most of these systems still require full-size signal processors and/or computers that must be miniaturized to be take-home ready. Here, we present a compact, portable BCI system that can be used by people who use wheelchairs for independent mobility. Material, Methods and Results: Our portable BCI system, as shown in the figure, consists of a medical-grade (IEC 60601-1 compliant) tablet PC (GeTac Technologies), a 256-channel Cereplex hub (wNSP), and two 128-channel Cereplex-E headstages (Blackrock Microsystems). Each Cereplex-E can record, amplify, and digitize up to 128 channels from a Neuroport pedestal, and transmits data over an HDMI cable to the wNSP hub. The hub functions as an isolated power supply to the Cereplex-Es and also transmits up to 256 channels of data to the tablet PC over USB. The tablet PC preprocesses the neural data using Blackrock nPlay Server and streams spike times and snippet waveforms to a custom BCI software suite adapted from the system presented in (Collinger 2013) and optimized to run on the tablet. The entire system is powered by the tablet's battery. Safety and performance testing was completed in accordance with IEC 60601 guidelines to support human testing under an FDA Investigational Device Exemption. The system was tested with a participant already enrolled in a clinical trial of an intracortical BCI (NCT 01894802). This participant has a C5/C6 spinal cord injury and was implanted with two Utah arrays in M1 and two arrays in S1, with a total of 240 recording channels. As an initial step towards validation, the portable BCI system was used to calibrate and test a 2D velocity-based decoder for cursor control on the tablet, without the use of any external computers or power. During preliminary testing, the subject successfully completed 45/48 trials in a 2D center out task (93.8% success rate). Discussion: This prototype serves as a proof-of-concept that an intracortical BCI system can function without bulky rack-mount hardware and can be miniaturized into a portable form-factor suitable for take-home use. While a simple 2D center out task was used for a proof-of-concept demonstration, the system can also be used for independent computer access by adding a "click" dimension of control to simulate a mouse. The tablet's peripheral connectors also allow external devices, such as wheelchair-mounted robotic limbs, to be controlled by the BCI. While wireless headstages eliminate the tether between the patient and amplifiers, they do not enable use outside of the home without a portable system in close proximity. Future experiments will characterize system performance as compared to a standard non-portable BCI system. Significance: This project demonstrated that an intracortical BCI system can be miniaturized into a compact and portable system that meets FDA safety standards and can be contained on a wheelchair. References: Nuyujukian P. et al. Bluetooth wireless brain-machine interface for general purpose computer use. Society for Neuroscience. 2015, 748.01. Saab J. et al. Wireless intracortical BCI cursor control by a person with tetraplegia. Society for Neuroscience. 2017, 230.05. Collinger J et al. High-performance neuroprosthetic control by an individual with tetraplegia. The Lancet, 2013, 381(9566) 557-564. Acknowledgements: This material is based upon work supported by the Defense Advanced Research Projects Agency (DARPA) and Space and Naval Warfare Systems Center Pacific (SSC Pacific) under Contract No. N66001-16-C-4051. Any opinions, findings and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of DARPA or SSC Pacific.

2-E-47 A comparison between spatial filtering techniques based on conventional methods and tripolar concentric ring electrodes

Sarah Ismail Hosni[1], Walter Besio[1], Yalda Shahriari[1]

[1]*University of Rhode Island*

Introduction: One of the major challenges in bridging the gap between invasive and non-invasive sensorimotor rhythms (SMR)-based brain-computer interfaces (BCIs) is spatial localization which plays an important role in the neural decoding of the cortical motor area. Previous studies have emphasized on the importance of applying spatial filtering methods to estimate the underlying cortical potentials associated with motor imaginary (MI). It has been shown that among conventional EEG spatial filters including Large Laplacian (LLAP) [Nunez et al., 1994], small Laplacian (SLAP) and common average referencing (CAR) [Bertrand et al., 1985], the most enhanced localization and reduced signal-to-noise ratio (SNR) can be achieved by applying LLAP in a SMR-BCI task [McFarland et al., 1997]. However,

spatial filtering characteristics of the Laplacian which performs based on the distance separating each electrode from the set of surrounding channels is highly dependent on the number of channels. Recent studies have shown that tripolar concentric ring electrodes (TCREs) enhance the spatial resolution and selectivity of the surface electrical activity by estimating the surface Laplacian directly through the nine-point method with significantly higher spatial resolution than conventional EEG recordings [Besio et al., 2006; Makeyev et al., 2013]. This study seeks to compare tripolar EEG (tEEG) recording using TCRE to conventional spatially filtering methods. Materials and Methods: Five healthy subjects performed MI tasks (left/right hand). The subjects wore an elastic cap with 16 electrodes, recording from 8 locations (FC3, FC4, C1, C2, C3, C4, CP3, CP4). The tEEG was recorded with TCREs and the t-Interface 20 (CREmedical) pre-amplifier. The signal was then amplified using a g.USBamp (g.tec) and digitized at 1200 Hz. All the stimulation presentation and signal monitoring were performed using BCI2000 [Schalk et al., 2004]. Each subject attended 3 runs recorded in one day. Each run consisted of 10 trials for each MI condition following a rest (10 seconds each). Power averaged over Mu and Beta frequency bands across each MI condition were calculated based on Morlet wavelet decomposition. To quantify the spatial localization features of EEG, tEEG, LAP-EEG, CAR-EEG, and SLAP-EEG, squared Pearson correlation coefficient (r2) was used to measure the proportion of variance of the EEG power that was accounted for by the MI task and rest which reflects SNR and localization. Results: Figure. 1 depicts the average r2 correlation values for each EEG type using scalp maps averaged over all subjects for both Mu and Beta bands. Generally, spatial localization was more prominent in case of right MI versus left, presumably because all the subjects were right-handed. Also, localization was more obvious in the Mu band for all of the cases except tEEG which demonstrated higher localization and correlation in the contralateral hemisphere to the body part MI for both Mu and Beta bands. The maximum r2 for were both achieved with tEEG: 0.3139, 0.2564, 0.1716, and 0.1603, for Mu-Left, Mu-Right, Beta-Left, and Beta-Left respectively. Discussion: The outcomes from this study emphasize the importance of spatial filtering for consistent and localized activity in a SMR-BCI task. Although tEEG demonstrates apparent superiority in terms of activity localization and correlation values consistent across the bands of interest, in our study the conventional spatial filtering methods might suffer from low number of channels which might have biased the results. In contrast, this highlights the superiority of tEEG in terms of the need for relatively few electrodes, and thus, less density EEG recording in a SMR task. Moreover, notably, tEEG was the only modality to clearly capture SMR characteristics in the Beta band with relatively high correlation. Significance: The comparative framework between conventional EEG spatial filtering and tEEG highlights the spatial mechanism of tripolar concentric recording on localization of neural activity from the motor area which can have application in multidimensional control of prosthetic devices. Such localization suggests less demand to high-density EEG recordings for an optimum spatial filtering in a SMR task.
Acknowledgement: This research was supported by the Institutional Development Award (IDeA) Network for Biomedical Research Excellence from the NIGMS of the NIH (P20GM103430).

2-E-48 High-gamma activity in tripolar electroencephalography correlates with hand movements

Walter Besio[1], Jason Mercier[1], Brandon Williams[1], Shunan Li[1]

[1]University of Rhode Island

INTRODUCTION Brain activity is a spatio-temporal process and it can be imaged by the phenomenon of electrical potentials on the scalp surface, called electroencephalography (EEG). The equipment used for EEG is non-invasive, inexpensive, and provides sufficient temporal resolution to study brain function. However, EEG has limited spatial resolution and selectivity. Tripolar concentric ring electrode (TCRE) sensors have been shown to estimate the surface Laplacian, the second spatial derivative, directly and have significantly better spatial resolution than conventional electrodes [1]. The TCRE sensor consists of three electrodes including the outer ring, a middle ring, and the central disc. They are distinctly different from conventional disc electrode sensors that have a single electrode. Previously we have shown that, compared to EEG with conventional disc electrode sensors, Laplacian EEG using TCREs (tEEG) has significantly better spatial selectivity (approx. 2.5 times higher), signal-to-noise ratio (approx. 3.7 times higher), and mutual information (approx. 12 times lower) [2]. We have also reported high-frequency activity in the fast-ripple range (200-500 Hz) prior to seizures that was well correlated with the diagnosed seizure onset zone or irritative zone [3]. METHODS The participants, 8 (4 females) all consented to the URI IRB approved protocol. They sat in a comfortable chair positioned in front of the computer screen and the BCI2000 software application acquired signals from TCREs placed at positions C3, C1, Cz, C2, C4, FC1, FCz, and FC2, with reference and ground on the right mastoid [4]. The tEEG was first preamplified with a t-Interface 20 (CREmedical Corp). Signals from all the channels were amplified (g.tec GmbH), filtered (0.1-100 Hz) and digitized (512 S/s). The participants were then asked to focus on the computer screen and a series of three pictures presented to the participants informing them of the appropriate action to perform; a left arrow, right arrow, or a rest image to indicate left hand movement, right hand movement, and to rest respectively, each with a duration of four seconds. A random order of left and right arrows was presented to the participants with rest segments in between hand movement segments. This was repeated until ten left hand and ten right hand segments were recorded for a total of twenty hand movements in one recording, a run. Each participant completed three runs. The recordings were analyzed using R^2 plots on BCI2000's offline analysis MATLAB script [5]. DISCUSSION All participants were able to complete the study. Figure 1. is from one participant that is representative of the participant's r^2 plots. Figure 1 is for a real right-hand movement compared to rest. Observing the figure closely it can be seen that C3 and C1, for both tEEG and EEG, are highly correlated with the right-hand movement. The r^2 values for tC3, tC1, C3, and C1 are: 0.39, 0.39, 0.35, and 0.37, respectively, where "t" stands for tripolar. The tFC1 has the greatest r^2 value of 0.47 at 99 Hz. Of the eight participants, r^2 values ≥ 0.45 in the high-gamma band (80-100 Hz) were observed in all eight participants with tEEG and only three with EEG. High-gamma activity was present in two of three runs for five participants with tEEG and for only two with EEG. In conclusion, high-gamma activity was correlated with right-hand movements in more participants from the tEEG signals than from EEG. The high-gamma activity was also more consistent with tEEG than with EEG. SIGNIFICANCE More participants need to be studied however, with the limited number we recorded we were able to see high r^2 values in the high-gamma band quite consistently with tEEG. This suggests that when using tEEG for BCI applications researchers should not limit the bandwidth of the signals. Doing so could result in loss of important features. [1] Besio et al., TCRE development for high resolution Laplacian EEG, IEEE Trans BME, 2006. [2] Koka and Besio, Improvement of spatial selectivity and decrease of mutual information of TCREs, Neurosci Meth, 2007. [3] Besio et al. High-Frequency Oscillations Recorded on the Scalp of Patients with Epilepsy Using TCREs, IEEE Translat Eng in Hlth 2014. [4] Schalk et al. BCI2000: a general-purpose brain-computer interface (BCI) system," IEEE Trans Biomed Eng 2004. [5] Wolpaw et al. Brain-computer interface for communication and control, Clin Neurophy 2002. Support- NSF 1539068 and 1430833

F- Signal Analysis

2-F-49 Swallowing related high gamma band oscillatory changes revealed by human electrocorticograms

Hiroaki Hashimoto[1], Masayuki Hirata[1], Kazutaka Takahashi[2], Seiji Kameda[1], Fumiaki Yoshida[3], Takufumi Yanagisawa[1], Satoru Oshino[4], Toshiki Yoshimine[1], Haruhiko Kishima[4]

[1]Global Center for Medical Engineering and Informatics, Osaka University, [2]University of Chicago, [3]Graduate School of Medical Sciences, Kyushu University, [4]Osaka University Graduate School of Medicine

Introduction:Swallowing is apt to be thought as reflective movement since its main driving force is the brainstem, but swallowing is also triggered voluntarily. Moreover, patients with disorders of the central neural system suffer from dysphagia. However, neural process involved in swallowing still remains unclear, especially in human. Neural activities involved in human swallowing have been studied using PET, NIRS, TMS, fMRI and MEG. Swallowing-related human neural oscillatory changes have rarely been investigated so far. There are only a few reports that focused on the oscillatory changes using MEG but the analyzed frequency band was limited to lower frequency band less than 50 Hz. This is the reports that electrocorticograms (ECoGs) are used and swallowing related high frequency (high gamma) oscillatory changes were revealed. High gamma activities are known as a useful source of decoding feature for brain-machine interfaces. If we could decode swallowing-related neural activities with characteristic high gamma activities, swallow-assisting BMIs which control a device supporting swallowing will be feasible as a novel approach to the effective treatment of dysphagia. Material, Methods and Results:Four epileptic patients with subdural electrodes participated in this study (4 females, all are temporal lobe epilepsy). We injected 2ml water bolus into their mouth by a syringe and asked them to swallow water self-paced without external cueing. For detection of swallowing timing, electroglottography electrodes (Laryngograph) and a throat microphone were placed to subjects' neck. We captured the motion of the larynx with a motion tracking system (RGB camera of Kinect v2, Microsoft, Redmond, Washington, USA) during swallowing. ECoG signals were measured using a 128-channel digital EEG system (EEG 2000; Nihon Koden Corporation) and digitized at a sampling rate of 1000 Hz. An electric stimulator (NS-101; Unique Medical, Tokyo, Japan) supplied trigger digital signals to the Laryngograph and EEG system, and make an LED light flash so that the light was captured as a trigger signal by the motion tracking system. A 20 channel ECoG grid (5 × 4 contacts) which was placed covering caudolateral primary somatosensorymotor cortex was chosen for analysis. The ECoG signals time-locked to the onset of swallowing from -5.0 to 2.5 s were set and divided into 15 intervals every 0.5 s without overlaps. The power spectra of each interval were calculated for each electrode every 1 Hz from 1 to 150 Hz using a Fast Fourier Transform using 0.25 s time windows with an overlap of 0.1s, and was averaged throughout each epoch. For creating of power contour map, we defined the frequency range of 8 to 32 Hz as representation of low-frequency band, and frequency range between 76 and 100 Hz was defined as representation of high-frequency band (the high gamma band). The summing power values for each electrode were z-normalized using resting data. A time-frequency analysis of the ECoG signals was performed. Power contour maps and time-frequency analysis showed that power increases in high gamma band appeared in the caudolateral primary somatosensorymotor cortex, the frontal operculum and the subcentral area around swallowing. Especially, high gamma increases in the subcentral area was observed from one second before swallowing and suddenly disappeared at approximately 0.5s after swallowing. On the other hand, power increases in lower frequency band (8 - 32 Hz) appeared in orofacial primary motor cortex at 1000 - 1500ms after the onset of swallowing. Discussion:Caudolateral somatosensory cortex represents orofacial and swallowing function. High gamma band activities are more spatiotemporally focal than lower frequency activity and well reflect neural function. Therefore, high gamma power increases in the subcentral area which we measured correlates with swallowing-related brain activities. Significance:We revealed that swallowing-related high gamma power increases appeared in the subcentral area. Our final goal is realizing swallow-assisting BMI. Our preliminary results about decoding swallowing using support vector machine (SVM) classifiers showed that high gamma features are more useful than lower frequency activities.Results from one participant showed that swallowing and other movement were predicted with an accuracy of approximately 80% with SVM using high gamma feature. We will continue to develop a swallowing decoding technique.

2-F-50 Deep convolutional neural network for the detection of attentive mental state in elderly

Fatemeh Fahimi[1], Zhuo Zhang[2], Tih-Shih Lee[3], Cuntai Guan[4]

*[1]Nanyang Technological University, Singapore, [2]Institute for Infocomm Research, A*STAR, [3]Duke-NUS Graduate Medical School, Singapore, [4]Nanyang Technological University*

Introduction: Human ability in obtaining and maintaining attention degrades with aging which consequently deteriorates human cognitive performance. Studies have shown cognitive training, especially electroencephalography (EEG)-based brain-computer interface (BCI) and neurofeedback can improve attention in elderly [1]. Accurate attention detection is a requisite for successful implementation of these BCI systems. While most studies use EEG spectral features for attention detection [2, 3], the need for a more effective feature learning technique arises. In this study, we addressed this intention through a deep convolutional neural network (CNN), which has been successfully deployed in computer vision, speech recognition, and is gaining attractions in BCI research [4, 5]. Material, Methods and Results: The EEG data were recorded by one prefrontal bipolar channel from 120 elderly subjects while they were performing an attention-demanded task (Stroop color test) with resting periods between trials. The EEG data were first band-pass filtered at [0.5 40] Hz and then segmented into 2-second intervals (with 50% overlapping). Moreover, the data were screened to discard noisy segments. The aim of the study was to distinguish attention (i.e. Stroop) from non-attention (i.e. rest) trials. We deployed linear discriminant analysis (LDA) as the classification framework. Band powers (delta, theta, alpha, beta and low gamma) were extracted using wavelet decomposition technique with 5 levels and then given to the LDA classifier, which ultimately yielded the average accuracy of 62.20%. Further, we performed an end-to-end EEG analysis, using raw EEG, by constructing a deep learning paradigm with CNN (deep CNN) for the attention detection. In this case, normalized raw EEG segments were fed into the network as input instead of spectral features. The deep CNN serves as feature learning and classification. The proposed network employs tensor-based modeling which can capture the information of the complex attentive behaviors and therefore is able to detect attentive/non-attentive mental states. Beside convolutional and pooling layers, we employed two fully connected (dense) layers as well as dropout layers to elude overfitting. Gradually, through the layers, the highly compact deep attentional features were formed for the discrimination between attentive and non-attentive states.

This technique led to a significantly higher accuracy (i.e. 71.73%) than baseline (p<0.0001). In both scenarios, we performed leave-one subject-out approach for classification purpose. Figure 1(a) illustrates the overall network structure and figure 1(b) depicts the box plots of results. Figure Discussion: Our results show that an end-to-end deep CNN is capable to differentiate between attentive and non-attentive mental states in elderly from single frontal channel EEG with a significantly higher accuracy than traditional feature extraction and classification method. The deep CNN is able to learn the features in an unsupervised manner. It is believed that the features learned are discriminative and compact. In the traditional feature extraction, the loss of information could be due to the simplified way of dividing the EEG spectrum into various frequency bands, while the deep CNN could learn the features in a more optimal manner. Significance: Our proposed deep CNN for attention detection has significantly improved the detection accuracy, which in turn is advantageous to build a responsive and effective cognitive training system. It can potentially lead to a better training outcome in elderly.References: [1] Y. Jiang et al., "Tuning Up the Old Brain with New Tricks: Attention Training via Neurofeedback," Front Aging Neurosci., vol. 9, 2017. [2] M. Gola, et al., "EEG beta band activity is related to attention and attentional deficits in the visual performance of elderly subjects," Int J Psychophysiol., vol. 89, 2013. [3] F. Fahimi, et al., "Personalized features for attention detection in children with Attention Deficit Hyperactivity Disorder," Conf Proc IEEE Eng Med Biol Soc., pp. 414-417, 2017. [4] R. T. Schirrmeister et al., "Deep learning with convolutional neural networks for EEG decoding and visualization," Hum. Brain Mapp., vol. 38, 2017. [5] S. Sakhavi, C. Guan and S. Yan, "Learning Temporal Information for Brain-Computer Interface using Convolutional Neural Networks", IEEE Trans. Neural Netw. Learn. Syst., 2018.

2-F-51 RCSP-based feature extraction and adaboost-based classification for MI-based BCI

Yangyang Miao[1], Ian Daly[2], Cili Zuo[1], Jing Jin[1]

[1]*East China University of Science and Technology,* [2]*University of Essex*

Introduction: The Common spatial pattern (CSP) algorithm is highly sensitive to noise and has low generalization capacity in motor imagery (MI)-based Brain-computer interfacing (BCI). In this paper, we applied regularized CSP (RCSP) in order to avoid this series of problems. Three classifiers, Support Vector Machine (SVM) [1], Decision Trees (DT) [2], and AdaBoost [3], were used to compare and evaluate RCSP. Materials, Methods and Results: We chose data set 1 of BCI Competition IV. More details can be found in the following website: http://www.bbci.de/competition/IV/ [4]. The original data include signals from 59 channels and were downsampled to 100 Hz. In this work, we used a 4 s time window and the EEG was filtered between 8 and 30 Hz using a third-order butterworth filter. After the preprocessing procedure, we applied regularized CSP to perform feature extraction by introducing two regularization parameters [5]. In contrast to the approach presented in [5], we applied two solutions to estimate the sum of covariance. Finally, we extracted 4 features from each trial. Fig.1 shows two-feature distributions from participants d and g with CSP and RCSP. In this work, three classifiers, Support Vector Machine (SVM), Decision Trees (DT), and AdaBoost, were used. The radial basis function (RBF) was used with the SVM classifier, the DT was used to form 20 weak classifiers for the AdaBoost algorithm. Furthermore, 10-fold cross validation is applied to minimize over-fitting. Classification accuracies from all participants with different methods are shown in Table 1. P values denote the results of paired t-tests between classification results of the CSP-SVM approach and other methods. In the RCSP-AdaBoost algorithm, classification accuracies for 6 out of 7 participants are over 75 percent (with the exception of participant b). Table.1 Comparison of classification accuracies Subject CSP-SVM RCSP-SVM RCSP-DT RCSP-AdaBoost a 52.5 83.5 79 83.5 b 46.5 59 62 62 c 75 75 74.5 76.5 d 84.5 85.5 84.5 88 e 94.5 94.5 93.5 95 f 49.5 70 70 76.5 g 77 89.5 90.5 91.5 Mean 68.5 79.6 79.1 81.9 Std 18.9 12.3 11.3 11.2 P value - 0.0478 0.0457 0.0282 Discussion: In this paper, RCSP was applied to perform feature extraction and three classifiers were used to compare performance. According to the official description of the dataset, data from participants c, d, and e were artificially generated. One of the interesting results is that extracted features from real participants via RCSP are more discriminative and that extracted features from artificially generated data with two of the methods seem to be the same. In the classification, AdaBoost outperforms two other algorithms. Significance: This study presented two major contributions. First, this study provided a way to optimize feature extraction (RCSP). Second, this study found a relatively efficient classification algorithm (AdaBoost). While classification accuracies from artificially generated data were not improved, classification accuracies from other participants were significantly improved with the RCSP-AdaBoost algorithm. In this work, we used data of all channels. Future research could optimize channel selection. We can apply the RCSP-AdaBoost algorithm to data of optimized channels, which could potentially lead to higher accuracies with the shorter computation times. References: [1] Singla R, Khosla A, Jha R. Influence of stimuli colour in SSVEP-based BCI wheelchair control using support vector machines[J]. Journal of Medical Engineering & Technology, 2014, 38(3):125-134. [2] Aydemir O, Kayikcioglu T. Decision tree structure based classification of EEG signals recorded during two dimensional cursor movement imagery[J]. Journal of Neuroscience Methods, 2014, 229(6):68. [3] Hu J. Automated Detection of Driver Fatigue Based on AdaBoost Classifier with EEG Signals[J]. Frontiers in Computational Neuroscience, 2017, 11:72. [4] Tangermann M, Müller K R, Aertsen A, et al. Review of the BCI competition IV[J]. Frontiers in Neuroscience, 2012, 6:55. [5] Lu H, Eng H L, Guan C, et al. Regularized common spatial pattern with aggregation for EEG classification in small-sample setting[J]. IEEE Transactions on Biomedical Engineering, 2010, 57(12):2936-2946.

2-F-52 Reading out reinforcement learning strategies underlying trial-by-trial choice behavior

Dongjae Kim[1], Sang Wan Lee[1]

[1]*Korea advanced institute of science and technology*

Introduction:Most of the EEG-based BCI studies have dealt with reading out movement preparation and motor intention. Although motor signals are relatively easy to detect, the nature of the signals from cognitive processes has not been fully investigated because there is no gold standard for labeling or evaluating such high-level functions. Especially in many applications of cognitive BCI, such as emotion recognition, training and evaluation of the BCI system requires predefined class types induced by task stimuli[1]. These approaches inevitably suffer from interpersonal bias issue and subjective judgment of the experimenter. To address this issue, we propose a BCI system based on a computational model for the brain cognitive process. In this work, we classified human learning strategies into model-based (MB) and model-free (MF) reinforcement learning (RL), by using a computational model of arbitration process between the two RL strategies. The proposed framework has two merits. First, our claim is supported by

the recent evidence that the arbitration process is reflected in neural activities in the prefrontal cortex[2], the region that non-invasive electrodes can easily access to. Second, our framework opens up a possibility of cognitive BCI that provides a readout of brain's high-level cognitive processes. Material, Methods and Results: Data acquisition: 18 participants performed two-stage Markov decision task while recording EEG, which recorded by using GES 400 by 64CH Hydrocel Geodesic Sensor Net (Electronic Geodesic Incorporated, USA). EEG signals recorded with 1000Hz and resampled to 500Hz. We filtered out noise from power-line and band-pass filtered for alpha band (8-12Hz). Two-stage Markov decision task: The subjects performed a two-stage Markov decision task with binary choices. Depending on the context, the subject obtains a reward after making two sequential choices (Fig1A). Participants receive monetary rewards only if the color of the coin they received is same as the color of the goal during a specific goal condition while can receive any coin during a flexible goal condition. State-transition uncertainty controls state transition probability of each choice. A computational model of arbitration process between MB and MF RL: Lee et al.[2] designed the state-of-the-art model with a reliability-based dynamical two-state transition process (Fig1B). MB and MF RL produces prediction error (PE) trial by trial and the reliability of each RL system is estimated through Bayesian inference, in which the reliability increases if each PE falls within the range of zero PE. Classifier: we used SVM with an RBF kernel function (100ms duration alpha band ERP was used as a feature) to train two classifiers for each subject. 1) the goal condition classifier that classifies whether the current goal condition is specific or flexible; 2) the learning strategy classifier that classifies the current dominant RL system of the arbitration model. Although both of them are significantly better than a chance level(Fig1C), the learning strategy classifier (85.51±11.7%) had shown significant improvement compared to the goal condition classifier (62.60±3.6%). Discussion:We found the learning-strategy classifier outperformed the goal-condition classifier even in the task in which the environment structures dynamically changes. Thus, we demonstrated the utility of using a computational model for the learning-strategy BCI, as opposed to using predefined classes (i.e. goal conditions). These results indicate that using a computational model in cognitive BCIs can better reflect the actual cognitive process. Significance:We tested and proved the utility of using a computational model for a cognitive BCI. Acknowledgements:This work was supported by Institute for Information Communications Technology Promotion (IITP) grant funded by the Korea government (No.2017-0-00451), the ICT RD program of MSIP/IITP. [2016-0-00563, Research on Adaptive Machine Learning Technology Development for Intelligent Autonomous Digital Companion], and Samsung Research Funding Center of Samsung Electronics under Project Number SRFC-TC1603-06.
References: 1.Alarcao SM, Fonseca MJ. Emotions recognition using EEG signals: a survey. IEEE Transactions on Affective Computing. 2017. 2.Lee SW, Shimojo S, O'Doherty JP. Neural computations underlying arbitration between model-based and model-free learning. Neuron. 2014;81(3):687-99.

2-F-53 simBCI - Tool to simulate EEG and BCI

Jussi Lindgren[1], Adrien Merlini[2], Anatole Lecuyer[1], Francesco Andriulli[3]

[1]Univ. Rennes, Inria, IRISA, CNRS, [2]IMT Atlantique, [3]Inria

Introduction: Electroencephalogram (EEG) data from human experiments is commonly used to study Brain-Computer Interface (BCI) methods. Unfortunately real data is costly to obtain and its composition is apriori unknown. The brain mechanisms generating the EEG are not directly observable and their states cannot be uniquely decided from the EEG due to the volume conduction process [1]. Subsequently, we do not have generative ground truth for real data. This makes it difficult to analyze, compare and understand the behavior of applied signal processing methods. We propose a free, open source tool called simBCI to alleviate the situation through simulation (downloadable from http://gitlab.inria.fr/sb/). Currently the tool depends on Matlab. Material, Methods and Results: simBCI is a tool for generating artificial EEG data and to test BCI classification methods. The tool enables the study of EEG models and BCI signal processing methods together in controllable conditions as each tested configuration features only what was specified. The core of simBCI defines the used conventions and provides a simulator that can execute large numbers of experiments. Typically the experiments are defined by specifications for the generative models and the classification (DSP) pipelines. These specifications can contain functions, subfunctions, and parameter sets. The simulator then instantiates these specifications to perform simulated experiments. The distribution includes several example specifications and their functions. On the generative side we include a motor imagery model [2], simple SSVEP and P300 models, various noise and artifact generators, and a volume conduction model. On the signal processing side, we include example pipelines based on e.g. CSP [3] and inverse models [4,5]. [Figure 1 here] [Caption: simBCI allows modeling the forward and inverse EEG processing with any number of chained modules in both directions. The signal processing methods can optionally learn their parameters from a training set.] The tool factorizes the generative process to 'when', 'what', and 'where' parts. To simulate an EEG recording according to some specification, simBCI first generates a BCI timeline of discrete events according to parameters ('when'). Then, chosen generators are triggered by these discrete events. The triggered generators are typically signal generators, noise generators or artifact generators ('what'). Finally the generated components are inserted to requested locations with respect to a head model ('where'). The tool mixes the different components by a linear superposition model [1]. Intuitively, the process 'renders' an EEG dataset from its abstract event timeline. This is illustrated in Figure 1. simBCI can be used to investigate and visualize the data after each modular step in the generation or signal processing phases. To compare methods, simBCI can provide numeric results such as average trial classification accuracies for different combinations of configurations. Discussion: The realism of the generated data depends on the models and parameters the researcher chooses to insert into the system. But even with reasonable models, simBCI should not be seen as a replacement for human experiments. Rather, it should be used like scientific simulation in general and followed by real experiments. Significance: The proposed tool can be used to study EEG models and BCI methods and to teach about them. The data it generates can be used to debug BCI signal processing pipelines of other systems. Finally, the tool may help in understanding existing models and methods and to design new ones. Acknowledgement: This work was funded by the Labex CominLabs project SABRE. References [1] S. Baillet & al. "Electromagnetic brain mapping". IEEE Signal Proc. Mag. 18 (6 2001), pp. 14-30. [2] M. Tangermann et al. "Review of the BCI Competition IV.". Frontiers in Neuroscience 6 (2012). [3] J. Müller-Gerking et al. "Designing optimal spatial filters for single-trial EEG classification in a movement task". Clinical Neurophys. 110.5 (1999), pp. 787-798. [4] F. Cincotti et al. "High-Resolution EEG Techniques for Brain-Computer Interface Applications., Journal of Neurosci Methods 167.1 (2008). [5] B. J. Edelman et al. "EEG Source Imaging Enhances the Decoding of Complex Right-Hand Motor Imagery Tasks". IEEE Trans. Biomed. Eng. 63 (1 2016), pp. 4-14.

2-F-54 A combined linear and deep neural network model for motor imagery classification

Jiahux Xu [1], Wu Zheng[1], Sabe Bernhard A[1], Andreas Nuernberger[1], Hermann Hinrichs[2]

[1]Otto-von-Guericke-Universität Magdeburg, [2]Leibniz-Institut für Neurobiologie

Introduction:This abstract presents a regularized sub-band common spatial pattern with optimized components and deep neural networks combined linear regression method (DNN_LR) for multiple-class brain computer interface based on motor imagery. Motor imagery gains attentions as an approach for brain computer interface classification problems which represents frequency phenomenon of Event-Related Desynchronization (ERD) and Event-Related Synchronization (ERS) in motor cortex, deep neural networks shows a significance improvement of performance in many applications for large-scale dataset which can learn better features we could not see from the training data. The traditional algorithms such as linear models are widely used for small and multiple features dataset. In this paper, we jointly train a logistic regression model and a feed-forward neural network with hundreds of neurons and layers. The similar model firstly was mentioned as for recommendation system from HT Cheng.etc [1], We separately apply spatial filter with a ledoit_wolf regularized the Common Spatial Pattern method on time course data and sub-band Common Spatial Pattern method for sub-band frequency time data. Linear Discriminant Analysis, support vector machine and winners' result from multi-class dataset BCI competition IV 2a are compared with proposed model. Material, Methods, Results: The dataset for evaluation of proposed model comes from BCI competition 2a 2008, there are 9 subjects and each subject has 72 trials with four kinds of label: right hand, left hand, foot, tongue. subjects were asked to start to imagery the movement after a 0.5 s fixation on the screen when a cue come out, finally 576 epochs of five seconds length data were obtained for each subject with the labels. A 7-25Hz notch filter was applied on EEG dataset, Then we applied the regularized common spatial pattern algorithm to obtain the spatial filters with a grid search, the components as seen in figure were selected as the classification features in a vector format to decompose the epoched data, and a sub-band common spatial filter was applied for extracting features for time frequency data. a two layers neural network was built separately each with 512, 64 neurons using the Relu activation function, backpropagation the gradients from the output to both the linear and deep part of the model simultaneously using mini-batch stochastic optimization. A Follow-the-regularized-leader(FTRL) algorithm as the optimizer for the linear, and AdaGrad for the deep neural networks with a dropout 0, 20 epochs with mini batch 4 instances were used to train the DNN_LR model, A 10-folder cross-validation was to measure the performance on time course data with a test size 0.5 comparing with the result of competition. We test the model with experiment data with a regularized common spatial pattern filter for subject 1, the peak value of accuracy of LDA on different time course was 0.69 comparing to peak value of accuracy 0.7 with SVM, as the figure shows the proposed model obtained a 0.73 peak accuracy, both the peak range located from 1-1.5 second after a cue appeared. We also test the sub-band common spatial pattern method for this three algorithm, from the figure we could see the propose model obtain an 82% on mu band as a reference LDA 76% and SVM 79%. The winner of completion reported a 68% accuracy for subject1. The optimized component based LDA and SVM gained a higher performance than the winner of the competition, the average accuracy for optimized component is 0.66 for LDA and 0.65 for SVM, while the winner of competition is 0.57 for evaluation data. Discussion:Comparing with the linear algorithms, the limitations of the deep neural networks need more computation resource and time to train the data. In this experiment, DNN_lR gains a 3-4% higher score than the LDA and SVM for subject 1 compared to LDA and SVM, the number of components to decompose the EEG signal with CSP algorithm should be chosen with a grid search method to make the model more effective. Significance:The numbers of compoents decomposing the EEG data are different for individual subjects, the propose model shows the improved performance for the motor imagery classification which could be an alternative method for brain computer interface in future. Reference [1]. HT Cheng .etc, Wide & deep learning for recommender systemsProceedings of the 1st Workshop on Deep Learning for Recommender Systems, 7-10, 2016.

2-F-55 Mental-task BCIs using convolutional networks with label aggregation and transfer learning

Elliott Forney[1], Charles Anderson[1], William Gavin[1], Patricia Davies[1]

[1]*Colorado State University*
<p>Introduction: Effective strategies for classifying Electroencephalography (EEG) signals produced during various mental tasks may lead to valuable new types of asynchronous Brain Computer Interfaces (BCIs). Current approaches for classifying these types of signals often rely heavily on manual feature engineering. We have found, however, that multilayer (deep) Convolutional Neural Networks (CNNs) are capable of automatically learning a hierarchy of multiscale filters that are capable of modeling EEG signals while relying on few prior assumptions and with little or no preprocessing. When combined with label aggregation readout layers, careful regularization and transfer learning approaches, these CNNs outperform highly tuned classifiers that utilize Power Spectral Densities (PSDs) as well as Time-Delay Neural Networks (TDNNs).</p> <p>Material, Methods and Results: EEG data were recorded from 14 participants, 10 with no impairments in a controlled laboratory environment and four with severe motor impairments in their home environments. All data were recorded using a portable, eight-channel g.tec g.MOBILab+ EEG acquisition system. Each participant performed four mental tasks: silently count backward from 100 by threes, imagine making a right-handed fist, visualize a rotating Rubik´s cube and silently singing a favorite song. Each task was performed in a randomized order for five trials lasting 10 seconds each, yielding a total of 200 seconds of data per subject.</p> <p>A series of model selection experiments indicates that CNNs with relatively few free parameters (3-4 convolutional layers of width three, average pooling and label aggregation readout layers) often perform well. These results are consistent with other recent works exploring CNNs for EEG signal classification [1,2]. The introduction of a transfer learning approach, where the network weights are pretrained using data from the other participants, consistently improves classification accuracy, suggesting some common types of patterns are present across individuals. These networks achieve a mean test accuracy of 58% (11 bits per minute) across all participants at two-second intervals. This is a 9% improvement in accuracy over a highly-tuned classifier that utilizes PSDs and Linear Discriminant Analysis. Our CNNs achieve a peak accuracy of 90% (41 bits per minute) for two individuals.</p> <p>Discussion: We have found that CNNs with relatively few free parameters and larger amounts of training data are well suited for classifying these types of EEG signals. We have achieved this by convolving only across the time axis, through the use of label aggregation readout layers and by incorporating a hybrid transfer learning approach. Our analysis also demonstrates that the convolutional layers in these networks can be interpreted as learned, multivariate, nonlinear, finite impulse response filters. Our examination of the patterns learned by these networks also supports our claim that CNNs are able to automatically learn multiscale hierarchical representations of EEG signals.</p> <p>Significance: We have proposed a novel variant of the CNN

architecture that is well suited for classifying EEG signals recorded during various mental tasks. We have also shown that these networks outperform standard approaches, especially for some individuals. This performance improvement is also seen under realistic operating conditions and with minimal preprocessing or manual tuning. This work may aid in the development of asynchronous BCIs that utilize mental-task communication paradigms. Our analysis of these networks also leads to new methods for interpreting CNNs and may yield new insights into the types of patterns found in EEG signals.</p>
<p>Acknowledgements: This work was supported in part by the National Science Foundation, grant number 1065513.</p>
<p>References:
[1] Vernon J Lawhern, Amelia J Solon, Nicholas R Waytowich, Stephen M Gordon, Chou P Hung, and Brent J Lance. EEGNet: A compact convolutional network for EEG-based brain-computer interfaces. arXiv preprint arXiv:1611.08024, 2016.
[2] Robin Tibor Schirrmeister, Jost Tobias Springenberg, Lukas Dominique Josef Fiederer, Martin Glasstetter, Katharina Eggensperger, Michael Tangermann, Frank Hutter, Wolfram Burgard, and Tonio Ball. Deep learning with convolutional neural networks for EEG decoding and visualization. Human Brain Mapping, 2017.</p>

2-F-56 Histogram of oriented gradients of signal plots applied to BCI

Rodrigo Ramele[1], Juan Santos[1], Ana Villar[1]

[1]Instituto Tecnológico de Buenos Aires

Introduction: Where are the waveforms ? By estimates from the 2016 BCI Award, around 71.2% of noninvasive BCI research is based on Electroencephalography (EEG) [1]. Although mature clinical EEG has traditionally focused on temporal waveforms, and a whole branch of electrophenomenology has arisen around EEG graphoelements [2], signal analysis methods which follow this path has been overshadow in BCI research. Few works have investigated the idea of exploiting signal waveforms to analyze the EEG signal on BCI applications. The seminal work of Bandt-Pompe Permutation Entropy [3] explores succinctly this concept and in [4] an approach based on Slope Horizontal Chain Code is presented. A similar methodology is implemented in [5] based on Mathematical Morphological Analysis. The work proposed here is based on waveform analysis of the shape of the EEG signal, but using the histogram of gradient orientations, mimicking what traditionally electroencephalographers have been doing for almost a century: visually inspecting raw EEG signal plots. Material, Methods and Results: The histogram of gradient orientations is a popular and powerful tool used in Computer Vision to characterize local features from images and is the basis of the feature generation algorithm in Lowe's SIFT Descriptor [7]. This technique can be applied to identify components in EEG signals in five steps, (1) signal preprocessing, (2) signal segmentation, (3) transformation on a channel by channel basis of each signal segment into a binary image of a signal plot, (4) assignment of keypoint location on the newly created image depending on the physiological phenomena under study and finally (5) calculation of the histogram of gradient orientations using finite differences from the image around the keypoint (Figure 1). This method generates a feature, a normalized 128-dimension SIFT descriptor, which can be used to compare the signal segments that were used to generate the plots, thus they can be used to analyze the underlying cognitive phenomena. This method was used to identify and detect Visual Occipital Alpha Waves, Motor Imagery Rolandinc Mu rhythms [6] with results above chance level. It was also tested on P300 detection for Visual P300 Speller Matrix on ALS public dataset and for an own dataset of healthy subjects as well as identifying K-Complexes in sleep EEG (unpublished, under review). Discussion: A procedure which is biomimetically based on how the visual cortex works by detecting orientations, ironically, is used precisely to detect information from the brain. Although we found that it is possible to decode with accuracy above chance level and to differentiate patterns with cognitive correlations, the stability of the signature of the component is a key and challenging aspect. The method was also applied to patterns which are more frequently studied by their spectral characteristics. Significance: A method to analyze EEG signals which is based on the waveform characterization is presented. The benefits of the proposed approach are twofold, (1) it has a universal applicability because the same basic methodology can be applied to detect different patterns in EEG signals with applications to BCI and (2) it has the potential to foster close collaboration with physicians and electroencephalograph technicians because the approach follows the established procedure of the clinical EEG community of analyzing waveforms by their shapes. References: [1] Guger C., Allison B.Z., Lebedev M.A. (2017) Recent Advances in Brain-Computer Interface Research--A Summary of the BCI Award 2016 and BCI Research Trends. [2] Schomer, D.L.; Silva, F.L.D. Niedermeyer's Electroencephalography: Basic Principles, Clinical Applications, and Related Fields. 2010 [3] Berger, S.; Schneider, G.; Kochs, E.; Jordan, D. Permutation Entropy: Too Complex a Measure for EEG Time Series? 2017 [4] Alvarado-González, M.; Garduño, E.; Bribiesca, E.; Yáñez-Suárez, O.; Medina-Bañuelos, V. P300 Detection Based on EEG Shape Features. 2016 [5] Yamaguchi, T.; Fujio, M.; Inoue, K.; Pfurtscheller, G. Design Method of Morphological Structural Function for Pattern Recognition of EEG Signals During Motor Imagery and Cognition. 2009 [6] Ramele, R.; Villar, A.J.; Santos, J.M. BCI classification based on signal plots and SIFT descriptors. 2016; [7] D. G. Lowe, Object recognition from local scale-invariant features.1999

2-F-57 Can transfer learning across motor tasks improve motor imagery BCI?

Fabien Lotte[1], Andrzej Cichocki[2]

[1]Inria, LaBRI (Univ. Bordeaux, CNRS, Bordeaux-INP), France / RIKEN BSI, Wakoshi, Japan, [2]RIKEN BSI, Wakoshi, Japan / SKOLTECH, Moscow, Russia

Introduction: Motor Imagery (MI)-BCIs are among the most used types of BCIs, and proved useful for multiple applications including assistive technologies, gaming or stroke rehabilitation, among others [1]. However, in practice, their performances are limited and typically 10-30% of users may fail to control them [2]. One of many potential causes could be that for many first time users, performing MI is new and difficult, and can thus lead to unclear and inconsistent MI EEG patterns. Therefore, calibrating an MI-BCI on such unclear EEG examples can lead to suboptimal EEG features and BCIs. In this work, we explored whether we could improve such features and BCI by using EEG from other motor tasks, e.g., executed or observed movements, for which the resulting EEG motor activity pattern may be stronger and more consistent. In particular, we proposed a machine learning method to take into account such data into spatial filters optimization. Material, Methods and Results: We recorded EEG data (64 channels, Biosemi) from 12 subjects who performed four types of foot motor tasks. They imagined (imagined walking), executed (feet dorsiflexion), observed (watched a video of someone walking, first person view) or simultaneously observed and imagined foot movements. Each motor task was performed both slowly and quickly (fast movements being twice faster than slow ones). Subjects also performed resting state trials. For each subject, there is on average 22.7 trials for each motor/rest task and each speed, after rejecting noisy trials. We aimed at improving foot MI classification (here, MI vs Rest) by using EEG from another foot motor task for calibration. To do so, we designed a new regularized variant of the common spatial patterns (CSP) spatial filter [3], which aims at finding spatial filters w that can maximize the discriminability of rest EEG versus foot MI and another foot motor task at the same time. In other words, we look for spatial filters targeting a common brain source between foot MI and another foot motor task. We expect this could ease the identification of good subject-specific motor-related EEG features. Formally, we optimize spatial filters w so that they extremise the function w' ((1-a)Cmi + aCo) w / w' Cr w, where Cmi, Co and Cr are the covariance matrices of foot MI, another foot motor task and rest EEG respectively. Variable 'a' is the regularization strength, optimized using MI vs Rest inner cross-validation (CV) classification accuracy (CA) on the training set. We used this method to optimize CSP filters in the 8-30Hz frequency band, applied this filter on MI vs Rest EEG data, and trained a Linear Discriminant Analysis to classify the resulting band power features from MI and Rest. Training and testing was done using leave-one-run-out CV. The standard CSP+LDA approach on MI vs Rest led to an average CA of 71.9%, while the proposed transfer learning method reached a CA of 74.4% when using executed foot movements as regularizer. A two-way repeated measure ANOVA with factors speed (slow vs fast movement) and method (standard vs regularized CSP) showed a trend towards significance for the performance difference between methods (p=0.07). The other two motor tasks did not seem to help when used as regularizer though (CA observed: 71.4%, observed+imagined: 72.6%). Discussion: This study needs to be extended by including more subjects, to confirm or infirm the usefulness of executed foot movements in improving foot MI BCI. We could also explore additional motor tasks, such as passive movements. Summarizing, we proposed a new method to incorporate EEG from additional motor tasks. On a relatively small subjects set (N=12), this method could improve average decoding performances, with a trend towards statistical significance. Significance: Although further analysis and confirmation is required (more subjects are being included), this study suggested a new way to improve MI-BCI design, by exploiting additional, non-MI, motor tasks and proposed a new machine learning method to do so. We acknowledge support from the Japanese Society for the Promotion of Science, the European Research Council (grant ERC-2016-STG-714567), the French National Research Agency (grant ANR-15-CE23-0013-01), MES Russian Federation (grant 14.756.310001) and Polish NSC grant (2016/20/W/NZ/00354). References: [1] Clerc et al, BCI 2, ISTE-Wiley, 2016 [2] Alison & Neuper, BCI, Springer, 2010 [3] Lotte & Guan, IEEE TBME, 2011

2-F-58 Noise tagging BCI: A fast and reliable methodology that requires no training

Peter Desain[1], Cristiano Micheli[2], Pieter Marsman[3], Jordy Thielen[3]

[1]Radboud university, Donders Center for Cognition, [2]MindAffect, [3]Donders Institute

Introduction Some recent BCI algorithms make use of fast flickering patterns for visual stimulation. The stimuli are represented by a pseudo random bit sequence like an M-sequence, or a Gold-code: the so called noise tag. These elicit Broadband Evoked Potentials that can be modulated by attention. Some approaches for analysis use generative models of the data, which predicts the EEG signal from the stimulation pattern after a learning phase. In [1] the model is derived by Canonical Correlation Analysis (CCA), in which single-trials are analyzed into a spatial and temporal response pattern, maximizing the correlation of the spatially filtered data with the convolution of a structure matrix (which describes the overlapping of responses) and the transient responses (which describe the response to a stimulus event). The method is able to explain up to 50% of the variance of the ERP. Figure 1. Application of transients derived from one stimulus to predict the EEG of another. This way to detect the attended class has beneficial characteristics: ● One can Stop Early at a set desired accuracy level as the distribution of template correlations is estimated. ● As codes can be many bits long, there is a virtually unlimited number of classes which allows selecting a subset that is optimally distinguishable and minimal crosstalk allocation of codes to screen items. ● The data used to train may be updated and later forgotten, yielding a BCI that is essentially adaptive and naturally deals with non-stationarities. ● Training can be based on one class data only, other templates are generated with the learned spatial filter and transients and new structure matrices. ● A zero train setup is possible by calculating the explained variance of each hypothesized structure matrice. After a while, in the unsupervised first trial, one of the models can be picked as winner. The class symbol is emitted and the model is used for subsequent trials. ● In the current research we test the one-class and zero training regimes and compare their performance against all-class calibration. Material, Methods and Results Modulated Gold codes were presentedthroughout the 4 minutes. In all testing blocks, participants performed a random copy-spelling task, and the performance of the pre-calibrated classifiers were assessed. The main result was that zero-training achieves the same performance as one-class or all-class, and the final speed is not different. Zero train starts emitting the result of the first trial at the time the other methods finish training, as such the overall timing advantage is marginal. However, the ability to start using the system immediately, without going through a training and calibration routine is a great asset for the user experience. Discussion The proposed setup allows for zero-training BCI with the same performance as a fully calibrated system. However, there are some technical issues left in the zero-train computations: the incremental CCA computation needs to be constructed carefully, otherwise numerical instability may occur. Also, picking the first CCA component only, as done in full-class and one-class training, no longer suffices for short noisy data. Significance The presented noise tag BCI setup allows for essentially robust BCI. The zero-train method is as good and as fast as calibrated methods. Moreover, the method may be useful in other types of evoked BCI too, as long as a generative model of responses is available. References [1] Thielen, J., Marsman, P., Farquhar, J., & Desain, P. (2017). Re(con)volution: Accurate response prediction for broad-band evoked potentials-based brain computer interfaces. In Brain-computer interface research (pp. 35-42). Springer.

2-F-59 Exploring single-trial detection of motor and cognitive imagery tasks with magnetoencephalography based Brain-Computer Interface

Dheeraj Rathee[1], Hubert Cecotti[2], Girijesh Prasad[1]

[1]Ulster University, [2]California State University, Fresno

Introduction: Majority of the current Brain-Computer Interface (BCI) related studies involved electroencephalography (EEG) recordings. Although several studies utilized magnetoencephalography (MEG) for BCI application, their analyses have been focused on motor imagery (MI) tasks only. Recently, MEG acquired enhanced attention for neural engineering applications preferably due to higher signal-to-noise ratio and diminished volume conduction effect as compared to EEG. A recent study performed

binary classification accuracy (CA) based comparison of several feature extraction methods for single-trial sensor-level MEG data of left- and right-hand MI [1]. However, the reported mean CAs remain low even with the crucial preprocessing steps of signal space separation (SSS) and head movement correction (MC). This study further extends the work by including a mixed imagery approach i.e., including motor and cognitive imagery (CI) tasks with comparatively larger sample size to assess the discriminability of imagery-related MEG responses. Furthermore, the effect of the SSS filtering and MC on the CAs has been evaluated. Material, Methods, and Results: 20 healthy adults (3 females, 17 males, age 28.6±5.5 years, two left-handed and 18 right-handed by self-report) participated to the study. None of the participants reported any neurological illnesses or motor deficits, and all participants had normal or corrected-to-normal vision. Seven participants had previous experience in MI related studies. MEG was recorded with a 306-channel Elekta Neuromag system (Elekta Oy, Helsinki, Finland) located at the NIFBM Facility, Ulster University. Data were filtered to 0.1-330 Hz and digitized at the rate of 1 kHz. Four head-position indicator (HPI) coils were attached to the participants' scalp for continuous head position estimation. The study consisted of two sessions (S01 & S02), recorded on separate days, each included 200 trials (50 for each class) of four imagery tasks i.e., hand movement (H), feet movement (F), mathematical subtraction (S), and word generation (W). Each trial consisted of 2s of fixation cross; a cue based imagery section of 5s; and jittered inter-trial-interval (1-1.5s). Due to issues with the trigger quality, data of two participants were excluded. SVM classifier with linear kernel was employed for bandpower features of mu (8-12 Hz) and beta (16-24 Hz) frequency bands to estimate CAs for two intra-session conditions i.e., 5-times 10-fold cross-validation for S01 and S02, and inter-session condition i.e., training on S01 and evaluation on S02. Figure 1 presents the mean CAs across for six pair-wise binary classification tasks with raw data and SSS with MC. H-W (a mixed imagery pair) performed best whereas H-F (a MI pair) performed worst for both inter-session and intra-session conditions with raw data as well as SSS+MC filtering. In comparative analysis with six pair-wise comparisons for three conditions, Wilcoxon signed rank test showed significant improvement of 7.8 % ($p=0.0001$) in the grand average CA with SSS+MC filtering as compared to raw data. Moreover, SSS+MC provided a significant improvement of 9.0% ($p=0.0392$) in mean CA with four-class classification problem. Discussion: The results support the conclusion that a mixed imagery task pair consisting of CI and MI classes provided significantly high accuracies for a MEG- BCI system. Moreover, SSS filtering and MC significantly improvised the CAs for both binary- and multi-class classifications, however, the algorithms exhibit high computation cost and hence, may not be compatible for online implementation. Significance: MEG- BCI systems can be effectively implemented for rehabilitation purposes of motor and cognitive impaired people. Moreover, promising advancements in the field of portable and non-cryogenic MEG systems have already been established [2]. The results of this study provided preliminary analysis of the conventional bandpower features related to motor and cognitive imagery tasks along with the effect of SSS and MC filtering. Future research will focus on the development of MEG-specific real-time MC and filtering methods.
References: [1] Halme, Hanna-Leena, et al. "Comparing Features for Classification of MEG Responses to Motor Imagery." PloS one 11.12 (2016): e0168766. [2] Boto, Elena, et al. "A new generation of magnetoencephalography: Room temperature measurements using optically-pumped magnetometers." Neuroimage 149 (2017): 404-414.

2-F-60 Use of EEG source localization to improve the accuracy of a BCI system in a three-task motor imagery paradigm

Eliana Santos[1], Marc-Antoine Moinnereau[2], Tiago H. Falk[2], Francisco Fraga[1]

[1]Federal University of ABC (UFABC), [2]Institut national de la recherche scientifique (INRS - MuSAE Lab)

Introduction: Motor imagery (MI) is one of the most used paradigms in Brain-Computer Interface (BCI) applications. However, many control signals for state-of-the-art BCI systems using the MI paradigm involve concentrating on body-part movements that have nothing to do with the intended output command, making the interface an unnatural one. The main factor contributing to this cognitive disconnection is the low spatial resolution of EEG signals, which make it difficult to accurately identify which movement is been imagined (see Fig. 1). Usage of EEG source localization methods was recently proposed to overcome this drawback [1][2][3]. Although there are reports of some improvements accomplished using source localization approaches, there is a lack of studies using them to increase the hit rate in MI tasks, since there is still no clear understanding of the advantages and disadvantages on the use of brain imaging techniques for BCI applications. In this study, we used a BCI competition public database and applied a well-known source localization technique in order to improve the accuracy achieved in the classification of motor imagery tasks. Material, Methods and Results: For this investigation we used Dataset V of BCI Competition III, where 32-channel EEG was recorded from three subjects sitting in common chairs with arms and legs relaxed during four sessions, three for training and one for test. While sitting in front of a computer screen, individuals performed the following imaginary tasks: (a) Imagination of left-hand movements (class K2); (b) Imagination of right-hand movements (class K3) and (c) Mental generation of words beginning with a random letter (class K7). We used MATLAB to minimize noise with frequency (1-40Hz) and spatial (Common Average Reference) filters. Segments of EEG data (two-second epochs with 87.5% overlap) were also extracted through MATLAB. For spectral analysis (delta 1-4 Hz, theta 4-7 Hz, alpha 8-12 Hz and beta 13-30 Hz), we employed the LORETA-KEY software, which was also used for source localization (voxels with active current densities) through the e-LORETA algorithm, statistical analysis (F-test for spectral power difference) and the selection of regions of interest. To perform two-class classification (K2xK3, K2xK7 and K7xK3), we applied Fisher's linear discriminant analysis. Finally, the classifier outputs were properly combined to deal with the three-class problem. An overall classification accuracy of 73.81% was achieved by our method, which means an increase of 7.53% when compared to the first-place score in the BCI competition (68.64%), using pre-calculated attributes provided by the BCI Competition organizers. More importantly, a 17.40% increase in the overall classification was obtained when comparing the result to the highest one (62.87%) achieved by the competition participants who analyzed the signals in their natural (raw) state, exactly as we did in our study. Discussion: Although these initial results are encouraging, we are currently working to improve them even more by performing some variations in the current density thresholds in the source space (voxel level), by trying out the use of different frequency bands and alternative classifiers. Moreover, the method should be evaluated over larger databases and needs to undergo several adaptations and optimizations when considering real-time applications. Significance: We got the first idea for this approach from [2], but the authors did not perform classification tests, so our main contribution relies on the use of LORETA-derived source-space features to improve the hit rate of BCI applications using the MI paradigm. References [1] B. J. Edelman, B. Baxter, and B. He. EEG Source Imaging Enhances the Decoding of Complex Right Hand Motor Imagery Tasks. IEEE Transactions on Biomedical Engineering, 63(1): 4-14, 2016. [2] A. Majkowski, L. Oskwarek, M. Kołodziej, and R. J. Rak. An attempt to localize brain electrical activity sources using EEG with limited number of electrodes.

Biocybernetics and Biomedical Engineering, 36(4):686-696, 2016. [3] B. Edelman, B. Baxter, B. He, Decoding and mapping of right hand motor imagery tasks using EEG source imaging. 7th International IEEE/EMBS Conference on Neural Engineering (NER), IEEE, pp. 194-197, 2015.

2-F-61 Toward real time estimation of brain connectivity as new feature for BCI application

Yuri Antonacci[1], Jlenia Toppi[1], Antonio Pietrabissa[1], Donatella Mattia[2], Laura Astolfi[1]

[1]Sapienza University of Rome, [2]Fondazione Santa Lucia IRCCS

Introduction Modern neuroimaging has provided unequivocal evidence that brain functions are subserved by multiple areas functionally interconnected. Brain computer interfaces (BCIs) may benefit from feature extraction based on metrics derived from brain connectivity [1]-[3]. However, reaching the minimally required accuracy when few data samples are available as in single trial or real-time connectivity applications is still challenging. Variables selection algorithms could represent a valuable alternative to the classical algorithms, since they provide accurate connectivity estimates even when the amount of data samples available is very scarce [4]. The aim of the present work is to propose an accurate and reliable approach for connectivity estimation that paves the way to the use of features extracted from a connectivity analysis for BCI applications. Methods and Results A. Variable selection approaches When few data samples are available for multivariate analysis, it is necessary to use estimators based on variable selection approaches. In this works, we selected LASSO, Group LASSO, Fused LASSO and Elastic Net algorithms [5]. The idea at the basis of variable selection techniques is to select only those connectivity parameters that have an effect on the response vector. The remaining parameters are set to zero. B. Simulation study Algorithms were tested on simulated data (N=50) according to the following steps: i. Generation of simulated EEG datasets, fitting predefined ground truth networks of 10 nodes under different condition of factor DL (80, 120, 160, 240, 320, 480), where DL is the number of data samples available for the estimation process. ii. Estimation of connectivity parameters by means of variable selection methods (factor TYPE: LASSO, E-NET, F-LASSO, G-LASSO). iii. Evaluation of their performances by means of MAPE (for parameters estimation) and AUC parameters (for the validation) [6], [7]. MAPE represents the error committed in estimating the connection strength, while AUC measures the accuracy in the assessment of null and non-null connections. A repeated measures ANOVA was computed on MAPE and AUC parameters considering as within factors DL and TYPE. C. Results As reported in Figure 1, we found that the MAPE parameter (panel a) decreased with the increasing of the number of data samples available ($F(15,735)=47.1$, $p<10-4$). Instead, the AUC parameter (panel b) showed the opposite trend ($F(15,735)=106.2$, $p<10-4$). Even if the trends were observed with all the algorithms tested, LASSO showed the best performances (lowest MAPE and highest AUC for all amount of data samples considered). Discussion The presented findings obtained by applying variable selection approaches demonstrated the possibility to reliably estimate brain connectivity based on few data samples. Despite the boundary conditions in which all the algorithms were analysed, they tend to the optimal values of MAPE (0%) and AUC (1) with the increase of number of data samples available for the estimation process. Noticeably, LASSO regression showed the best performances for both estimation and validation procedures as compared with other considered algorithms. Even if variable selection approaches have already been used for brain connectivity estimation from EEG [8] and fMRI [9] data, to our knowledge this is the first time in which these algorithms are tested on EEG simulated dataset for different conditions of data samples available for the estimation process. Significance We showed how variable selection approaches could overcome the limitations of current brain connectivity estimation based on limited amount of data available. The LASSO regression outperformed other algorithms. Our findings on the use of variable selection approaches could substantially foster the integration of brain connectivity derived features, in the BCI system operational pipeline. References [1] H. Zhang, NeuroImage, 2015. [2] E. Mandonnet, Front. Syst. Neurosci., 2014. [3] M. Billinger, J. Neural Eng., 2013. [4] M. H. Ahmad, Matematika, 2006. [5] Vidaurre, Int. Stat. Rev, 2013. [6] C. Tofallis, J. Oper. Res. Soc., 2015. [7] J. Toppi ,EMBC, 2016. [8] T. R. Mullen, IEEE Trans. Biomed. Eng., 2015. [9] P. A. Valdés-Sosa, Phil. Trans. B, 2005 Acknowledgements Sapienza University of Rome-Progetti di Ateneo 2016 (PI1161550696379A) and 2017 (RM11715C82606455).

2-F-62 Classifier-based source localisation in independent component space: Progress report

Laurens Krol[1], Mahta Mousavi[2], Thorsten Zander[3]

[1]Technical University of Berlin, [2]University of California San Diego, [3]Zander Laboratories B.V.

Introduction: A brain-computer interface (BCI) ideally works solely on brain activity, i.e. signals originating from the cortex or other brain structures. Many BCI systems use electroencephalography (EEG) to monitor brain activity. Here, especially with dry and mobile EEG systems [1], the recordings invariably also include artefacts, i.e. non-brain signals. It is important to validate BCI classifiers to determine to what extent their performance relies on artefacts rather than brain activity. Earlier we proposed a method to source-localise the signals isolated by a spatio-temporal linear discriminant analysis (LDA)-based classifier [2]. Here, we present work in progress validating that approach using simulated EEG data. We furthermore propose an extension of this method for classifiers based on common spatial patterns (CSP). Material, Methods and Results: The approach uses independent component analysis (ICA [3]) to first obtain a source model of the data, independent of the classifier. The result of this is an unmixing matrix that transforms sensor activity into source activity. Following [4], the filter weights of a spatio-temporal LDA classifier can be transformed into a forward model. These LDA pattern weights can then be distributed to the independent components (ICs) via the ICA's unmixing matrix. As such, LDA filter weights can be transformed into ``relevance weights'' in source space, weighting the ICs with their relative contribution to classification [2]. We apply two additional weighting factors to compensate for 1) LDA's amplitude alignment, and 2) noise representations in the LDA weights. We are currently simulating EEG data with known signal sources among noise, and applying the proposed method to evaluate its accuracy. The figure shows the ground-truth and reconstructed locations of two sources in one time window. The results are based on the simulation of 20 ``participants'' with 62 randomly chosen noise sources and 2 relevant sources in the illustrated locations. Visual inspection shows that these sources are accurately identified. We are testing how many different sources can be detected in one filter, and what factors influence this number. Furthermore, we are evaluating the influence of the two compensatory weights that we apply, as well as the method's dependence on ICA. We are also working to extend this method to CSP-based classifiers. After estimating the CSP filters, selected patterns (i.e. those sets of patterns of the eigenvalue decomposition that best describe the classes' variance changes) will be mapped to IC space via the ICA's unmixing matrix. Since in CSP-based methods, an LDA is trained on the CSP-filtered signals, the weights in source space will be corrected through multiplication by the corresponding LDA weight to account for their relevance to the classifier. As above, potential additional corrections will be investigated. We will verify our methodology using simulations as well as real motor imagery EEG data [5]. Discussion: It is valuable to be able to identify the origin of the signals taken into account by a classifier. The proposed method has already produced reliable source localisation results, but given that it uses a number of parameters external to the classifier itself, it must still be determined to what extent these results reflect the exact signals isolated by the classifier. This is ongoing work. The CSP-based method is being developed to generalise our approach to CSP-based classifiers. Significance: A source localisation method that identifies the sources used by the exact same classifier as the one used online is valuable to evaluate BCI system performance. Our proposed approach also enables BCI methodology to be used as a novel source-localisation tool for general neuroscientific experiments. Acknowledgements: Parts of this work were supported by the Deutsche Forschungsgemeinschaft (ZA 821/3-1), and a DAAD Short-Term Research Grant. References: 1. Zander, T.O. et al., Front. Hum. Neurosci., 11, 2017. doi:10.3389/fnhum.2017.00078 2. Zander, T.O. et al., Proc. Natl. Acad. Sci. USA, 113(52), 2016. doi:10.1073/pnas.1605155114 3. Makeig, S. et al., Adv. Neural. Inf. Process. Syst., 8, 1996. 4. Haufe, S. et al., NeuroImage, 87(0), 2014. doi:10.1016/j.neuroimage.2013.10.067 5. Mousavi, M. et al., Brain-Comput. Interfaces, 4(1-2), 2017. doi:10.1080/2326263X.2017.1303253

2-F-63 Architectural choices for P300 deep learning models

Sriram Ravindran[1], Virginia de Sa[1]

[1]*University of California, San Diego*

Introduction: P300 is an event-related potential evoked as a response to external stimuli. The P300-speller is a widely used BCI that has proven to be a reliable method in enabling people who cannot communicate via normal methods. Improving single-trial P300 classification helps increase communication bandwidth as it reduces the averaging process necessary to reduce noise. Deep learning approaches have become more popular recently [1][2]. Certain architectural choices result in a better classifier. In this paper, we performed an ablation study of EEGNet [1] as it performed well in our experiments. We report some of the attributes that contribute to the performance and other choices that further improved the performance of EEGNet. Material, Methods and Results: We used BCI Competition III Dataset II, P300-speller data of two subjects, which we preprocessed to have 156 time points per training sample, sampled at 240 KHz frequency with 64 channels. EEGNet [1] has 3 convolution layers with kernel sizes (64 channels x 1 time sample), (2, 32), (8, 4) respectively with 16 kernels in layer 1 and 4 kernels in layers 2 and 3. ELU(exponential linear unit) is used as the non-linear activation function. We tested the effect of using linear activation function and found that it led to an improvement in the metrics for all the models listed below. Then, we tested the contribution of rectangular kernels in the second and third layers by turning all rectangular kernels after the first layer into regular 3x3 kernels (denoted CNN3x3), and found that this led to a drop in the f-measure. We also tested the effect of using spatio-temporal convolutions in the first layer by using (64x3) kernels (denoted

EEGNet v2) similar to [3]. The improvement in performance indicates that looking at the spatio-temporal dynamics at the lower layers may increase the information available to the rest of the network. We finally report the effect of large convolution width along the temporal axis in both the 2nd and last layer by turning the (8x4) kernel in the last layer into a (4x8) kernel (denoted EEGNet v3). Finally, we incorporated all the above changes and increased the number of kernels to 16 in each layer (denoted EEGNet v4) resulting in an improvement of ~12 % over EEGNet in terms of f-measure. Discussion and Significance: Deep learning has become more popular in raw P300 classification. This ablation study provides some insight into design choices that might improve the performance of a classifier. Our results suggest that using linear activation functions, spatio-temporal convolution in the first layer and larger convolution widths on the temporal axis are some steps that can be easily incorporated in a network for better temporal EEG classification. We hope that others who are designing similar models may benefit from this work. Acknowledgements: This work was supported by NSF IIS 1528214, SMA 1041755, and Adobe. References: [1] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A Compact Convolutional Network for EEG-based Brain-Computer Interfaces," arXiv:1611.08024 [cs, q-bio, stat], Nov. 2016, arXiv:1611.08024. [Online]. Available: http://arxiv.org/abs/1611.08024 [2] R.K. Maddula, J. Stivers, M. Mousavi, S. Ravindran and V.R. de Sa. "Deep Recurrent Convolutional Neural Networks for Classifying P300 BCI Signals.", Proceedings of the 7th Graz BCI Conference 2017. [3] D. Maryanovsky, M. Mousavi, N.G. Moreno, and V.R. de Sa. "CSP-NN: A convolutional neural network implementation of common spatial patterns.", Proceedings of the 7th Graz BCI Conference 2017.

2-F-64 Improving data quality and noise assessment in EEG signals: Bootstrapped SE as a general and principled method

Andrew Stewart[1], Steve Luck[1]

[1]*University of California, Davis*

Improving data quality and noise assessment in EEG signals: Bootstrapped standard error as a general and principled method Introduction: In EEG data, the relevant signals are tiny (in microvolts) and embedded in noise that might be an order of magnitude larger. This means that careful consideration of how to handle noise is crucial for any work using EEG data. The manner in which good data is retained and bad data is rejected is key in increasing the experimentally-useful signal-to-noise ratio. While mature methods and great expertise already exist in many research labs, these may be idiosyncratic and perhaps error-prone. We suggest that a transparent, well-documented, generalizable and mathematically-principled method for assessing EEG noise and data quality would be particularly advantageous. Significance: Having more trials tends to increase statistical power, yet including trials with high noise can decrease statistical power. In practice, high noise can also increase the likelihood of false-positive apparent effects - where an effect is statistically significant, but not real. Better assessment of noise and data quality should reduce these false effects, and so improve the robustness and reproducibility of our science. In order to improve consistency, transparency and experimental repeatability, we propose a reporting a universal metric of ERP data quality that can be applied to virtually any kind of measurement of any ERP signal in any experiment. One possible metric to report is the parametric Standard Error of the Mean (pSEM). This has the advantage of clear interpretation [2], but cannot be calculated for nonlinear parameters, like the peak amplitude or peak latency of an ERP. In both simulations and real data, we show that the Bootstrap Estimate of the Standard Error (BESE) is very close to pSEM. BESE has the further advantages that it is robust to non-normal distributions and can be generated for any ERP parameter [3]. We provide examples of using BESE to report noise in a simple EEG experiment, along with example code. * Material, Methods, and Results, and Discussion: Broadly, bootstrap methods use random resampling of the data with replacement, and can offer a measure of how well a sample estimate might match the population. In this case, we are sampling single-trial EEG epochs from the population of possible trials for a given participant. With repeated sampling and averaging of ERPs, we can construct many sets of sample ERPs for a given participant, and assess the variability among these sets. This makes it possible to estimate the likelihood that the measured value for a given participant is representative of that participant's true value. Here, we validated our approach using experimental data from a P3 experiment, in which deliberate differences in the recording setup produced subtle differences in data quality [1]. The resulting ERPs in the high- and low-noise conditions were broadly similar when averaged across participants, but the variability was higher in the high-noise condition. With our BESE data quality metric, we were able to quantify the differences in data quality. The BESE metric closely matched the traditional pSEM metric for linear measures, and it produced sensible values for cases that cannot be quantified with the pSEM. Refs: 1 - Kappenman, E. S., & Luck, S. J. (2010). The effects of electrode impedance on data quality and statistical significance in ERP recordings. Psychophysiology, 47(5), 888-904. https://doi.org/10.1111/j.1469-8986.2010.01009.x 2 - Gurland, J., & Tripathi, R. C. (1971). A simple approximation for unbiased estimation of the standard deviation. American Statistician, 25(4), 30-32. https://doi.org/10.1080/00031305.1971.10477279 3 - Efron, B. (1987). "Better Bootstrap Confidence Intervals". Journal of the American Statistical Association. Journal of the American Statistical Association, Vol. 82, No. 397. 82 (397): 171-185

2-F-65 Self-paced upper limb movement intention recognition from EEG signals

Luis Hernandez Rojas[1], Javier Antelis[1]

[1]*Tecnológico de Monterrey*

Introduction: Currently, one of the challenges in brain computer interfaces from neurorehabilitation is to recognize and discriminate different movements of the same limb from Electroencephalographic signals (EEG). This would allow higher control of neurorehabilitation and motor recovery devices by end-users, e.g. functional electro-stimulation orthesis. Recent studies has proposed decoding upper limb information from EEG signals [1]. Nevertheless, it is necessary to extend these investigations to a larger number of movements to determinate their validity. In this research, we assess the feasibility of recognizing two different movements of the right upper limb from EEG signals during robot-assisted rehabilitation therapy. Material, Methods and Results: Seven healthy subjects participated in this study. The experimental task consisted of self-selected and self-initiated movements of the right arm using a neurorehabilitation device called Tee-R. The movements were (A) Supination/pronation of the forearm and (B) Flexion/extension of the arm.The experiment consisted of many trials which was controlled by three visual clues. The first clue indicated to relax by 3s. The second clue showed an image with a cross during 12s and indicated to perform any of two movements and to start whenever they want. The last clue indicated to rest by 3s. 120 trials were recorded per participant. EEG signals were recorded from 62 scalp locations at a sampling frequency of 1200 Hz using a g.HIamp amplifier. Signals from the Tee-R device which encoded the movement onset were also recorded. EEG signals were low-pass filtered at a cutoff frequency of 45 Hz using a 2nd-order zero-phase shift Chebychev-type filter and then common average referenced (CAR). Afterwards, EEG signals were segmented in trials starting from the first visual cue and up to the second visual cue. The zero time reference was aligned with movement onset signals obtained from the Tee-R. Features were extracted through the Common Spatial Pattern (CSP) algorithm. Spatial filters were constructed for two independent bi-class classification scenarios: i)rest versus movement intention (both movements) and ii) movement intention A versus movement intention B. Linear discriminant analysis (LDA) was used as classification algorithm. Classifiers performance was assessed for each participant and classification scenario independently using a ten-fold cross-validation procedure. The significant classification accuracy chance level was the computed with the binomial distribution. Distribution of classification accuracy are shown in figure 1. All participants presented significant classification accuracies above chance level. Overall, recognition of rest versus movement intention is lower that recognition of the two movement intention. Discussion: We have shown the feasibility to recognize different movement intentions of same upper limb in two different classification scenarios. This is important for a BCI applicable for end users in neurorehabilitation therapies. It is still necessary to extend the numbers of subjects to achieve significant statistics. Also, for further studies have to explore on-line and three-class scenarios to validate the feasibility of our model with real end-users. Significance: Recognition of movement intentions of same upper limb would allow to increase to natural control for future neuroprostheses and motor neurotherapy devices. Additionally, this would increase neurofeedback level in neurorehabilitation pacients. Acknowledgements: This work is supported by the National Council of Science and Technology of Mexico (CONACyT) through grants 268958 and PN2015-873. References: [1]. Patrick Ofner, Andreas Schwarz, Joana Pereira, and Gernot R. Muller-Putz. Upper limb movements can be decoded from the time-domain of low-frequency eeg. PLoS One, 12(8):e0182578, Aug 2017. PONE-D-17-04785[PII]. [2]. I. Figueroa-Garcia, O. Aguilar-Leal, A. G. Hernandez-Reynoso, J. Madrigal, R. Q. Fuentes, J. C. Huegel, and A. Garcia-Gonzalez. Platform for the study of virtual task-oriented motion and its evaluation by eeg and emg biopotentials. In 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, pages 1174-1177, Aug 2014.

2-F-66 Dynamic emotion transition detection for affective BCI

Yu Hao[1], Lin Yao[2], Disha Gupta[1], Edward Sorel[3], Megan Gelsinger[1], David Matteson[1], Gary Evans[1]

[1]Cornell University, [2]University of Waterloo, [3]Psychology Resource Group

Introduction: Brain-computer Interface (BCI) provides a promising way for patients with motor impairments to gain functional control [1]. Analogous possibilities may exist for persons with emotional impairments, such as emotion dysregulation. Therefore, affective BCI for emotion recognition and regulation has received considerable interest [2]. EEG features of emotional states, such as happiness, sadness, fear and stress, have been explored for affective BCI development. However, emotional states are known to be dynamic with an association with the pre-existing state [3]. Hence, we propose that an affective BCI based on dynamic emotional transition (i.e., DET) instead of static emotions. We present a first step towards this hypothesis where we extract neural correlates that discriminate the direction of emotion transition, e.g. from neutral to negative emotion vs. negative to neutral state. Material and, Methods: Thirty-three healthy participants (16m/17f, age 22.4±3.8) watched image sequences of four images (two neutral and two negative) chosen from a standardized dataset of emotional images (IAPS) [4]. The transition of affect was elicited by sequences either changing from neutral to negative or from negative to neutral in 18sec intervals over 18 trials each. Each image was presented for a duration of 4.5sec. The control trial sequences consisted of all neutral or all negative images. All four different trial-types were randomly presented to each participant. In each trial, they rated their negative arousal on a scale of 0-4. EEG was collected using a 128-channel active BioSemi EEG setup, with a mastoid reference. Results: On average the subjective rating of each image showed that the participants' emotional response corresponded with the stimuli presented (neutral mean rating of 0.22 and negative mean rating of 2.04 on a 0-4 scale). The spatial and spectral EEG features that significantly distinguished neural responses to neutral and negative images were found in the left and right parietal region in the upper alpha band (10-13Hz) (Fig 1a,1b). The negative images resulted in a significantly reduced alpha as compared with neutral images. The difference of alpha power between consecutive stimuli was found to be significant at the emotion transition points ($p=0.001$, ANOVA) (Fig1c). It's important to note that the absolute values in the neutral and negative image transitions (C3-C2: neutral to negative and D3-D2: negative to neutral) begin to emerge as well ($p=0.016$, Cohen's $d=0.43$, paired t-test), which suggests the directional effect. Discussion: Using the feature of the upper alpha power difference in the parietal region, we could distinguish the image sequences, i.e. negative to neutral and neutral to negative. Next, we aim to test it for offline single-trial classification and towards a continuous asychronized detection paradigm. Significance: Recognition of the direction of emotional transition from the affective BCI system could allow a closed-loop system that provides timely feedback or generates stimuli that could influence a person's behavior and prevents an emotional tipping point. References [1] J. R. Wolpaw et al., "Brain-computer interfaces for communication and control," Clin. Neurophysiol., vol. 113, no. 6, pp. 767-791, Jun. 2002. [2] C. Mühl et al., "A survey of affective brain computer interfaces: principles, state-of-the-art, and challenges," Brain-Computer Interfaces, vol. 1, no. 2, pp. 66-84, 2014. [3] K. R. Scherer, "Emotions as episodes of subsystem synchronization driven by nonlinear appraisal processes," Emot. Dev. self-organization Dyn. Syst. approaches to Emot. Dev., vol. 7099, 2000. [4] P. J. Lang et al., "International affective picture system (IAPS): Affective ratings of pictures and instruction manual," Tech. Rep. A-8, 2008.

G- User Aspect: Experience, Ethics

2-G-67 Patient feedback on self-managed brain computer interface treatment of central neuropathic pain in spinal cord injury: Steps towards service design

Nina Petric-Gray[1], Manaf Al-Taleb[1], Mariel Purcell[2], Matthew Fraser[2], Aleksandra Vuckovic[1]

[1]University of Glasgow, [2]Queen Elizabeth University Hospital

Introduction: As part of a wider study into the user centred design of Brain Computer Interface (BCI) for treatment of neuropathic pain [1], patient feedback was evaluated to identify themes and prioritise future developments. Material, Methods and Results: Twenty participants with chronic Spinal Cord Injury (SCI) (17 males and 3 females, aged 50.6 ± 14.1 years, para- and tetraplegic) with Central Neuropathic Pain larger than 4 on a Visual Analogue Scale participated in this study. Fifteen participants had a response to neurofeedback and were given a portable BCI headset (Emotiv, Epoch, USA) to use, practicing neurofeedback therapy on their own or with assistance from their caregivers (2 tetra and 4 paraplegic patients). They used BCI for a period ranging from several weeks to several months. Eight out of fifteen experienced clinically significant reduction of pain, greater than 30%. The neurofeedback protocol consisted of upregulating alpha (9 to 12Hz) and suppressing theta (4 to 8Hz) and higher beta (20 to 30 Hz) band relative powers above/below the pre-determined threshold from electrode location C4 [2]. Patients and caregivers received two to four training sessions before taking BCI (headset and a tablet computer) home. Interviews were carried out on patient check-up visits to the hospital after they had been using the device on their own for few weeks and after the quality of recorded EEG signal was checked to ensure that it did not contain excessive noise, i.e. that patients were doing feedback correctly. In addition, some of the information was taken from emails or SMS messages by patients to researchers. All material type was printed verbatim and analysed independently by two researchers, one of whom was not involved in the interviews. Thematic analysis was used to extract patterns within the qualitative data in order to identify patient feedback themes. Four main themes were identified: effects of treatment, usage, hardware and software. Within these topics further subtopics were identified. Fig 1 shows two classification tiers. Theme "Effects of treatment" had two categories: -Location (at and under the level of injury), pain reduction (more than 30% and less than 30%), descriptors (burning, stinging etc.) -Side effects: positive (better sleep, less spasm), negative (hypersensitivity, headache) Theme "Usage" had four categories: -Preferred time of use (morning, evening) -Location of use (place with no distractions) -Usage pattern (1-7 times a week, 20-30 minutes daily) -Reasons for abandonment (changes of daily routine such as infections and negative opinion of a trusted person) and reasons to re-use (recurring pain) Theme "Software" comprised of two categories: -Usage pattern and related problems: easy to use, forgetting instructions, small font of warning signs -Suggested improvements (step-by-step instruction on screen, better measure of daily performance) Theme "Hardware" comprised on three categories: -Usage patterns and related problems: no problems, awkward to put on, unsure about the quality of EEG, robustness, electrodes braking, caregiver training/time -Setup time: ranging from 5 to 20 minutes -Suggested improvements: dedicated headset for pain treatment, increased robustness, unambiguous location on the head Discussion: An important area of patient oriented BCI is home/community use. This requires design of the whole service, including understanding patient predisposition to using assistive technology [3], patient and caregiver education and training, effective user support, dedicated hardware and software design, understanding preferred usage patterns and most common reasons for abandonment and re-use. This study provides important feedback on usage pattern and technical problems which cannot be collected based on patients BCI experience in clinical trials. Reasons for abandoning the use and reasons for re-use are particularly relevant for creating a successful service support for future applications. Significance: Informing future service design studies of BCI as a home-based therapy. Acknowledgements: This work was partially supported by Inspire foundation UK, Higher Committee for Education Development, Iraq and EPSRC UK.
References: [1] Al-Taleb MKH et al. Proc 7th Int Graz BCI Conference 2017, doi:10.3217/978-3-85125-

533-1-93 [2] Hassan MA BMC Neurology, 2015;15: 200. [3] Arthanat S. et al. Disabil Rehabil Assist Technol 2: 235-248.

2-G-68 Can children use simple Brain Computer Interfaces?

Jack Zhang[1], Zeanna Jadavji[1], Ephrem Zewdie[2], Adam Kirton[2]

[1]University of Calgary, [2]Cumming School of Medicine, University of Calgary

Introduction: A brain computer interface has the potential to allow severely disabled persons to meaningfully interact with their environment. While the pediatric population might benefit most from BCI technology, research to date has been predominantly in adults. With BCI technology progressing rapidly, there is a pressing need to determine if and how children can use such systems. Our goal was to quantify the ability of healthy school-aged children to perform simple tasks using a basic, commercially available, EEG-based brain computer interface. Materials, Methods, and Results: A prospective cross-over study that began in 2016 recruited healthy children for two 1-hour sessions separated by a week. We choose to use the Emotiv EPOC as it was commercially available and relatively affordable for families. Brain computer interface training consisted of a brief set-up and EEG recording using the programs provided by Emotiv while performing specific tasks. Two tasks were trained (driving a remote-control car and moving a computer cursor) each using two strategies (sensorimotor and visual imagery). We aimed to determine which combinations of task and strategies achieved the greatest success in children. The tasks relied upon on two commands: neutral and movement. The strategy for neutral was to count down from 10 and remained constant, while the strategy for movement altered between sensorimotor and visual imagery. Participants used a single strategy to complete a task and the system was retrained for the subsequent task. To successfully complete the task, participants needed to hold neutral for 5s and then move the car or cursor to a target within 20s. Each task was completed 10 times. Overall, participants were trained on all combinations of task and strategy. (Figure 1) Families from the surrounding communities who have expressed interest in research by consenting to enrollment in a research database were recruited to the study. Typically developing children aged 6-18 years were recruited. Twenty-seven families were contacted, 10 declined to participate. From the 17 families, 27 individuals were recruited and 26 (mean age 13.2 ± 3.6 years, 27% female) completed the entire study; 1 child dropped out. Primary outcome was the Cohen's kappa coefficient between requested and achieved performance in the 10 trials of a task. Tolerability was excellent with >90% reporting the experience as neutral or pleasant. Older children achieved performance comparable to adult studies - average kappa of 0.46 ± 0.21 and range of 0.025 - 0.90. Younger age was correlated with lesser though still good performance ($r = 0.632$, $p < 0.001$). Only 42% of all participants achieved a Cohen's kappa of 0.4 or higher which is the cut-off used in the adult literature for BCI competency. The car task demonstrated higher performance compared to the cursor task ($p = 0.027$). Thought strategy was also associated with performance with visual imagery strategies outperforming sensorimotor approaches ($p = 0.031$). There were no changes in performance across the 10 trials to suggest learning effects. Discussion: One limitation of this study was the difficulty in relating our findings to the current adult literature. While only 42% of our participants were classified as BCI "competent", it cannot be concluded that children are less able to control BCI as compared to adults. There are substantial differences between our primary outcome measure of BCI skill and previous research. By using the Emotiv system, we were not provided the power of an action during testing which led to our all-or-none measurement of skill, in which we looked for the action to be performed within a pre-specified time window. Studies of invasive cerebral monitoring suggest that the same fundamental EEG properties used to drive most BCI in adults are present in children. To better compare children and adults, trials should expand to test both populations on identical systems and protocols. Significance: Children can quickly achieve control and execute multiple tasks using simple EEG-based brain computer interface systems. Performance depends on strategy, task and age. Such success in the developing brain mandates exploration of such practical systems in severely disabled children.

2-G-69 Trends in BCI meeting abstracts on research participant categories and descriptions between 1999 and 2013

Sean Garrett[1], Brandon Eddy[2], Betts Peters[3], Sneha Rajen[1], Jane Huggins[1], Melanie Fried-Oken[2]

[1]Direct Brain Interface Laboratory, University of Michigan, [2]Institute on Development and Disabilities, Oregon Health and Science University, [3]Institute on Development and Disabilities, Oregon Health & Science University

Introduction: The six International BCI Meetings from 1999 to 2016 reported on BCI innovations and applications of BCIs as assistive technology for people with disabilities (PWD). The growth of BCI Meeting attendance from 22 research labs in 1999 to 188 labs in 2016 also represents a growth in collaborating disciplines [1]. Diversity in clinical backgrounds and experience working with PWD may contribute to changes in recruited study participants and variations in participant descriptions. This study examines trends regarding intended end-users, study participants, and descriptions of diagnoses and impairments. This ongoing study will eventually report data from all six BCI Meetings. Here we report on Meeting abstracts from 1999 and 2013 [2, 3]. Material, Methods, and Results: A rating tool was developed to characterize study elements including targeted end-users and description of study participants. We refined the tool through an iterative process including several pilot tests in which we reviewed abstracts, reached consensus, and modified the tool to achieve interrater agreement. Only abstracts describing participants controlling a BCI system were included. Published abstracts from the 1999 First International Brain-Computer Interface meeting (n=20) were reviewed and coded by a trained researcher. A second rater independently reviewed 25% of the 1999 abstracts, selected at random. Overall interrater agreement was 88.24%. These two researchers then independently reviewed half of the abstracts from the 2013 Fifth International Brain-Computer Interface meeting abstracts (n=179). A third researcher randomly assigned 25% of the abstracts for double-entry to assess for interrater agreement. Overall agreement was 85.08%. PWD were the intended end-users for 14 of 20 (70%) of the 1999 studies and 106 of 179 (59%) of the 2013 studies, with about 1/3 (1999: 32%, 2013: 40%) not specifying intended users. However, in both years, study participants were frequently controls (1999: 12 or 60%, 2013: 122 or 68%). Potential end-users participated in research studies less frequently (1999: 35%, 2013: 17%) [see Figure 1]. Of studies that included PWD, there was little change in the number of abstracts that provided a specific participant diagnosis (e.g. ALS onset type, lesion location) (1999=43%, 2013=27%). There was an increase in the percentage of abstracts from 1999 (28%) to 2013 (37%) that

described a participant's area of functional impairment and provided a measure of impairment. Additionally, there was an increase in the number of diagnoses reported among study participants from 1999 (7 diagnoses) to 2013 (16 diagnoses). Discussion: Despite the large increase in studies from 1999 to 2013 and PWD remaining the most common target BCI user, the percentage of studies including PWD as participants actually decreased. Early BCI research frequently attempted to demonstrate proof-of-concept with control participants. However, BCI performance for controls does not always predict performance with end-users (e.g., 4). Thus it is critical that PWD are involved in BCI research. The increase in specific description of functional impairments is encouraging, but contrasts with the decline in specificity of diagnosis. However, the limited space provided in an abstract might deter authors from including specifics of diagnostic and functional description; review of longer journal articles may produce different results. Significance: The importance of including PWD as study participants, and describing them accurately, may compel new BCI Meeting submission guidelines requiring detailed diagnostic and functional descriptions of study participants and encouraging testing with PWD.
References: [1] Müller-Putz, G, et al. (2016). Proceedings of the Sixth International Brain-Computer Interface Meeting: BCI Past, Present, and Future. DOI: 10.3217/978-3-85125-467-9 [2] Wolpaw, JR et al. (2000). Brain-computer interface technology: a review of the first international meeting. IEEE Trans Rehab Eng, 8(2), 164-173. DOI: 10.1109/TRE.2000.847807 [3] Huggins, JE, & Wolpaw, JR (2014). Papers from the Fifth International Brain-Computer Interface Meeting. Journal of Neural Engineering, 11(3), 030301. DOI: 10.1088/1741-2560/11/3/030301 [4] Oken, BS, et al.(2014). Brain-computer interface with language model-electroencephalography fusion for locked-in syndrome. Neurorehabil Neural Repair, 28(4), 387-394. DOI: 10.1177/154

Poster and Exhibitor Demonstrations Session 3

A- BCI Implant- Control

3-A-1 Finding the bipolar Error-related Potential (bErrP) in an ALS patient implanted with a daily use communications brain-computer interface (BCI)

Zachary Freudenburg[1], Khaterah Kohneshin[1], Erik Aarnoutse[1], Mariska Vansteensel[1], Mariana Branco[1], Sacha Leinders[1], Max van den Boom[1], Elmar G. M. Pels[1], Nick Ramsey[1]

[1]Rudolf Magnus Institute of Neuroscience, University Medical Center Utrecht

Introduction: We developed a method for communication in a person with Locked-In Syndrome (LIS) due to late stage ALS [1]. This Utrecht Neural Prosthesis (UNP) is a fully implanted communication Brain-Computer Interface (BCI) based on bi-polar electrocorticography (ECoG) signals recorded from the hand area of primary motor cortex (M1) and the dorsolateral pre-frontal cortex (dLPFC). Currently, the participant uses the UNP to operate a speech computer. The brain signal from M1 is amplified, filtered with an Activa PC+S and transmitted with Nexus-1 (both Medtronic; investigational devices) to a tablet with custom software. The system is able to detect the activity in M1 during attempted hand movement, which is translated into a 'click' which is used to select letters on a screen. While there is no decreasing or increasing trend in performance over time and the performance is generally very high, errors (unintended clicks) are still made. An approach to improve the accuracy of BCI's has been by looking into error-related potentials (ErrP's) in electroencephalogram (EEG) [2] and error-related neural responses (ERNRs) in ECoG signals [3]. These signal features are recorded right after the occurrence of an error and could be used to correct for system errors and consequently improve performance. In this study, we looked for these error-related potentials in the ECoG signals of the UNP during a click-based game. Material, Methods, and Results: Data was collected during 40 sessions of a BCI game in which the objective was to make clicks using the UNP system during specific time moments (Figure 1A). This game has four types of feedback moments: 1) when a scanning selection box changes position (true negatives,TNs), 2) when a click was made during a correct click period (true positives; TPs), 3) when the feedback indicated that a click failed to be made during an intended click period (false negatives; FNs), and 4) when a click was made outside a correct click period (FPs). Since the user reports that she never intends to make such FP clicks, these clicks are perceived to be system errors. ECoG data was recorded at a sampling rate of 200Hz and time locked to the game feedback (refresh rate of 40Hz). The bipolar potentials of the M1 and dLPFC signals were tested for significant peaks and troughs locked to each of the four feedback types. A significant positive peak in the dLPFC potential is seen ~800ms after the feedback moment in the FP condition (Figure 1B). Discussion: In our study, we showed a significant potential peak of the bipolar dLPFC signal related exclusively to feedback indicating system errors (bErrP). This potential is likely related to the ErrPs reported earlier using EEG [2], which are believed to originate in the Anterior cingulate cortex (ACC). While the local nature of the ECoG signal, makes it unlikely that this potential is a direct measurement of the ACC ErrP, the fact that both the dLPFC and the AAC are part of the corticolimbic system [4] suggests that it is closely related. The difference in timing of the UNP ErrP (+800ms) from the 320ms delay of the large positive peak in the EEG signal could be due to the differing roles of ACC and dLPFC. The ACC is more engaged in processing emotional experiences while the dLPFC is more engaged in regulating motivational responses [4]. Another factor to consider when interpreting our results is our use of bipolar referenced signals, making the actual direction and temporal shape of the potential change under the individual electrodes unclear. Because the previously reported ERNRs using ECoG [3] were over sensorimotor cortex and defined in the spectral domain it is difficult to relate our findings to this work. However, it is noteworthy that we saw no marked difference in potential response to FPs in the M1 bipolar electrode, despite the fact it's signal was highly correlated to the feedback (i.e. it was used to produce clicks and overall task performance was 85%). Significance: We believe that this finding motivates future work aimed at real-time error detection and correction using the bipolar dLPFC signal in the UNP system. Literature [1] Vansteensel et al., 2016. https://doi.org/10.1056/NEJMoa1608085 [2] Ferrez and Millán, 2008. https://doi.org/10.1109/TBME.2007.908083 [3] Milekovic et al., 2013. https://doi.org/10.1371/journal.pone.0055235 [4] Benes, 2010. https://www.nature.com/articles/npp2009116

3-A-2 Simultaneous real-time control of a high degree-of-freedom virtual object by a person with paralysis using an intracortical BCI

Sergey Stavisky[1], Paul Nuyujukian[1], Chethan Pandarinath[2], Beata Jarosiewicz[1], Nir Even-Chen[1], Paymon Rezaii[1], Francis Willett[1], Sharlene Flesher[1], Heidi Peterson[1], Leigh Hochberg[3], Krishna Shenoy[1], Jaimie

Henderson[1]

[1]Stanford University, [2]Emory University, [3]Brown University

Introduction: Intracortical brain-computer interfaces (iBCIs) are being developed to restore movement to people with paralysis. A major goal for this medical technology is to enable patients to perform actions requiring simultaneous control of many degrees-of-freedom (DOFs) of the arm. iBCIs can can provide an intuitive way to command such complex movements by decoding spiking activity of populations of neurons. Most prior iBCI arm control studies [e.g., Hochberg 2012, Collinger 2013, Ajiboye 2017] demonstrated the performance of end-to-end systems using functional tasks. Here, we focused on the decoding component of a high DOF iBCI system. Identifying the capabilities and limitations of this key element will facilitate a better understanding of the underlying control scheme and will likely enable improvements across a variety of effectors. We therefore primarily used a virtual reality setup to rigorously assess closed-loop iBCI control without the additional variability introduced by a robot or muscle stimulator. We report performance metrics of a person with tetraplegia accurately commanding at least 4 DOFs, both simultaneously and individually, using decoded movement imagery. Material, Methods and Results: A BrainGate2 clinical trial participant ('T5') with tetraplegia (C2-3 ASIA C spinal cord injury) had two 96-electrode Blackrock arrays chronically implanted in left motor cortex (Fig. B). The described experiments were performed between 6 and 15 months after array implantation. The participant manipulated a virtual object (Fig. A) by attempting right arm movements. The controlled and target object were spheres (3 DOF) or rods with 3 DOFs of translation and 1 DOF of rotation. Velocities in all DOFs were simultaneously decoded from multiunit spikes (Fig. C) using a high DOF extension of the ReFIT-KF algorithm [Pandarinath 2017]. The task required holding the object center and orientation within 2 cm and 13° of the target, respectively, for 500 ms. Independent neural DOFs (linear readouts of electrodes' firing rates) were linked 1:1 to independent object DOFs (e.g., forward/back, left/right). We measured whether the neural DOFs could be controlled both in isolation and simultaneously (Fig. D) by comparing the path efficiency (PE) of movements to different subsets of targets; each target subset required isolated and/or simultaneous control of a different subset of DOFs (Fig. E). The participant acquired 22.6 targets per minute in a 4D task with PE = 0.76. These metrics were similar across target subsets requiring moving 1, 2, 3 or all 4 DOFs (Fig. F), demonstrating specific control of each DOF as well as the ability to simultaneously control all the DOFs. Even higher PE (0.91) was achieved in a task variant that encouraged higher precision. Additional experiments revealed that neural control of the DOFs was not truly independent because the maximum neural push vector magnitude is constrained across the DOFs. While the focus of this study was high DOF decoding performance, an eventual goal is to perform activities of daily living with an iBCI-controlled prosthetic arm. We conducted pilot experiments in which 3 and 4 DOF decoders trained in the VR task were used to control the hand endpoint of a Kinova robotic arm. An additional binary grasp state was toggled using the HMM decoder from Pandarinath 2017. The participant successfully performed a 3 DOF modified box and blocks task (Fig G) and a 4 DOF pouring task. Discussion: We showed that highly accurate and simultaneous neural control of at least 4 DOFs is possible using an iBCI. It is encouraging that this performance was achieved using just 192 electrodes, and we expect iBCI capabilities to continue to improve as ongoing efforts progress toward substantially increasing the channel count of implantable sensors. Although our initial robotic arm results are promising, future experiments will determine whether the high decoder quality observed in VR will be maintained when the user controls physical effectors to interact with objects.

Neural changes related to object manipulation may need to be accounted for [Downey 2017], and the system will likely benefit from incorporating somatosensory feedback [Flesher 2016]. Significance: Understanding the capabilities of high DOF decoders used for simultaneous and intuitive control of multiple DOFs is critical to restoring independence to people with paralysis.

3-A-3 An optical brain-machine interface using two-photon calcium imaging in primate motor cortex.

Eric Trautmann[1], Daniel O'Shea[1], Xulu Sun[1], Stephen Ryu[1], Lucas Cofer[1], James Marshel[1], Will Allen[1], Isaac Kauver[1], Gergo Bohner[2], Charu Ramakrishnan[1], Maneesh Sahani[3], Karl Deisseroth[1], Krishna Shenoy[1]

[1]Stanford University, [2]Gatsby, UCL, [3]Gatsby

Introduction: Optical techniques such as two-photon (2P) calcium imaging hold the potential to transform the way we interface with neural circuits, both for advancing our understanding of basic science, as well as for improving brain-machine interfaces (BMIs). Optical imaging enables several key advantages over common electrophysiology techniques, such as: a) genetic targeting of specific cell types, b) targeting projections of inputs to or outputs from a given region, c) dense recording from most neurons within a given region, d) simple scaling for recording from many hundreds or thousands of cells simultaneously, and e) trivially selecting a recording site without moving an array or probe. We have developed a platform that enables chronic 2P functional imaging at cellular resolution in awake rhesus macaque monkeys performing motor tasks and demonstrates a proof of concept optical brain machine interface (oBMI) using a discrete target selection task. Material, Methods and Results: Developing 2P imaging in primates requires addressing several key challenges: 1) obtaining optical access to cortex, 2) stabilizing the head and brain tissue at the scale of microns during motor behavior, and 3) expressing GCaMP proteins at healthy levels during imaging. To obtain optical access, we developed an implant with a transparent silicone artificial dura and geometry that can accommodate large multiphoton lenses and allows for routine cleaning (Fig 1A). Stabilizing neural tissue during imaging requires restricting motion of both the neural tissue within the implant and the implant with respect to the imaging system (Fig1B). For the former, we've developed a stabilizer that places gentle pressure on the artificial dura during imaging. For the latter, we developed a low-profile three-point head fixation system capable of ensuring micron scale head stability. We observed less than five microns of tissue motion during most imaging sessions. Lastly, to screen for GCaMP constructs that express in monkeys, we injected three constructs at six sites in PMd and M1, and monitored GCaMP expression with widefield and 2p imaging (Fig 1C). We implemented a real-time BMI using image processing on raw imaging data from the microscope to decode the monkey's intended reach target from a set of either two or four radially spaced targets in a center-out delayed reach task (Fig 1D). Following the go cue and a fixed skip time, imaging frames were integrated for between 180-250 ms, then decoded using a minimum mean squared error decoder using raw pixel values. Decode was complete within 5-15 ms following the last acquired frame, at which point success or failure was then displayed to the monkey, often before reach completion. We obtained decode accuracy of up to 86.6% for two-target and 65.2% for four-target decode. Discussion: The technology required for human clinical oBMI is not foreseeable in the near future and this demonstration is not intended as a direct path towards translation. Rather, we view primate oBMI as a pre-clinical tool, which provides the potential to deepen the connection between advances in basic science and advances in BMI algorithms and hardware. Recent work has demonstrated the utility of BMI as a tool to address questions in basic science [Sadtler et al. 2014, Stavisky et al. 2017], while advances in basic science have lead to direct improvements in BMI [Kao, Ryu, and Shenoy 2017]. Calcium imaging should be seen as complementary to electrophysiology. While 2P imaging provides several advantages, temporal resolution and imaging depth are both limited. Despite these significant limitations, imaging provides the opportunity to merge genetic neural circuit dissection techniques with BMI to better understand the neural substrate for neural prosthetic control. Significance: We've developed an end-to-end preclinical primate model using two-photon calcium imaging. The implant affords imaging access to many hundreds of thousands of neurons across PMd and M1, and is compatible with other brain regions. In addition, we have demonstrated an oBMI using closed-loop image processing to provide low-latency visual feedback based on decoded neural activity. This paradigm will enable new classes of experiments in both BMI and basic science with relevance to improving BMI for human use. [1] Sadtler et al. Nature 2014; [2] Stavisky et al. Neuron 2017; [3] Kao et al. Scientific Reports 2017

3-A-4 Case study: Eye movement related motor activity overlaps with hand-knob area in late stage ALS

Sacha Leinders[1], Janne Luppi[2], Mariana Branco1, Zachary Freudenburg[1], Elmar G. M. Pels1, Max van den Boom1, Erik Aarnoutse1, Mariska Vansteensel1, Nick Ramsey1

[1]Brain Center Rudolf Magnus, UMC Utrecht, [2]University of Amsterdam

Case Study: Eye Movement Related Motor Activity Overlaps with Hand-Knob Area in Late Stage ALS Leinders,S.1, Luppi,J.J.2, Branco,MP.1, Freudenburg,ZF.1, Pels,EGM.1, VanDenBoom,MA. 1, Aarnoutse,EJ. 1, Vansteensel,MJ.1,& Ramsey,NF. 1 1 BCRM, UMCU, Dpt. of Neurology and Neurosurgery, Utrecht, the Netherlands 2 UVA, Amsterdam, the Netherlands Introduction: As part of the Utrecht NeuroProsthesis (UNP) project, a woman with late stage ALS (58y at time of surgery in 2015) has been implanted with a BCI system for communication. Neural signals for BCI control are acquired with ECoG electrodes placed on her left sensorimotor hand area. The system allows her to select on-screen options in scanning software by producing correctly timed clicks by ways of attempted right-hand movement (Vansteensel et al., 2016). She uses an eye tracker for communication and computer control in her daily life and during research sessions for providing us with feedback. During an online test of the UNP system in one session, we noticed that eye tracker use caused the UNP system to register brain clicks. Here we report on results from a formal test of activation of the hand motor area during eye movements. Material, Methods and Results: Our participant was diagnosed with ALS in 2008, and can with some effort move her eyes. The implanted system used to record data consists of subdurally placed electrodes (Resume®II, Medtronic, investigational use) on the hand motor area of the left hemisphere and an Activa®PC+s amplifier (Medtronic, investigational use) implanted subcutaneously under the left clavicle (Vansteensel 2016). Brain signal was recorded with the implant during two tasks: attempted right hand movement and movement of the eyes following the edges of a computer screen (both 5 min duration). Data was recorded in a bipolar fashion across two electrodes on hand motor cortex at 200Hz. For comparison, the eye task was performed by 2 epilepsy patients (1 female, 18y; 1 male, 17y) with similar ECoG electrodes (2.3mm diameter and 1cm distance) temporarily implanted on the motor cortex (data recorded at 512Hz). We used a block design, with alternating active and rest blocks of 15 seconds. During rest blocks, participants were instructed to look at an on-screen fixation cross. All data was converted to power using wavelet analysis (1-100Hz, 1Hz bins). Signed R^2 was computed for active versus rest for each bin, and for bandwidths used for UNP control by our participant (10-30Hz and 65-95Hz). For the UNP user, attempted hand movement resulted in a suppression of 10-30Hz power (R^2=-0.87, p<0.001) and a power increase in 65-95Hz (R^2=0.89, p<0.001; fig. 1a). During the eye movement task, similar changes occurred (10-30 Hz: R^2=-0.8, p<0.001; 65-95Hz: R^2=0.65, p=0.001; fig. 1b). The same activity pattern was not found in epilepsy patients. Neither of them displayed any significant effects of eye movements in the hand region. Discussion: Results indicate that in our UNP user eye movements strongly elicit activity very similar to attempted hand movement activity. The same activity pattern was not found in epilepsy patients. Eye movement related activity in the participant's hand area could be due to a functional overlap between the two cortical areas (Melamed et al., 1979). However, that does not explain why the same activity was not clearly observed in the epilepsy patients. A more likely explanation is encroachment of the hand area by eye movement function, as our participant has been unable to move her hand for over 7 years, and has been using an eye tracker for several years. Encroachment of motor regions has been reported following extremity amputation (Merzenich et al., 1984). Moreover, Shen et al. (2015) conclude in a meta-analysis that ALS patients show enhanced motor activity in M1 when performing motor tasks. The results suggest that prolonged paralysis may cause eye movements to activate the hand region. More research is needed to verify whether this generalizes to other people with paralysis. Significance: The hand region of the motor cortex, which is often targeted for BCI control, may respond to eye movement in paralyzed users. Elucidating this phenomenon is important for optimizing BCI performance. References Melamed E et al, AnnNeurol,1979, 5:79-88 Vansteensel MJ et al, N Engl J Med 2016;375:2060-2066 Merzenich MM et al., JCompNeurol, 1984;224(4):591-605 Shen D et al, Front.Neurol,2015,6:246

B- BCI Non-Invasive- Control

3-C-5 Finding optimal stimulation patterns for BCIs based on visual evoked potentials

Sebastian Nagel[1], Wolfgang Rosenstiel[2], Martin Spüler[2]

[1]University of Tuebingen, [2]University of Tübingen

Introduction: The brain responses to visual stimuli, called visual evoked potentials (VEPs), can be used for BCI control as proposed by Sutter in 1984 [1]. To get best classification performance, it is required to find modulation patterns evoking brains responses which can be differentiated between others as effectively as possible. In our previous paper [2] we have shown that fully random bit-sequences can be used for modulation sequences. In this paper we propose a new approach to find optimal modulation patterns by proving that a specific property of modulation sequences significantly improve the prediction accuracy. Material, Methods and Results: To find a property of the stimulation sequences which leads to better results, we used the data of our previous study [2]. By analyzing the bit prediction accuracy of each 15 bit (250 ms) window, we found that the bit prediction accuracy was maximized for sequences with 7 bit toggles, as shown in figure 1. To proof our findings, we performed an offline experiment with 9 participants. Data was recorded using a g.USBamp (g.tec, Austria) EEG amplifier and Brainproducts Acticap system with 32 channels. The presentation layer is an 8x4-matrix keyboard layout (32 targets) programmed in MATLAB using the PsychToolbox and presented on a LCD monitor (BenQ XL2430-B). A stimulus can either be black or white, which is represented by 0 or 1 in a binary sequence and is synchronized with the monitors refresh rate (60 Hz) which in turn is synchronized with the EEG amplifier by using the parallel port. The participants are seated approximately 80 cm in front of the monitor. The methodology was the same as in our previous study [2], but the experimental procedure differs. For better understanding: the underlying regression model predicts each single bit of the binary stimulation sequence by using 250 ms of EEG data post-stimulus, since the most prominent parts of a VEP to a single stimulus lasts for approximately 250 ms post-stimulus. Additionally, we corrected the monitor raster latency a described in our previous paper [3]. During the online experiment, the participants had to perform 2 runs to train a spatial filter using canonical-correlation analysis (CCA), followed by 3 trainings runs. Once the training was done, the participants had to perform 14 test runs with 2 seconds per target. Each run consists of 32 trials with an inter-trial time of 750 ms. The stimulation patterns of the training runs and 7 of the test runs were fully random bit sequences for each target. For the remaining 7 test runs we created a set of 150 sequences with a length of 15 bit and 7 bit toggles, based on the findings above. Those sequences in turn were used for target modulation by randomly assigning them. Since we want to proof that this property of the stimulation sequences leads to better results compared to fully random stimulation sequences, we analyzed the bit prediction accuracies and found a significant ($p<0.05$, t-test) increase of the bit prediction accuracy. The random sequences can be predicted with an average accuracy of 63.57% whereas the predefined sequences can be predicted with an average accuracy of 65.44%. This corresponds to an information transfer rate of 193.7 bpm and 251.7 bpm, respectively. Discussion: In this paper we have shown, that modulation sequences can be optimized by using specific properties. Based on our model, which predicts the bit-sequences of arbitrary stimulation patterns, we could proof that the number of bit changes plays a significant role for the prediction accuracy. In a future work, we will investigate in finding more properties to further optimize the stimulation pattern. Significance: Using our random VEP BCI model, we proposed a completely new approach to find optimal stimulation patterns increasing the prediction accuracy of VEP BCIs. Resources: [1] E. E. Sutter, The visual evoked response as a communication channel, in: Proceedings of the IEEE Symposium on Biosensors, 1984, pp. 95-100. [2] S. Nagel, W. Rosenstiel, M. Spüler, Random Visual Evoked Pontentials (RVEP) for Brain-Computer Interface (BCI) Control, Proceedings of the 7th Graz Brain-Computer Interface Conference 2017, p.349-354. [3] S. Nagel, W. Dreher, W. Rosenstiel, M. Spüler, The effect of monitor raster latency on VEPs, ERPs and Brain-Computer Interface performance, Journal of Neuroscience Methods, 2018, 295, p.45-50

3-C-7 A novel Brain-Machine Interface for controlling dynamic systems

Jinling Lian[1], Luzheng Bi[1]

[1]*Beijing Institute of Technology*

1. Introduction: Brain-machine interface (BCI) has a wide range of applications, such as spellers [1], browsing internet [2], cursor control [3, 4], brain-controlled wheelchairs [5] and brain-controlled vehicles [6]. These applications can be divided into to two categories: task-level applications for static systems and procedure-level applications for dynamic systems. For task-level applications, the output command of BCI systems directly represents a task, which will be performed by an autonomous system. For procedure-level applications, the output command of BCI system should be sent accurately and fast to directly control a dynamic system (such as a wheelchair) to ensure an efficient procedure-level applications. Compared to BCIs based on ERD/ERS, P300 BCIs require rather less training. Compared to P300 BCIs, SSVEP stimuli tend to make users more annoyed and high-frequency SSVEP response is weaker and harder to detect accurately. In this paper, we design a new P300 paradigm for controlling a dynamic system, which can send control commands quickly and accurately. In the interface, nine characters with every three same characters (A, A, A, B, B, B, C, C, C) representing a command are distributed in 3*3 matrix. Each character is flashed for 120 ms and there is no break between two successive characters, so the time length for one round is 1.08 s (120 ms*9). In 2 round, i.e. 2.16s, six flashing repetition number of characters for inducing P300 signals are obtained. 2. Experimental data: EEG signals were collected from 16 standard locations (i.e. Cz, Fz, Pz, Oz, CPz, POz, F3, F4, C3, C4, P3, P4, P7, P8, O1, O2) based on an international 10-20 system. The reference potential was set to be the mean of the potentials on the left and right ear lobes. The EEG signals were amplified and digitalized with a sampling rate of 1000 Hz and a power-line notch filter was used to remove the line noise. Six subjects performed the experiment for 12 sessions and every session contained 9 trials. 3. Method: The collected EEG signals are first preprocessed and independent component analysis (ICA) is then used to transform EEG into independent components (ICs). After that, these ICs selected by using the sequential forward floating search algorithm (SFFS) are used as initial features, which are further reduced by using the principal component analysis (PCA). Then, these features selected by PCA are fed into a liner discriminant analysis classifier. 4. Results and Discussion: Accuracy is shown in Figure 1. We can see that the average accuracy reached 87%, given about 1-second detection time and Subject 5 outperformed other subjects with the accuracy of 93%. 5. Significance: This paper proposed a new P300 paradigm along with the proposed detection algorithm for controlling a dynamic system. More efforts in feature extraction and classification methods should be done to further improve the accuracy given a short detection time. References: [1] B. Hong, F. Guo, T. Liu, X. Gao, and S. Gao, "N200-speller using motion-onset visual response," Clinical neurophysiology, vol. 120, pp. 1658-1666, 2009. [2] E. Muglerab, M. Benschc, S. Haldera, W. Rosenstielc, M. Bogdancd, N. Birbaumerae, et al., "Control of an internet browser using the P300 event-related potential," International Journal of Bioelectromagnetism, vol. 10, pp. 56-63, 2008. [3] L. Bi, J. Lian, K. Jie, R. Lai, and Y. Liu, "A speed and direction-based cursor control system with P300 and SSVEP," Biomedical Signal Processing and Control, vol. 14, pp. 126-133, 2014. [4] J. R. Wolpaw, D. J. McFarland, G. W. Neat, and C. A. Forneris, "An EEG-based brain-computer interface for cursor control," Electroencephalography and clinical neurophysiology, vol. 78, pp. 252-259, 1991. [5] R. Zhang, Y. Li, Y. Yan, H. Zhang, S. Wu, T. Yu, et al., "Control of a Wheelchair in an Indoor Environment Based on a Brain-Computer Interface and Automated Navigation," IEEE transactions on neural systems and rehabilitation engineering, vol. 24, pp. 128-139, 2016. [6] L. Bi, X. A. Fan, K. Jie, T. Teng, H. Ding, and Y. Liu, "Using a Head-up Display-Based Steady-State Visually Evoked Potential Brain-Computer Interface to Control a Simulated Vehicle," IEEE Transactions on Intelligent Transportation Systems, vol. 15, pp. 959-966, 2014.

3-C-8 SSVEP based BCI for 3 Dof robot arm control using LabVIEW

Sandesh R S[1], Nithya Venkatesan[2]

[1]VIT, Chennai, [2]VIT

Introduction: Patients suffering from motor impairments like Amyotrophic Lateral Scleroses (ALS), Spino Cerebellar Ataxia (SCA) requires a specific movement of robotic arm/limb to reduce the nursing labor load and to increase the autonomy. Brain computer interface (BCI) is one such method which uses EEG signals (SSVEP) from the subject's brain to acquire, classify and translate commands for robot control. This work recommends both hilbert transform with time averaging methods to evaluate the performance classification of phase encoded SSVEP signals under LabVIEW environment. Materials, Methods and Results: The simulation panel consists of 4 stimuli with LED as visual source, flickering at frequency of 25Hz, having phase shift of 0˚, 90˚, 180˚, 270˚, driven by Arduino ATMEGA 328P microcontroller. The SSVEP signal is acquired and amplified using customized SSVEP EEG amplifier [1]. The amplified SSVEP signal is then transformed using hilbert method to estimate the phase content of the signal using extract single tone information using sub vi. The amplified SSVEP signal is then time averaged at a sampling rate of 8 KHz frequency to obtain 320 samples per epoch for each stimuli flickering at frequency of 25Hz. At first, the subjects are allowed to gaze the stimuli 1 having a phase shift of 0˚ for a time period of ~ 21 seconds (512 epochs) and averaged for 256 samples to detect the reference time [2]. The time interval between two phase shifts is calculated as 10m Seconds. The practical and theoretical time predicted values for subject gazing at different stimulus are calculated and compared. The time and phase obtained from both the signal processing algorithms is compared before translating the commands for control of 3DoF robot arm. Initially custom made simulated robotic arm [3] is at state of rest ($\theta1= \theta2= \theta3=0˚$) and corresponding θ values are then passed upon subject gazes at stimuli for various angles, 1. Stimuli 1(0˚)- $\theta1= 30˚$ and $\theta2= \theta3=0˚$. 2. Stimuli 2(90˚) -$\theta1= 30˚$, $\theta2= 20˚$ and $\theta3=0˚$. 3. Stimuli 3(180˚) - $\theta1= 30˚$,$\theta2=20˚$ and $\theta3=0˚$. 4. Stimuli 4(270˚) -$\theta1= \theta2=\theta3=0˚$. This process is repeated for two cycles (1and2) to improve the accuracy followed by an audio feedback (Audio Buzzer). Results: Fig 1 shows SSVEP signal for the time duration of 0.32 seconds (8 epochs), the signal is band pass filtered (25Hz) to obtain filtered SSVEPfiltered signal. The subject-1has focused on stimulus 1 to extract the phase value and time predicted value for stimulus 1. A limit is set for both phase value obtained (± 10˚) and time predicted value (±5m Seconds) of SSVEP signal. If the detected phase value and time predicted value falls in range for the subject gazing at stimuli, then respective θ values are passed to control the simulated robotic arm. Table I (Table A) shows the experimental results obtained experimentation for a seven different subjects. Discussion: This work also compared with earlier mechanism on SSVEP based BCI experiment robotic control, From the Table 1(Table B), the performance classification of SSVEP signal for robotic control has mean accuracy of 92.85% and ITR of 26.36 bits/min. The identified wrong commands are due to, the subjects unfamiliar in the SSVEP based BCI experimentation or either due to low SNR caused by electrode location. The limitations of this work are, control of end effectors is beyond scope of this work. Significance: The LabVIEW based SSVEP experimentation enables to create one's own GUI, and can be focused on real time robot arm control in future for patients with severe disabilities as mentioned References: [1] Sandesh R.S and Nithya Venkatesan, " LabVIEW based design and control of 5 digit Anthropromorphic Robotic hand using EEG signals", Int. J. Biomedical Engineering and Technology (IJBET- Inderscience) Vol. 22, No. 3, October

2016, pp 258- 271. [2] Kuo-kai shyu, Poi Lei Lee, Ming Huan Lee, Ming Hon Lin, Ren-Jie Lai, Yun-Jen Chiu, " Development of Low Cost FPGA Based SSVEP Multimedia control system", IEEE transactions on Biomedical circuits and systems, vol. 4, No. 2,April 2010, pp 125-133. [3] https://forums.ni.com/t5/Example-Program-Drafts/Robotic-Arm-Simulation/ta-p/3499776 [4] Piotr Stawicki, Felix Gembler, and Ivan Volosyak, "Driving a Semiautonomous Mobile Robotic Car Controlled by an SSVEP-Based BCI", Computational Intelligence and Neuroscience, 2016 July 26. doi: 10.1155/2016/4909685.

3-C-9 SSVEP controlled BCI inferring complex tasks from low-level-commands

Matthias Will[1], Tim Pfeiffer[1], Nicolai Heinze[2], Georg Rose[1]

[1]Otto-von-Guericke-Universität Magdeburg, [2]Leibniz Institute for Neurobiology Magdeburg

Background: One aim of brain-computer-interfaces (BCIs) is to give mobility to motion-disabled people, therefore they are used to control external devices sending low-level-commands to manipulate single degrees of freedom or high-level commands to directly reach for pre-defined targets. Low-level commands are not suitable for complex tasks, as a lot of simple commands are required in general which may cause frustration for the user. On the other side, high-level commands enable complex tasks but lack free navigation. Approaches combining both low- and high-level commands, using prior knowledge to spare simple commands have been developed. For spelling devices, [1] showed the possibility for users to select single letters along with the opportunity to automatically complete words. This study investigates the possibility to apply such a combined approach to control movable objects. Material, Methods and Results: Brain activity was measured with EEG in a steady-state visual evoked potential (SSVEP) experiment. Canonical correlation analysis (CCA) was used for feature generation. Classification was compared between a thresholding and a Naive Bayes approach. The experimental setup contained of five stimuli, four of which were associated to moving a cursor in a 2D space, one is used to automatically reach a predicted target. Target prediction was based on the extrapolation of the cursors trajectory in combination with prior knowledge about the position of possible targets. Using a cartesian coordinatesystem (CS) or a polar CS to describe the cursors environment two different modalities of cursor motion were applied. In an experiment with six different targets the paths users chose to reach these targets were observed. Differences between the modalities of motion and the resulting effects for target prediction were examined. Additionally, tools for predictions in ambigious situations were developed und tested. For one, a cost-term $0<\alpha<1$ was applied on the calculated probability of a predicted target if it was not confirmed by the auto-complete command. Furthermore, different inital probabilities were assigned to the targets. Regarding classification the thresholding approach outperformed the Naive Bayes classifier as the recognition rates were 92±12% and 86±16% respectively. Regarding the number of required commands to reach the targets 0.8 times fewer steps were needed in the cartesian CS than in the polar CS. Using the cost-parameter the required number of commands until the right target was detected was just 54% of the original number on average. Additionally applying different inital probabilities crucailly reduced the amount of commands to only 33%. Discussion: Both classifiers showed a good performance. Calibration of the threshold classifier was substantially faster than for the Naive Bayes classifier as it required a big amount of data to estimate a

distribution. The long calibration of the latter is also hold to account for the inferior performance as it did not reflect the situation in the experiment properly. Substantive differences were observed for cursor motion comparing both motion modalilities. In the cartesian CS trajectories had a cornerd shape whereas in the polar CS paths pointed directly to the targets typically. Moreover, the number of required commands for target prediction was critically dependend on the targets location in both motion paradigms. As a cartesian CS represents the most intuitive orientation for most people more training may be nessecary to control the cursor in the polar paradigm. Furthermore, combining both CS, i.e. a rotatable two axes system, may benefit target prediction. Supplementary usage of a cost-parameter and inital probabilities substantially aided target prediction in a situation where several possible targets were located proximate to each other. Significance: The investigated approach enables control of different movable objects (e.g. a wheelchair) in a combined low-level and high-level command fashion, closing the gap between free navigation and the possibility to automatically attain a specific target. This study serves as, to the authors best knowledge, the first working proof-of-concept for a new, more practical BCI control for movable objects. Funding: BMBF, FC STIMULATE (13GW0095A)
References: [1] Ryan, David B et al., "Predictive spelling with a P300-based brain-computer interface: increasing the rate of communication", Int J Hum Comput Interact 27, 1 (2010)

3-C-10 Controlling high-complexity robotic swarms with low-complexity EEG brain-computer interfaces

Gregory Canal[1], Yancy Diaz-Mercado[1], Magnus Egerstedt[1], Christopher Rozell[1]

[1]Georgia Institute of Technology

Introduction: While the fidelity and communication rate of non-invasive BCIs for control has increased in recent years, the system effectors have mostly remained in the class of applications involving discrete menu selection or continuous control of a cursor or robot in two or three-dimensional space. This is due to lower input complexity and higher noise levels than invasive systems, resulting in end effector behavior that suffers from these limitations if they are not addressed in system design. Here, we present a BCI that explicitly incorporates effector feedback to allow for a new class of high-complexity control using only noisy, low-complexity inputs. We demonstrate its utility in the task of controlling mobile robotic swarms with only binary motor imagery inputs detected via EEG. Material, Methods and Results: By modeling the user, EEG, and effector as a communications system with feedback, tools from feedback-information theory and channel coding can be used to convey the user's desired behavior. Specifically, the communication link is made digital by constraining the user to issuing binary motor imagery commands, which are susceptible to classification errors but have been widely studied as an EEG input mechanism [1]. These noisy, binary inputs subsequently alter the state of the high-complexity effector, which is fully observable to the user and hence forms a noiseless feedback link. With this model, an algorithm known as posterior-matching (PM) can be used to efficiently specify high-complexity behaviors in a manner scalable in the effector complexity, implementable by human users, and with arbitrary accuracy even in the presence of input noise [2]. The algorithm assigns a lexicographical ordering to the space of effector behaviors and allows the effector to systematically guess the user's desired behavior, to which the user issues binary inputs to refine the guess by alphabetizing it with respect to their desired behavior. In this heterogeneous lexicon, the letters of each word belong to alphabets that differ based on letter position, allowing for a rich class of system behaviors to be specified. This algorithm was applied to robotic swarm control by developing a heterogeneous lexicon of global swarm behaviors including combinations of translation, resizing, and reshaping. After learning this lexicon, a single subject was able to use PM to successfully drive a simulated swarm to desired configurations. Over the course of 70 trials with a randomly selected target configuration per trial, 75.71% of trials converged to the correct complex, high-dimensional configuration. This was achieved with 21.80% empirical binary input error, demonstrating the power of PM. At this input error level, the empirical results matched the expected performance of PM in simulation, with an information-transfer-rate of 10.19 bits/trial for PM in comparison to 4.80 bits/trial for a baseline algorithm. The subject was also able to utilize PM to successfully control a real robotic swarm. To generalize these findings, the learnability of the heterogeneous swarm lexicon was evaluated in a user study. 150 subjects were able to learn the lexicon from a set of instructions and apply it to ordering 150 randomly generated pairs of configurations with an overall accuracy of 95.98%. Discussion and Significance: The efficacy of utilizing PM with a heterogeneous lexicon for swarm control was demonstrated for both simulated and real robotic swarms over multiple trials. The theoretical performance of PM was met even after combining human, EEG, and swarm subsystems, providing support for the use of PM in real-world BCI settings. Furthermore, the successful learning and ordering of the swarm lexicon was shown to be generalizable through a large user study. This result demonstrates the efficacy of explicitly utilizing adaptive effector feedback for specifying high-complexity BCI behavior with only noisy, low-complexity inputs. Acknowledgements: This work is supported by NSF CAREER grant number CCF-1350954 and the Georgia Tech Neural Engineering Center. References: [1] H. Ramoser et al., "Optimal spatial filtering of single trial eeg during imagined hand movement," IEEE Trans. Rehabil. Eng., vol. 8, no. 4, pp. 441-446, 2000. [2] C. Omar et al., "A feedback information-theoretic approach to the design of brain-computer interfaces," Intl. J. of Human-Comput. Interaction, vol. 27, no. 1, pp. 5-23, 2010.

3-C-11 Effect of custom electrode selection on P300 BCI performance for people with CP, ALS, NMD and controls

Jane Huggins[1]

[1]*Direct Brain Interface Laboratory, University of Michigan*

Introduction: A default set of electrodes are usually used in EEG P300-based BCI and studies have shown better performance for controls than those with disabilities1,2. We hypothesize that performance difference may partially result from brain differences in people with disabilities, and a custom electrode subset could address the differences and improve BCI accuracy. We found custom subsets to significantly increase BCI training accuracy for people with cerebral palsy (CP)3. Here, we include people with spinal cord injury (SCI), neuromuscular disease (NMD), or amyotrophic lateral sclerosis (ALS). Methods and Results: Data for this offline analysis were collected in three different experiments. Data for 10 subjects with CP (2F 8M, 18.6±6.1 yrs), and 10 typically developing (TD) subjects (6F 4M, 14.9±4.2yrs), came from the cognitive testing protocol5. Data for 13 subjects with ALS (4F 7M, 61.9±8.8

yrs), and 8 subjects with NMD (1F 7M, 20.1±3.9 yrs), came from the Keyboard Replacement Protocol6,7. Data for 8 subjects with SCI (3F 5M, 39.5±9.1yrs) came from the P300 Mouse study, which assessed the ability to the BCI use to move the mouse cursor (unpublished). The protocols differed, but similar numbers of flashes from each protocols are used. Electrode were selected with the forward-search greedy algorithm described in our previous work3,4. BCI performance differences between the default 8-electrode subset (Fz,Cz,P3,Pz,P4,PO7,PO8,Oz) and a custom subset for each subject chosen from 16 electrodes (F3,Fz,F4,T7,C3,Cz,C4,T8,CP3,CP4,P3,Pz,P4,PO7,Oz,PO8) were evaluated with a paired t-test. Only the CP group had significantly improved BCI performance (3.4±2.1%, p=0.0003) with custom subsets (Table 1). Discussion: Age is a possible confounding factor as the youngest groups (CP, TD, NMD) have the lowest p-values, but the etiology of the disabilities also support greater variability in these groups and in CP in particular. ALS and CP primarily affect the brain8,9, while SCI and NMD affect spinal cord or muscles. CP and NMD, particularly Duchene muscular dystrophy, have a birth or childhood onset10 and could affect brain development. As CP has both early onset and direct brain effects, it could produce the largest variations in the P300. Abnormalities in the brain of people with CP are seen in MRI studies11. Thus, custom selection may identify electrode locations that accommodate the differences. Conclusion: We draw two main conclusions. First, the standard electrode subset provides people with ALS, NMD, SCI and TD individuals, BCI accuracy that is not statistically different from custom subset accuracy. Second, custom electrode selection would be valuable to improve BCI accuracy for people with CP and other disabilities with an early onset that affects the brain. References 1Piccione F. et al. P300-based brain computer interface: Reliability and performance in healthy and paralysed participants. Clin Neurophysiol, 2006. 2Halder S. et al. Brain-controlled applications using dynamic P300 speller matrices. Artif Intell Med, 2015. 3Tou et al. Subject-Specific Electrode Subsets for P300 BCI: Typically Developing and Cerebral Palsy Populations. Proceedings of the 6th Int'l BCI Meeting, 2016. 4Colwell K.A. et al. Channel Selection Methods for the P300 Speller. J Neurosci Methods, 2014. 5Huggins, J. E. et al. 2015. Brain-Computer Interface Administration of the Peabody Picture Vocabulary Test-IV. Neural Eng, 7th Int'l IEEE/EMBS Conf. 6Thompson, D. E. et al 2014. A plug-and-play brain-computer interface to operate commercial assistive technology. Disabil Rehabil Assist Technol. 7Aref AW et al. The P300-Certainty Algorithm: Improving accuracy by withholding erroneous selections, ECNS Conference, Bristol, TN, 12-16 September 2012 8Centers for Disease Control and Prevention 2015. Facts about Cerebral Palsy. www.cdc.gov/ncbddd/cp/facts.html 9The ALS Association 2017. Cognitive and Behavioral Changes in ALS: A Guide for People with ALS and their Families. www.alsa.org/als-care/resources/publications-videos/factsheets/cognitive-changes-family.html 10Johns Hopkins Health System. Types of Muscular Dystrophy and Neuromuscular Diseases. www.hopkinsmedicine.org/healthlibrary/ 11Yin R et al 2000. Magnetic resonance imaging findings in cerebral palsy. J Paediatr Child Health Ack: Supported by NIH R21HD054697 and UL1TR000433, NIDRR H133G090005, and Mildred E Swanson Foundation. Views presented belong to the authors, not the funding agencies.

3-C-12 MR-Braintap: Mixed reality-Brain Computer Interface for children with disability

Ephrem Zewdie[1], Dennis Dietz[2], Ehud Sharlin[3], Zeanna Jadavji[3], Adam Kirton[1]

[1]Cumming School of Medicine, University of Calgary, [2]Ludwig Maximilian University of Munich, [3]University of Calgary

Introduction: Augmented reality (AR) is a real-world environment whose elements are augmented by computer-generated sensory inputs such as a graphics display. Similarly, mixed reality (MR) refers to the ability to mix digitally rendered objects into our real environment, where physical and digital objects co-exist and interact in real time. Applications in AR/MR environments have been developed to assist children with disability to improve learning and cognitive capacity. However, children with severe physical disabilities are still unable to use such systems though they are increasingly capable of using emerging Brain Computer Interface (BCI) systems. We aim to develop an integrated MR-BCI system for such children. Material, Methods and Results: An MR-BCI system is being designed to enable children with quadriplegic cerebral palsy and preserved intellectual function to control a virtual avatar super-imposed on the real environment. To expand the range of capabilities of these two systems, we combined mixed reality with P300-based BCI. We are using custom designed Unity 3D-based games installed in the Microsoft Hololens mixed reality system to create the desired environment. We are using g.tec P300 hardware and software as the BCI control mechanism. The P300 system utilizes specific visual evoked potentials that are detected 300ms following induced events such as a flashing letter. A two-way communication between Hololens and g.tec P300 systems has been established using a universal datagram protocol (UDP). We have successfully established and tested the two-way communication between the Hololens and g.tec P300 systems. In order to avoid synchronization errors and keep the network traffic low, UDP has been chosen as the network protocol. The custom Unity 3D game includes flashing signals for P300 control as well as activity to assess and improve attention. The control panel remains steady in the foreground in the virtual space is always visible to the user. We will shortly be testing the MR-BCI system in our large database of children with severe CP. The test setup will use the MR-Braintap as an input medium to control a virtual car, which is projected in real space. In a series of training sessions, the change in cognitive capacity including attention will be assessed by the game performance and the Child Behaviour Rating Scale. Discussion/Significance: Controlling combined real and virtual environments with integrated MR-BCI systems appears feasible with promising therapeutic and learning applications in disabled children. It opens opportunities to a new way of interaction of virtual and real world by utilizing surface EEG signals as a control mechanism. In addition to the P300 systems, other EEG based event related potentials can also be incorporated. Using such systems, therapeutic training might be designed not only for children with CP but also other neurodevelopmental disorders.

3-C-13 Online decoding of gait-related lower-limb movement intention

Kyuhwa Lee[1], Tiffany Corbet[2], Ruslan Aydarkhanov[1], Luca Randazzo[3], Ricardo Chavarriaga[1], José del R. Millán[3]

[1]EPFL, [2]Ecole Polytechnique Fédérale de Lausanne (EPFL), [3]École Polytechnique Fédérale de Lausanne (EPFL)

Introduction: We present an ongoing case study on neural decoding of gait using non-invasive electroencephalography (EEG) with an ultimate goal of using brain signals to trigger individual leg prosthesis. A subject with chronic paraplegia (T12 spinal cord injury, 12 years since injury) attempted to move legs in a slow pace of 3 to 4 seconds per step without any overt movement. After training, long-term evaluation yielded increasingly high online decoding accuracy over 4-month testing period. The results suggest that it is feasible to perform a continuous lower-limb decoding with sufficient reliability and has a potential for assistive and neurorehabilitation applications. Material, Methods and Results: For each trial, the subject performed a motor attempt of moving lower limbs by actively trying to move disabled legs while mounted on a powered lower-limb exoskeleton, Rex (Rex Bionics). The subject performs motor attempts of actively trying to lift his legs in an alternating order. The subject was instructed to avoid any overt movement in the upper body to prevent motion artifact. We sampled signals using AntNeuro eego mylab at 512 Hz with 64 electrically shielded active electrodes following the standard 10-10 system. A total of 230 attempted left and right steps were recorded for training a decoder and testing was done on separate sessions over the period of 4 months, 3-4 sessions per month depending the patient's condition. No decoder retraining was performed during the testing period. Unlike other treadmill-based experiments, we did not impose any periodicity assumption in the model as the gait step length was randomized. For decoding, we first applied a common-average filter (CAR) on raw signals and estimated power spectrum density (PSD) using multitaper to compute features. We used Random Forests as a classifier since it can automatically find important features during the training phase and avoid overfitting from data that has low trials-to-features ratio. Asynchronous decoding was performed using a sliding window of 500ms that yields a BMI output at approximately 15 Hz with a visual feedback to the user. The grand average time-frequency plots from the training data are shown in the upper part of the figure. Upper left and right plots show the modulation in beta band for left and right trials, respectively, with the motor attempt onset being at time 0. Event-related synchronization (ERS) in the beta band was observed on C1 when the subject was attempting to lift the left leg, while event-related desynchronization (ERD) in the beta band was observed in the same channel when the subject was trying to lift the right leg. Online decoding accuracy consistently increased throughout the testing period as shown in the lower part of the figure (average accuracies of month 1 to month 4 were 71.3%, 78.8%, 83.3% and 82.2%, respectively). It can be also observed from the plot that the stability has increased over time on month 4 compared to month 1. Discussion: Although the lower-limb cortical representation mainly lies on the interhemispheric area which may limit the information that can be obtained from surface EEG, recent works provide supporting evidence for non-invasive BMIs for gait decoding. We report reliable single-trial decoding of motor attempt of individual legs. In our approach, we employed motor attempt as it is known to produce a stronger signal modulation than that of motor imagery which requires inhibition. Last but not least, we used a sophisticated non-linear machine learning algorithm that can efficiently generalize from the data having low number of samples with large feature dimension. Significance: Most non-invasive BMI systems for gait have focused on decoding between idle and walking states. To the best of authors' knowledge, it is the first online experiment of decoding between individual left and right leg movement intention in a subject with paraplegia. It has a potential to be utilized for neurorehabilitation on paraplegic and tetraplegic population when coupled with assistive technologies by providing congruent sensory feedback such as proprioceptive feedback.

3-C-14 Emotion-inducing imagery versus motor imagery based BCI: Performance, perceived control and imagery preference

Alain Bigirimana[1], Nazmul Siddique[1], Damien Coyle[1]

[1]Ulster University

Introduction: An initial preliminary investigation into alternative imagery strategies to motor imagery (MI) for modulating brain activity for brain-computer interface (BCI) control [1] suggested emotion-inducing imagery (EII) could offer comparable performance to motor imagery. Here we present a more comprehensive analysis of the viability of EII, comparing multiple online feedback sessions and single-trial classification accuracy (CA) for EII tasks vs MI with 10 participants, scheduled across different days. Beside the CA comparison, we compare the participants´ subjective responses on favourite control approach and the imagery with most perceived control over feedback provided during the experiment. Material, Methods and Results: Electroencephalogram (EEG) data were recorded from 30 electrodes, mounted based on 10-20 system, with 125Hz sampling rate. The Study involved 10 healthy volunteering participants (2 females and 8 males, mean age 29, SD = 8). Each session, as previously reported in [1], includes a calibration run and feedback run for EII and MI, i.e. 4 runs per session. In EII runs, participants recalled a real or imagined fictitious happy event and sad event for each class (left or right cue), happy. Happy and sad emotions were used as they are likely to be associated with hemispheric asymmetric activation [2] which may enhance separability between classes. For MI runs, participants imagine left hand movement and right hand movement. Each run had 60 trials, 30 for each class. Each participants participated in 3 to 5 sessions. In feedback runs, a continuous feedback was provided using a game in which the character moved along the horizontal axis to collect spikes falling on the left or right side on the screen. At the end of the session, the participant is asked, via a questionnaire, what their favourite control approach was and which imagery strategy was perceived to provide most control over the game character. The online single-trial CA for feedback runs averaged across sessions for each participant are reported in Figure 1(a). Most of the participants achieved acceptable performance (CA > 70%) with EII in at least one of their sessions, but this performance was not maintained in other sessions leading to overall low CA across sessions. Wilcoxon signed rank test showed that for MI CA averaged across sessions are significantly higher than EII CA ($p < 0.05$). The subjective responses showed that participants preferred MI to EII in 89.19% of the total sessions across participants, and MI was the approach with most perceived control in 87.84% of the total sessions. Each participant´s votes for favourite and approach with most perceived control are shown in Figure 1(b) and Figure 1(c), respectively. Discussion: The aim of this study was to investigate the comparable performance of EII and MI previously reported in single-session based studies [1] is maintained in multiple sessions with online feedback. The results show that performance with MI is significantly higher than EII. Additionally, participants prefer MI to EII as a BCI control approach, and this preference is likely influenced by difficulty experienced in executing EII tasks that involve accessing repeatedly same events in the memory in limited amount of time. This difficulty might be the reason why the one participant who maintained EII CA across sessions (ay) did not vote even once for EII as the favourite approach or approach with most perceived control over the feedback. Significance: The current multiple sessions study suggests that emotion-inducing imagery is not yet a viable alternative imagery to motor imagery for BCI control strategy for the majority of subjects. Further investigation is needed to identify effective EII tasks that might be easy to execute in a BCI paradigm. References [1] A. D. Bigirimana, N. Siddique, and D. Coyle, "Brain-Computer Interfacing with Emotion-Inducing Imagery: A Pilot Study," in 7th Graz Brain-Computer Interface Conference (GBCIC), 2017. [2] R. J. Davidson, P. Ekman, C. D. Saron, J. A. Senulis, and W. V Friesen, "Approachwithdrawal and cerebral asymmetry: emotional expression and brain physiology. I.," Journal of personality and social psychology, vol. 58, no. 2. pp. 330-341, 1990.

3-C-15 Brain Computer Interfaces for motor rehabilitation in hemiparetic children with perinatal stroke

Zeanna Jadavji[1], Jack Zhang[1], Ephrem Zewdie[2], Adam Kirton[2]

[1]University of Calgary, [2]Cumming School of Medicine, University of Calgary

Introduction: Perinatal stroke causes most hemiparetic cerebral palsy and lifelong disability for 10000 Canadian children. As a focal injury of defined timing in an otherwise healthy brain, perinatal stroke is an ideal model of human developmental plasticity. Improving models of such motor recovery are affording new therapeutic opportunities. We have recently completed multiple clinical trials demonstrating that non-invasive brain stimulation (rTMS, tDCS) can enhance motor learning and generate larger gains in hemiparetic children undergoing intensive motor rehabilitation. However, effect sizes are modest and such treatments may not be capable of reducing disability in the most severely affected children. Brain computer interfaces (BCI) are an emerging rehabilitation tool that could change this. Adult BCI research suggests improved motor function in stroke patients. Functional electrical stimulation (FES) has also been used to support motor recovery in hemiparesis and BCI-activated FES may enhance upper extremity function in adult stroke. How such performance is affected by the large brain lesions present in children with perinatal stroke has not been investigated. Materials, Methods and Results: We aimed to explore the ability of children with perinatal stroke to operate simple BCI systems. Objective: Determine if children with perinatal stroke can use a commercially available, simple BCI to complete multiple basic tasks. Hypothesis: BCI performance of children with perinatal stroke is comparable to adults and typically developing children. Participants were recruited through the Alberta Perinatal Stroke Project, a population based research cohort. Inclusion criteria were: (1) MRI-confirmed perinatal stroke, (2) hemiplegic cerebral palsy, (3) age 6-18 years old, and (4) informed consent/assent. Individuals with neurological comorbidities and/or unstable epilepsy were excluded. Typically developing controls of comparable age were recruited from an established community program. Participants used an EPOC Emotiv device over two sessions and utilized different strategies to move a computer cursor and remote controlled car to a designated target. Different strategies were employed to assess effectiveness of various imagery techniques. During motor imagery children were instructed to visualize the opening and closing of their hands while goal oriented visualization required the participant to imagine the car or cursor moving toward its target. The primary outcome was agreement between instructed and completed task using Cohen's Kappa with a score of 0.40 or greater suggesting BCI competence. Two-way repeated measures ANOVA explored effects of task and strategy on performance. Fifteen of an intended 26 participants with perinatal stroke have initiated the study. Complete data available for 8 children (75% male, mean age 12 years (SD=2.83), range 7-16) were analyzed here. The comparative sample of 26 children had a mean age of 13.2 (SD=3.6) years (range 6-18 years, 63% male). Average kappa score across all tasks and strategies for children with perinatal stroke was 0.40 (SD=0.28; range -.10-1.0) and not significantly different than healthy controls 0.46 (SD=0.21), p=0.353. A main effect of both task and strategy was observed. Participants achieved higher mean scores on car tasks (M=0.469, SE= 0.087) as compared to cursor tasks (M=0.356, SE=0.092), F(1,8)=6.831, p=0.035. These results were comparable to those observed in healthy controls. In contrast to typically developing children, participants with perinatal stroke had higher mean scores when using motor imagery (M=0.463, SE=0.91) as compared to the goal-oriented strategy (M=0.363, SE=0.87), F(1,8)=8.615, p=0.022. Discussion: We demonstrated that typically developing school-aged children can learn to control a simple BCI system with similar competency to adults. Our findings suggest that children with perinatal stroke can achieve proficiency in basic tasks using simple BCI systems. Future directions include comparisons to more advanced BCI systems and extrapolation to FES paired BCI rehab systems for hemiparetic children. Significance: This study addresses the general absence of BCI research in the developing brain. Additionally, lack of effective rehabilitation options is most impactful for children with severe motor deficits. This study explores BCI and its potential as a rehabilitation tool for disabled children.

3-C-16 A new region-based SSVEP BCI speller

Bijay Guragain, Ali Haider[1], Reza Fazel-Rezai[1]

[1]University of North Dakota

A New Region-based SSVEP BCI Speller Bijay Guragain*, Ali Haider, Reza Fazel-Rezai *E-mail: bijay.guragain@und.edu Introduction: In this paper, a region-based paradigm for spelling 49 characters/symbols is introduced based on steady state visual evoked potentials (SSVEP) extracted from electroencephalogram (EEG) signals. This paradigm is the extension of previous work done [1] and uses only seven frequencies implemented on computer screen by flashing small circles. Materials, Methods and Results: A seven region-based SSVEP BCI speller with two levels [2] was designed using MATLAB [3] and displayed on a computer monitor. The computer screen contains seven regions with seven characters in each region. Earlier, row-column, single character, and two region based paradigms, one with characters in alphabetical order and other with frequency of use were compared, and accuracy and the user acceptability was highest in the region based paradigm with characters grouped as per frequency of usage [4]. In this study, a region based two levels SSVEP paradigm was proposed in which circular bubble flickers at a fixed frequency in each region to elicit SSVEP. At first level, a region containing target character was chosen and the particular region was highlighted, then the target character was selected at the second level. Both levels are depicted in figure 1. All seven regions flickered at respective frequencies 15, 18, 13, 16, 17, 14 and 20 Hz. Canonical correlation analysis (CCA) was used to find the maximum correlation of EEG signals with the seven reference sine-cosine signals, and the target region (1st level) then the character (2nd level) was selected. The paradigm was tested on 7 subjects with mean age 25±5 years who voluntarily participated after signing informed consent. They were instructed to spell A, S, B, 2, 6, /, and $ characters from each region. The selected characters were chosen in a manner so that each region was weighted with equal preference. The objective of this study was to see how comfortable the subjects are with this new paradigm. The accuracy ranged from 14 to 70%. Although all the subjects stated that they were comfortable with this SSVEP paradigm, interestingly, subjects with a low SSVEP accuracy simply justified that some subjects might be SSVEP illiterate [5]. (a) 1st level, 2nd region enlarged (b) 1st level with all 7 regions (c) 2nd level to spell character 'S' Figure 1. Region based SSVEP paradigm Discussion: Visual speller of 49 characters with just seven flickering frequencies was used in this paradigm and the future goal will be towards enhancing the performance using time and phase locking of EEG with the reference signals as well as combining with P300 to form an efficient hybrid BCI model for real time applications. References: [1] M. A. Haider, B. Cosatto, N. Alam, K. Tavakolian, and R. Fazel-Rezai, "A New Region-based BCI Speller Design using Steady State Visual Evoked Potentials," in Proceedings of the 6th International Brain-Computer Interface Meeting, organized by the BCI Society, 2016, p. 1. [2] R. Fazel-Rezai and K. Abhari, "A region-based P300 speller for brain-computer interface," Can. J. Electr. Comput. Eng., vol. 34, no. 3, pp. 81-85, 2009. [3] "MathWorks - Makers of MATLAB and Simulink." [Online]. Available: https://www.mathworks.com/. [4] R. Fazel-Rezai, S. Gavett, W. Ahmad, A. Rabbi, and E. Schneider, "A Comparison among Several P300 Brain-Computer Interface Speller Paradigms," Clin. EEG Neurosci., vol. 42, no. 4, pp. 209-213, Oct. 2011. [5] B. Allison, T. Luth, D. Valbuena, A. Teymourian, I. Volosyak, and A. Graser, "BCI Demographics: How Many (and What Kinds of) People Can Use an SSVEP BCI?," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 18, no. 2, pp. 107-116, Apr. 2010.

3-C-17 Data-driven adaptive stimulus selection for the P300 speller

Dmitry Kalika[1], Leslie Collins[1], Boyla Mainsah[1], Chandra Throckmorton[1]

[1]*Duke University*

Introduction: Most stimulus presentation paradigms for the P300 speller use pseudo-randomly generated stimulus presentation schedules [e.g., 1], or do not adapt the stimulus selection process based on current data [e.g., 2]. In this work, we extend a previous predictive framework to optimize the P300 speller stimulus presentation schedules [3] by developing a novel data-driven stimulus selection algorithm that relies on previous user responses as feedback to inform the selection process of future stimuli. We present preliminary results to demonstrate the utility of our proposed data-driven stimulus selection method with online BCI use. Material, Methods and Results: Our goal is to select flash groups that facilitate identification of the user's intended target character given the user responses to previous flash group presentations. We use the sampling strategy developed in [3] to select a future flash group that maximizes the amount of information gained with a hypothetical future user response, conditioned on the previous user responses: the amount of information is quantified using the expected discrimination gain (EDG) metric. With the Bayesian algorithm developed in [4], the EDG can be precomputed as a function of the sum of the probabilities of characters in a presented flash group and the classifier likelihood PDFs that are estimated during the BCI calibration phase [5]. Precomputing the EDG function allows for a time-efficient greedy search over all possible flash group choices, which provides the flexibility to select variably-sized flash groups to maximize the EDG metric. For real-time BCI use, design constraints were considered to account for system computational limitations as well as to mitigate potential psycho-physiological factors during the stimulus selection process. Our proposed stimulus presentation paradigm is termed the "greedy EDG adaptive" paradigm. An online study with non-disabled participants performing copy-spelling tasks was conducted to compare the greedy EDG adaptive and CB paradigms. The accuracy and expected stopping time (EST) results are shown in Fig 1. On average, the accuracy decreased by 5%, the EST decreased by 36% and the bit-rate increased by 9.2% for the greedy EDG adaptive paradigm compared to the CB paradigm. Discussion: We have demonstrated the feasibility of using previous user responses as feedback to adaptively design variably-sized flash groups in real-time for the P300 speller to improve BCI performance. Anecdotes from post-BCI use surveys revealed repetitive presentation of adjacent characters around the target character occurred in the data-driven paradigm, which was distracting to most users while they focused on the target character. Nonetheless, these results provide initial evidence of the potential of our closed-loop stimulus selection method. Future algorithm refinements for the greedy EDG adaptive paradigm include incorporating additional design constraints during stimulus selection to better mitigate adjacency distraction errors, as well as other unpredictable changes in user behavior during BCI use. Significance: While this work focuses on a P300 speller, the proposed data-driven stimulus selection could be applicable to any probabilistic-based BCI that executes a number of possible action queries prior to decision-making. References [1] G. Townsend, B. K. LaPallo, C. B. Boulay, D. J. Krusienski, G. E. Frye, C. K. Hauser, et al., "A novel P300-based brain-computer interface stimulus presentation paradigm: moving beyond rows and columns," Clin. Neuro., vol. 121, pp. 1109-20, 2010. [2] B. O. Mainsah, G. Reeves, L. M. Collins, and C. S. Throckmorton, "Optimizing the stimulus presentation paradigm design for the P300-based brain-computer interface using performance prediction," J Neural Eng, vol. 14, p. 046025, 2017. [3] K. Kastella, "Discrimination gain to optimize detection and classification," IEEE Trans on Sys Man and Cyber Part A-Sys and Humans, vol. 27, pp. 112-116, 1997. [4] C. S. Throckmorton, K. A. Colwell, D. B. Ryan, E. W. Sellers, and L. M. Collins, "Bayesian approach to dynamically controlling data collection in P300 spellers," IEEE Trans Neural Sys Rehabil Eng, vol. 21, pp. 508-17, 2013. [5] D. Kalika, L. M. Collins, C. S. Throckmorton, and B. O. Mainsah, "Adaptive stimulus selection in ERP-based brain-computer interfaces by maximizing expected discrimination gain," in IEEE International Conf on Sys, Man, and Cyber 2017, pp. 1405-10.

3-C-18 Command following assessment and communication with vibro-tactile P300 and motor imagery BCIs in patients with disorders of consciousness and (complete) locked-in syndrome

Christoph Guger[1], Rossella Spataro[2], Frederic Pellas[3], Rupert Ortner[4], Woosang Cho[4], Ren Xu[5], Begonya Otal[6], Vincenzo La Bella[2], Krzysztof Malej[7], Alexander Heilinger[4], Günter Edlinger[8]

[1]g.tec medical engineering GmbH, Guger Technologies OG, [2]ALS Clinical Research Center, BioNeC, University of Palermo, [3]Post-ICU Neurorehabilitation Unit - University Hospital of Nîlmes, [4]g.tec medical engineering GmbH, [5]Guger Technologies OG, [6]g.tec medic

Many patients with disorders of consciousness (DOC), locked-in syndrome (LIS) or complete locked-in syndrome (CLIS) also need brain-computer interface (BCI) platforms that do not rely on visual stimuli and are easy to use [1]. DOC patients are in the unresponsive wakefulness state (UWS) or minimal consciousness state (MCS). We investigate command following and communication functions using BCI paradigms with 9 LIS, 3 CLIS, 13 UWS patients and three healthy controls. These tests were done with vibro-tactile stimulation with 2 or 3 stimulators (VT2 and VT3 mode) and with motor imagery (MI) paradigms. In VT2 the stimulators are fixed on the left and right wrist and the participant has the task to count the stimuli on the target hand in order to elicit a P300 response. In VT3 mode an additional stimulator is placed as a distractor on the shoulder and the participant is counting stimuli either on the right or left hand. In motor imagery mode the participant is instructed to imagine left or right hand movement. VT3 and MI also allow the participant to answer yes and no questions. Healthy controls achieved a mean assessment accuracy of 94% in VT2, 88% in VT3, and 73% in MI modes. They were able to communicate with VT3 (86.7%) and MI (83.3%) after 2 training runs. The LIS/CLIS patients achieved a mean accuracy of 76.6% in VT2, 63.1% in VT3, and 58.2% in MI modes after 1-2 training runs. 9 out of 12 LIS patients could communicate by using the vibro-tactile P300 paradigms (answered on average 8 out of 10 questions correctly) and 3 out of 12 could communicate with the motor imagery paradigm (answered correctly 4,7 out of 5 questions). 2 out of the 3 CLIS patients could use the system to communicate with VT3 (90 and 70% accuracy). The UWS patients achieved a mean accuracy of 53.8% in VT2 and 31.2% in VT3. MI was not tested in these UWS patients. 3 out of 13 UWS patients could establish communication with the VT3 paradigm and achieved a mean accuracy of 75% within 1-4 training runs. Table I further subdivides these results into UWS patients that communicated and UWS patients that did not communicate and a clear difference in VT2 and VT3 accuracies can be noted. Table I. BCI assessment accuracy and communication accuracy for different patients and healthy controls. Table I also shows that best results are obviously achieved with healthy controls. Interestingly LIS and CLIS patients that communicated show almost the same results as healthy controls. LIS and CLIS patients are clearly worse, but better than UWS patients that could not communicate. The results show that paradigms based on non-visual evoked potentials can be effective for these users. MI paradigms are effective for less users than the VT2 and VT3 ones. The study is important because it showed that a majority of LIS patients can use a BCI system for communication and it also proved that it is effective in CLIS and UWS patients. Further testing is of course necessary to study stability and long-term effects. Reference Guger, C., Spataro, R., Allison, B. Z., Heilinger, A., Ortner, R., Cho, W., & La Bella, V. (2017). Complete Locked-in and Locked-in patients: Command following assessment and communication with vibro-tactile P300 and motor imagery brain-computer interface tools. Frontiers in Neuroscience, 11, 251.

D- BCI Non-Invasive- Other

3-D-19 How to train ErrP-based BMIs: A speller application

Iñaki Iturrate[1], Ricardo Chavarriaga[2], Alessia Colucciello[2], José del Millán[1]

[1]Ecole Polytechnique Fédérale de Lausanne (EPFL), [2]EPFL

Introduction: Error-related potentials (ErrPs), signals generated during an erroneous interaction with machines, have recently received much interest in the field of brain-machine interfacing (BMI). Nonetheless, closed-loop applications using these signals are still scarce. Practical applications require means to efficiently calibrate a decoder that yields high, stable performance. However, ErrP classifier accuracy may affected by two limiting issues: (i) the amount of errors during closed-loop interaction may vary, and thus characteristics of the signals will also vary accordingly; and (ii) ErrPs carry cognitive information and are not solely a bottom-up process and thus modulated by human factors. We show that traditional training paradigms, including offline recordings without feedback concomitant to subject state, are suboptimal and propose a new training paradigm for ErrPs decoders that allows a reliable detection of these signals. This is demonstrated in a closed-loop ErrP-based spelling device (Fig. 1a). Material, Methods and Results: EEG was recorded using 16 active electrodes on healthy subjects (N=7).

During the task, a cursor performed discrete movements within a 6x5 letters array, with the objective of reaching one pre-defined target position (i.e. letter). Meanwhile, subjects had to evaluate the movements of the cursor as correct or incorrect, generating neural activity elicited from both conditions (Fig. 1a). These ErrP signals were filtered within [1-10] Hz and decoded using a weighted combination of spatio-temporal features using linear-discriminant analysis. We hypothesized that ErrPs can also be modulated with user's training, similarly to spontaneous signals such as motor imagery. To prove this concept, we designed an experimental protocol where subjects performed four offline and five online closed-loop runs. During the offline runs (100 actions each), the device was moving with a fixed percentage of errors, 20%. During the online runs (125 actions each), the cursor movements to the desired letter were ruled by a reinforcement learning algorithm that used ErrPs decoding as reward. Thus, these movements provide feedback to the user about the quality of the decoding. For the first online run, we trained a classifier with all the offline data. Data from the first online run was combined with the offline runs to train another classifier that was fixed for the remaining online runs. We evaluated different classifiers built a posteriori from the data recorded, using as testing sets the last two recorded online runs. Fig. 1b reports the classification accuracies obtained when training a classifier using incrementally 1 to 4 offline runs (first four points), and then adding 1-3 online runs to the classifier (last 3 points). As expected, as the training data increases during the offline runs so does the accuracy, yet not significantly ($p>0.05$, paired t-test FDR corrected). However, adding data from a single online run (Off1-4+On1) significantly increased the average accuracies (from 69.53% to 75.36%, $p=0.03$). Whereas the addition of more offline runs led to a quasi-linear increase, the inclusion of one online run yielded an exponential increase in performance. Importantly, despite a slight decrease in the accuracy for the correct class, overall performance increase is largely due to a statistically significant improvement in the accuracy for the error class (from 61.17% to 74.38%, $p=0.03$), as shown in Fig. 1c. Discussion: These analyses suggest that the addition of online runs to the training data--reflecting the actual behavior of the closed-loop BMI system--helped in two ways: first, it boosted the overall performance by an increase in accuracy on the error class; and second, it unbiased the classifier, as decoding became similar for both classes. Importantly, this effect was seen for all the subjects. We believe that, by using online runs, subjects get better acquainted to the task helping them to perform the targeted cognitive process. Conversely, this allows the decoder to have a more reliable sampling of the corresponding neural correlates. Significance: Error-related potentials are still in their infancy for online BMI applications. In this work, we have shown the effect that a training paradigm for ErrPs can have in boosting single-trial recognition. We believe that any BMI relying on these signals will directly benefit from the proposed training approach.

3-D-20 EEG correlates of decision confidence in feedback processing

Tanja Krumpe[1], Peter Gerjets[2], Wolfgang Rosenstiel[3], Martin Spüler[3]

[1]University of Tuebingen, [2]Leibniz-Institut für Wissensmedien, [3]University of Tübingen

Introduction: Making decisions is part of daily life. What kind of decisions we make is often based on the level of confidence we have, or in other words how sure we are about the facts related to the decision. But investigation of decision confidence is difficult, as level of confidence influences the speed with which decisions are made, the outcome of future decision, the likelihood of making errors and thereby results can easily be confounded. A plain evaluation of different levels of confidence during judgement of knowing decisions was the focus of the here presented study. The main question was to investigate if differences in the neural correlates related to feedback processing can be found based on the level of confidence with which the decision was made. Material, Methods and Results: The study at hand is based on a study originally performed by Woodman and Fukuda[1]. A series of pictures is presented in a study phase and in a test phase. The subjects were asked to memorize as many pictures as possible in the study phase and to decide if a picture has already been seen or is entirely new in the test phase. A series of 750 pictures was presented in the test phase from which all 500 pictures from the study phase were presented again and 250 new ones, in a completely randomized order. In addition to categorizing the picture as new or already known a level of confidence needs to be specified with which the answer is given (100% or 75%). After entering the answer, the subject received a categorical feedback stating if the answer was correct or wrong. EEG data of 10 healthy subjects was recorded with a 32 electrode Brainproducts Acticap system. Classical ERP analysis was performed and a SVM based classification approach was used to reveal differences in the EEG signals between the levels of confidence throughout the feedback phase of the experiment. A Wilcoxon ranksum test (Bonferroni corrected) was used to reveal statistical significant differences. For classification the CCA filtered data of 21 channels was used (*3, *z, *4 positions) and a 1.25 s time frame throughout a 10-fold cross-validation. The subjects categorized 64% of all pictures correctly as new or already known. 44% of the correct answers were given with 100% confidence, 19% of the answers with a confidence of 75%. For the wrong answers the distribution was 16% and 20% (for the levels 100 and 75% respectively). Figure 1 shows the ERPs during the feedback phase at electrode position Cz (D) and Pz (D) of the two levels of confidence. It can be seen, that several areas within the 1.25 s time frame differ significantly between the two levels of confidence ($p < 0.05$). Classification revealed that a distinction of the confidence level based on the ERPs is possible with an accuracy of 69.63%. Figure 1. A shows the stimulus timing in the study phase and B stimulus timing in the test phase of the experiment. The blue circle indicates that the buttons on the left side should be used to answer if the picture is known. The yellow circle indicates that the buttons on the right should be used to answer if the picture is new. Figure 1 C shows the ERP for electrode position Cz during feedback presentation and Figure 1 D the same for position Pz. Discussion: The two levels of confidence can be distinguished based on ERPs during feedback presentation. The self-assessment of the current progress in learning is an important marker for deciding when a specific content has been learned sufficiently well. Being able to extract and identify content that is not entirely secured in memory could be beneficial for the process of learning. Content which cannot be recapitulated with a high confidence could be repeated until the subject reaches a higher confidence during answering the question related to the content. This would be a useful extension to error adaptive learning systems,that would only represent the content that has not been learned at all. Significance: Differences in neural correlates during feedback processing can be found based on the level of confidence with which the answer was given, independent of the correctness of the answer. References: [1] K. Fukuda and G. F. Woodman. Predicting and improving recognition memory using multiple electrophysiological signals in real time. Psychological Science, 2015.

3-D-21 Similarity representation analysis of human grasps in EMG, kinematics and EEG signals

Andreea Sburlea[1], Gernot Müller-Putz[1]

[1]Graz University of Technology

<p>Introduction: The human hand can perform a wide variety of movements. Goal-directed daily interactions involving the human hand, such as grasping a cup of coffee, require coordinated movement of the fingers. Any movement can be accomplished by combining neural and behavioral mechanisms. More specifically, the generation of grasping movements requires the involvement of several cortical and subcortical structures, and different combinations of muscle contractions and joint positions [1, 2]. In this study we explore the similarity between neural and behavioral representations of a broad dictionary of grasps. We address three questions at the group level: (1) Can EEG capture the differences in patterns between multiple types of grasps?, (2) Which behavioral model best explains the representation of grasps at the neural level?, (3) To what extent do representations among brain regions and behavioral models resemble each other? </p> <p>Material, Methods and Results: To address these questions we recorded noninvasively neural data (64 EEG channels) and behavioral data (8 EMG channels, and kinematics of 19 joint-angles) in 31 healthy subjects, with no neurological or motor disorders. Subjects were instructed to perform 33 different grasping movements in blocks of 8 repetitions, using their right hand. We used time-frequency representation (TFR) to compute neural activity patterns from EEG. For the behavioral patterns we used the EMG envelope of the recorded channels and the first 5 principal components (PCs) of the joint angles (>95% explained variance). We also implemented computational models based on grasp type, object shape, and thumb position. We conducted an exploratory analysis at the neural level, by implementing a searchlight in the multidimensional space spanned by sensors, frequency bins and time points. For the analysis we used Representational Similarity Analysis (RSA) [3] which is a multivariate pattern analysis method that compares representational dissimilarity matrices (RDMs) computed from the patterns of activity recorded by different modalities (neural, behavioral, and computational).</p> <p>Our findings show that at the population level, the representation of grasps given by the muscular patterns has a moderate correlation ($r = 0.32$, SEM = 0.01) with their neural representation in the mu band in the contralateral side (left) in the centro-parietal and parietal regions. We also observed a slightly lower correlation ($r = 0.2$, SEM = 0.008) between a computational model describing the shape of the grasped object and the neural representation of the grasps at the start of the movement. The latter finding emphasizes the relevance of the object's properties in the pre-shaping phase of grasping.</p> <p>Discussion: It is a longstanding question how the human hand can attain a variety of postural configurations required to perform all the complex tasks that we encounter in the activities of daily living. In this study by combining EMG, kinematics and activity measures using EEG, we show that the left centro-parietal and parietal regions of the brain have the most similar activity patterns with the ones underlining muscular representation of grasps. Furthermore, the shape of the grasped object is encoded in the brain patterns and it allows separating between grasps.</p> <p>Significance: In this study we conducted an exploratory analysis of the similarity in terms of distances between EEG neural activity patterns and behavioral patterns. We found the involvement of centro-parietal and parietal sides of the cortex. Moreover, from the proposed computational models the shape of the grasped object predicted the best the neural patterns of the grasps. We also found that the muscular patterns explain better the grasp patterns at the neural level than kinematic synergies.</p> <p>Acknowledgements: This work has been supported by the ERC Consolidator Grant ERC-681231, Feel Your Reach.</p> <p>References:</p> <p>1. Castiello, U. (2005). The neuroscience of grasping. Nature Reviews Neuroscience, 6(9), 726-736.</p>

<p>2. Grafton, S. T. (2010). The cognitive neuroscience of prehension: recent developments. Experimental brain research, 204(4), 475-491.</p> <p>3. Kriegeskorte, N., Mur, M., & Bandettini, P. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. Frontiers in systems neuroscience, 2.</p>

3-D-22 BciPy: A Python framework for Brain- Computer Interface research

Tab Memmott[1], Aziz Kocanaogullari[2], Deniz Erdogmus[2], Steven Bedrick[1], Betts Peters[3], Melanie Fried-Oken[4], Barry Oken[1]

[1]Oregon Health & Science University, [2]Northeastern University, [3]Institute on Development and Disabilities, Oregon Health & Science University, [4]Institute on Development and Disabilities, Oregon Health and Science University

Introduction: Interest in BCI has increased in recent years with productive collaboration across fields such as engineering, neuroscience, allied health, and computer science. Laboratories interested in exploring BCI must either construct a working system from scratch or use an off-the-shelf option. Technology that is able to solve the architectural and ease of access barriers to the BCI field will be essential in maintaining momentum and opening the field to even more diverse expertise. Here we review popular software suites for BCI research and propose a new system, BciPy, to address existing gaps. Material, Methods and Results: There are BCI frameworks currently available, most notably the widely used BCI2000 and OpenViBE. These systems save time to set up or modify BCI experiments. They are free for research, generally written in lower level programming languages (C++) and have been used by many laboratories. However, many in the BCI field do not have training in lower level programming languages, if any at all. These libraries also lack some desirable BCI features, such as easily usable data formats, graphical user interface (GUI), and modularity to support new research questions. Modularity and usability of the code for future scientists is critical in a development environment. Code should be written in a language that is easily understood and widely used for programming tasks across disciplines. Python should be considered, as it's becoming the dominant language in many scientific fields and is increasing in usage yearly [1]. In this abstract, we present a modular, Python-based BCI framework, BciPy (See Figure 1 for a closed-loop view of framework). This software 1) utilizes a higher-level programming language without comprising timing; 2) outputs session data into immediately usable formats (.txt, .json, .csv, .pdf), with helper functions and full documentation; 3) allows for closed-loop BCI control, with usage of modules outside of the loop; 4) is free; 5) works on major OS; 6) is architecturally modular; 7) contains test and demo scripts; and 8) has few outside dependencies. The suite uses well-known Python packages, such as SciPy [2] and Psychopy [3]. These are well maintained and include functionality of interest for future software iterations. The initial version is pre-packaged with an RSVPKeyboardTM paradigm [4] for BCI communication, data acquisition (for use with Wearable Sensing and Lab Streaming Layer supported devices), EEG signal and language modeling, display, and GUI with parameter editing. The data types exported will allow users to manipulate and understand their data without conversion and is conveniently uploadable into major EEG processing softwares (ex. EEGLAB). The code is approved for open source. V1.0 will be available to all in late Spring 2018. It is also freely available, with any published features, via request to the authors. Discussion: There are still many

features and enhancements to be added the initial BciPy release to facilitate future BCI research. The code will go through 6-month development cycles. Contributions from the public will be encouraged and authorship granted to code integrated. Future developments are set to include additional user inputs (eye gaze, switches), enhancements to data acquisition, new language models and signal classifiers, and user interface enhancements. Significance: A Python-based BCI framework will significantly reduce the barriers to contribute to the field and encourage participation from across disciplines.
Acknowledgements: Dani Smektala for GUI work; Berkan Kadioglu, Andac Demir, Paula Gonzalez-Navarro for signal processing and classification work; Shiran Dudy and Shaobin Xu for language model integration; Matthew Lawhead for DAQ work; Brandon Eddy and David Smith for design contributions. Support provided by NIH (2R01DC009834) and NIDILRR (90RE5017). References: [1] Robinson, David. (September 14, 2017). Why Is Python Growing So Quickly? https://stackoverflow.blog/2017/09/14/python-growing-quickly/ [2] Jones E, Oliphant E, Peterson P, et al. SciPy: Open Source Scientific Tools for Python, 2001-, http://www.scipy.org/. [3] doi:10.1016/j.jneumeth.2006.11.017. [4] doi:10.1109/ICASSP.2012.6287966.

3-D-23 Decoding differences in continuously executed and observed tracking movements from EEG signals

Reinmar Kobler[1], Andreea Sburlea[1], Gernot Müller-Putz[1]

[1]*Graz University of Technology*

<p>Introduction: Closed-loop control of an end-effector requires continuous feedback processing, state estimation and motor plan updates. We studied these processes in a 2D tracking task by decoding target and end-effector kinematics from slow cortical potentials (SCPs). We hypothesize that SCPs carry more information about end-effector kinematics if a subject is actually controlling it rather than merely observing it. We present results of position and velocity decoders in 15 healthy subjects.</p>
<p>Material, Methods and Results: The paradigm, depicted in Figure 1A, implements a pursuit tracking task (PTT). In the execution condition subjects had to minimize the distance between target and cursor (Figure 1B), while in the observation condition the computer replayed a cursor trajectory. The target trajectories were generated offline and identical for each subject. We ensured uncorrelated signals (Figure 1C).
We recorded Electroencephalography (EEG) and Electrooculography (EOG) (64 + 6 channels) during 180 trials. Offline EEG preprocessing is summarized in Figure 1D. Eye artifacts were attenuated with an artifact subspace subtraction algorithm [1]. We then applied Robust Principal Component Analysis (Robust PCA) [2] to attenuate electrode pops and low frequency drifts. A subsequent low pass filter extracted SCPs. Similar to [3], a partial least squares (PLS) regression model was applied to decode movement parameters. The model was evaluated per condition using 10x5 fold cross-validation (CV).
We did not observe significant differences in the correlation of the target and cursor stimuli between the two conditions. Regarding eye movements, we observed significant differences of the correlation between target position and the associated EOG derivative. On the horizontal axis, the correlation was slightly lower in the execution condition (EXE=0.88, OBS=0.90, p=0.0054), whereas on the vertical axis it was higher (EXE=0.79, OBS=0.70, p=0.0015).
Figure 1E summarizes decoder correlations. Estimated densities indicate that the group level averages lie in the

range 0.25 to 0.4. In Figure 1D paired differences show the effect of the condition on decoding performance. We observed a significant positive effect (EXE > OBS) on decoding the horizontal cursor velocity and all variables on the vertical axis except the target velocity. Figure 1G indicates that cursor velocities correlated more with fronto-central, primary sensorimotor and parietal areas in the execution condition.</p>Discussion: In the PTT the target and cursor were strongly correlated (Figure 1B). That is, their decoders exhibit similar effects (Figures 1F). On the horizontal axis, a significant positive effect was observed for the instantaneous cursor velocity, while no effect was detected for the position signals. We can rule out that the effect was caused by residual eye artifacts, since they were correlated slightly stronger with the target in the observation condition. Also, the group level decoder patterns in Figure 1G indicate cortical origins.
On the vertical axis we could observe a positive effect on all decoded variables, alongside a larger correlation between target position and vertical EOG derivative. The findings suggest a stronger engagement in tracking this axis in the execution condition. The decoder patterns in Figure 1G also indicate that the effect on instantaneous cursor velocity decoding is of cortical origin.</p><p>Significance: We found that execution of tracking movements in contrast to mere observation has distinct effects on decoding end-effector kinematics. By comparing decoder performance between conditions, we could show that in the execution condition the SCPs encode significantly more information about end-effector instantaneous velocity</p><p>Acknowledgements: This work has been supported by the ERC Consolidator Grant 681231 "Feel Your Reach".</p><p>References:
[1] Candès, E. et al. (2011). Robust principal component analysis? Journal of the ACM, 58(3), 1-37.
[2] Kobler, R. J. et al. (2017). A Comparison of Ocular Artifact Removal Methods for Block Design Based Electroencephalography Experiments. In Proceedings of the 7th Graz Brain-Computer Interface Conference 2017 (pp. 236-241).
[3] Ofner, P. et al. (2015). Using a noninvasive decoding method to classify rhythmic movement imaginations of the arm in two planes. IEEE Trans. on Bio-Medical Eng., 62(3), 972-981.

3-D-24 Within and across subject analysis for hybrid brain Computer Interfaces based on electroencephalography and functional transcranial doppler ultrasound

Ervin Sejdic[1], Aya Khalaf[1], Murat Akcakaya[1]

[1]*University of Pittsburgh*

Introduction: Recently, hybrid brain computer interfaces (BCIs) have been introduced to overcome limitations of BCIs employing single modality for measuring brain activity. In literature, many studies investigated the feasibility of using fNIRS as a second modality beside the EEG to boost the performance of motor imagery BCIs. However, fNIRS has a slow response time and is difficult to setup. To avoid complications associated with fNIRS, we introduce functional transcranial Doppler (fTCD) ultrasound as a substitute for fNIRS to be simultaneously recorded with EEG for motor imagery BCI [1]. fTCD has a faster response time compared to fNIRS. In addition, it is easier to setup and requires less number of sensors. Materials, Methods and Results: A basic motor imagery task is visualized for each participant, and data was collected from six participants. The screen shows 3 static components including: two horizontal arrows; one pointing to the right and one pointing to the left as well as a fixation cross that resembles the resting state as seen in Fig.1. During each trial, a vertical arrow points randomly to one of the 3 components for duration of 10 seconds and the user has to imagine moving either left or right arm depending on the direction of the horizontal arrow specified by the vertical arrow. A total of 150 trials are presented in each session. EEG and fTCD signals were simultaneously recorded during the visual presentation. EEG was collected using 16 electrodes placed according to the 10-10 system over frontal, central, parietal, and occipital lobes. fTCD assesses the cerebral blood velocity using two ultrasound sensors placed on the left-side and right-side transtemporal window located above the zygomatic arch. EEG data as well as fTCD data corresponding to each task were segmented. The features corresponding to each segment included the raw power spectrum for that segment. The number of features obtained from each power spectrum was reduced by considering the average power over each consecutive 2 Hz/ 50 Hz for the EEG/ fTCD data as features. For each observation, the feature vector was formed by concatenating the reduced power spectrums corresponding to the 16 EEG segments and the 2 fTCD segments. Mutual information and support vector machines were used for feature selection and classification respectively. A classification problem to recognize left versus right arm motor imagery was formulated. For each participant, a within-subject problem was solved using leave-one-out cross validation. In addition, to test the generalization of the system, the same classification problem was solved across all the participants. Since feature values are expected to vary from person to person, feature values were normalized within each participant. For each participant, average values of baseline features were subtracted from feature values corresponding to left and right arm tasks. Then, the resultant values were normalized to be within the range from 0 to 1. For the within-subject problem, right versus left motor imagery classification achieved 81.91%, 82.96%, and 81.13% average accuracy, right arm sensitivity, and left arm sensitivity using EEG-fTCD combination within 3.5 s from the task onset while EEG data only obtained 78.01%, 80.13%, and 76.10% respectively. Moreover, fTCD only achieved low average accuracy of 50.24%. The EEG-fTCD combination is significant since it scored higher accuracy for all the participants compared to accuracy obtained using EEG only. On the other hand, solving the classification problem across subjects yielded average accuracy, right arm sensitivity, and left arm sensitivity of 75.40%, 77.72%, and 72.68% for the combination while EEG only obtained 65.08%, 62.35%, 67.86% respectively. Discussion: EEG-fTCD combination was proved to be significant compared to EEG only, since, in within-subject problem, the combination boosted the performance by 2.90% on average. Moreover, in across-subject problem, the EEG-fTCD combination outperformed EEG only by 10.32%. Significance: The proposed hybrid system is a viable candidate for developing real-time BCI applications. Acknowledgement: Our work is supported by NSF IIS-1717654. References: [1] A. Khalaf and et al "A Novel Motor Imagery Hybrid Brain Computer Interface using EEG and Functional Transcranial Doppler Ultrasound," IEEE Trans. Neural Syst. Rehabil. Eng. Under Rev. Under Rev., 2017.

3-D-25 Effect of query length and prospect symbol confidence in EEG-based typing systems

Paula Gonzalez -Navarro[1], Aziz Kocanaogullari[1], Berkan kadioglu[1], Murat Akcakaya[2], Melanie Fried-Oken[3], Deniz Erdogmus[1]

[1]Northeastern University, [2]University of Pittsburgh, [3]Institute on Development and Disabilities, Oregon Health and Science University

Introduction:Improving human-machine communication is a main goal in the area of brain computer interfaces (BCIs). Different brain responses have been utilized towards building typing applications. Event Related Potentials (ERPs) and more specifically P300 responses have been used for intent detection in BCI typing systems. In addition, feedback related potentials, a form of error-related potentials (ErrP) have also been successfully utilized. While some methods have shown positive results, still the accuracy and robustness are big concerns for deploying these systems in real scenarios. In this work, we investigate the use of two types of stimuli for BCI typing systems: rapid serial visual presentation (RSVP) sequences (i.e., rapid visual presentation of the most probable symbols according to the current posterior probability) and prospect symbols (i.e., the top candidate in the alphabet according to the current posterior probability), which generate two different brain responses, ERP and ErrP respectively. We show that the decision of which stimuli is shown and the length of the sequence (Nrsvp) play a key role for the typing performance (speed and accuracy). Using recorded EEG data from 12 healthy participants on RSVP KeyboardTM, we assess the typing performance when varying the RSVP sequence length and the confidence level that determines when the prospect symbol is displayed. The results show that the best typing performance is obtained when we reduce the query length to 12 symbols and use a confidence level of 0.7 to display the prospect symbol. Material:We use RSVP KeyboardTM [1] (a non-invasive BCI spelling system), with EEG data acquired using a g.USBAmp with 16 g.Butterfly electrodes (g.Tec, Graz, Austria), and a simulation framework developed in Matlab. Methods:RSVP KeyboardTM is a speller that employs RSVP sequences and a Bayesian Maximum-A-Posteriori (MAP) inference engine based on event related potentials (ERP) fused with a 6-gram language model to detect user intent [1]. In addition, it uses feedback related potentials, a form of error-related potentials (ErrP), in a Bayesian fashion. In our approach, we display a prospect symbol when the system reaches a given confidence level. Our goal is to maximize the typing speed and accuracy by choosing the most effective sequence length and confidence level. To analyze the effect of these parameters, we employ the simulation mode of the RSVP KeyboardTM. Using Monte Carlo simulations, we evaluate alternative configurations and measure the performance for each case. Results:Results of 40 Monte Carlo simulations of a copy-phrase task with 10 predetermined sentences for which the language model contribution ranges from friendly (correct letters are more likely than competitor letters) to adversarial (competitor letters are the more likely ones) are performed using the EEG data obtained from twelve healthy participants. The results, summarized in Figure1, demonstrate that when we reduce the query length to Nrsvp =12 and use a confidence level of 0.7 to display the prospect symbol, we get the the best trade-off between typing speed and accuracy. Discussion: We note that that the decision of which stimuli is used at each moment and the length of the sequence (Nrsvp) play a key role for the performance (speed and accuracy) of BCI typing systems. The scheme proposed in this paper improves previous approaches by combining these two types of stimuli and makes a step towards deploying these systems in real scenarios. Significance:Results show that choosing an effective sequence length and confidence level on a Bayesian fusion of ERP/Errp/LM improves human-machine communication in terms of speed and accuracy for deploying EEG-based typing systems in real scenarios.

Acknowledgements:This work is supported by NSF IIS-1149570, IIS-1118061, CNS-1136027, CNS-1544895, IIS-1717654, SMA-0835976; NIDLRR 90RE5017-02-01 and by NIH 5R01DC009834. References:

[1] Moghadamfalahi, M., et al. Language-model assisted BCI for typing: a comparison of matrix and RSVP. IEEE TNSRE, 2015.

3-D-26 Longitudinal BCI data acquisition using a tile-matching game

Joe Rexwinkle[1], Gregory Lieberman[1], Matthew Jaswa[2], Derek Netto[3], Paul DeGuzman[3], Brent Lance[1]

[1]U.S. Army Research Laboratory, [2]DCS Corp, [3]Neuromatters LLC

Introduction: Collection of electroencephalographic (EEG) data for use with brain-computer interfaces (BCI) often involves highly specified, repetitive tasks that can be tedious for participants. As a result, longitudinal BCI studies are susceptible to high levels of participant dropout or distraction. This can make it difficult to assess the effects of variability in brain states (indicative of stress, sleep pressure, fatigue, etc.) on BCI performance. A more fun and varied experience may increase intrinsic reward, leading to better retention of participants and higher quality data. This proof-of-concept study explores the use of an engaging tile-matching game (similar to Candy Crush) that incorporates BCI-relevant tasks as mini-games that provide participants opportunities to earn power-ups. This game will be used for longitudinal assessment of natural variability in user state, which may lead to the development of novel and increasingly robust BCI algorithms and a stronger understanding of BCI literacy. Materials, Methods, Results: We present here a tile-matching game in which players fight a progression of enemy robots by matching rows or columns of three or more identical gems. Matching longer rows/columns or cascades earn players more points which translate to increased damage done to the enemy robots. Throughout the game, BCI-relevant tasks are presented as mini-games that allow players to earn power-ups that improve their ability to attack or defend against enemy robots. Players wear an EEG headset for collection of BCI-relevant data during gameplay. Other contextual data such as game performance, physiological measures (electrocardiography, pupillometry), and eye tracking may also be integrated into the game. Five BCI-relevant tasks/outcomes are included: rapid serial visual presentations (RSVP), steady state visually evoked potentials (SSVEP), motor imagery (MI), error-related potentials (ErrP), and an N-back task. Preliminary analysis was performed in EEGLab and ERPLab on data from two participants who underwent four and five one-hour game sessions, respectively. Data show that these BCI-relevant tasks elicit characteristic patterns of EEG activity. For example, in the RSVP and N-back tasks, P300s are observed in the Pz electrode after recognition of targets, while the SSVEP task results in increased EEG power density at target frequencies. Recognition of gem substitutions causes a textbook ErrP in the theta wave and MI results in sufficient motor activity for machine learning classification. Discussion: Early testing of this game has proven it capable of eliciting the responses expected from the respective BCI-relevant tasks. Couching the BCI-relevant tasks in the context of a game facilitates longitudinal study of learning and natural variability in cognitive states (such as sleep pressure and stress), which may improve the performance of online and post hoc BCI classification algorithms. Additionally, inclusion of different game modes (e.g., time- or move-limited), variable session durations, and variable task difficulty (e.g., levels of "n" in the n-back task) allow for manipulation of workload and fatigue to further assess within-session EEG variability. Significance: Including BCI-relevant tasks in the context of a fun, engaging game will support the collection of longitudinal BCI datasets. This will enable quantification of variability in state-related variables (e.g., sleep pressure, stress, fatigue, workload, and learning) and their impact on neural signals that cannot be captured using cross-sectional or short-duration research approaches, providing valuable insight into inter- and intra-individual differences in BCI literacy that have been regularly observed but not yet explained. Acknowledgements: This project was sponsored by the U.S. Army Research Laboratory under ARL-H70-HR51, ARL-H70-HR52, and through Cooperative

Agreement Number W911NF-17-2-0153. The views and conclusions contained in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. Government. Figure 1. Results from the BCI-relevant mini-games. Figure 1A shows results from an RSVP task with a 5 Hz display rate at electrode Pz for both a target and non-target at time 0. Figure 1B shows the PSD applied to EEG taken from electrode Oz during an SSVEP task with a 7Hz target.

3-D-27 Combining eye tracking and EEG data to predict initial phases of motor imagery

Jingru Xu[1], Shiwei Cheng[1]

[1]*Zhejiang University of Technologys*

Introduction: It is already demonstrated that motor imagery can cause event related desynchronization / synchronization (ERD / ERS) phenomenon [1]. Usually, when the cue of the experimental paradigm appears during motor imagery experiment, users begin to imagine timely. But in some cases the users don't really begin to imagine after the cue appeared, and the EEG data collected at this timing may become noise data. In our work, we found that eye tracking data, such as the size of the pupil and the position of the gaze point, have regular changes during motor imagery. So we proposed a method that combining eye tracking and EEG data to predict when the user starts to motor imagery. Material, Methods and Results: An experiment was conducted to collect users' eye tracking and EEG data. The users sat in front of the computer and wore the electroencephalograph device and eye tracker. Firstly, the users watched a blue ball on the computer screen when the experiment began. When digits "3", "2", and "1" countdown appeared on the ball, the users did not have to imagine. Then the cue appeared, in order to know when the users really start to imagine, we asked the users to press the space key on the keyboard and start imaging. After pressing the space bar and users imagined for 6 seconds [2], the process of motor imagery finished. During the imaging process, the users need to watch the blue ball all the time. At the same time, the pupil diameter, gaze point and EEG data were recorded. As shown in Figure 1 (a), the pupil diameter increased when motor imagery starting, and decreased after motor imagery finished (the gray bar indicates the time window of image motor for each 6 seconds). Figure 1 (b) showed that the gaze point position changed during the imagine process. To train the classification, we labeled two statuses: labeled the data as "no motor imagery" during digits countdown, and the data as "motor imagery" after users pressing the space bar. The data analyzed included pupil diameter, gaze point position and EEG data. Then the two state data were extracted in a time window (e.g., 1 second) for analysis. Data preprocessing includes filtering noise data, removing baseline and normalization. We used SVM to construct the classifier. Because person's performance has different characteristics during motor imagery, everyone needs to train the model separately. The average classification accuracy reached up to 82.6%. Discussion: As shown in Figure 1 (a), after the users pressing the space bar, the pupil diameter gradually increased, indicating that the intention of the user's motor imagery gradually increased. We classify the EEG data at the moment when the pupil diameter up to the peak, so that we could obtain higher classification accuracy of motor imagery. As shown in Figure 1 (b), although the users were asked to keep watching the blue ball on the screen, they might scan other places unconsciously timely. This phenomenon would lead to a suddenly sharp change of the gaze point positions, and the related gaze data was useless to analyze the motor imagery. So we filtered these noise data. In general, the experiment results showed that our method is effective. The data of pupil size and gaze point position could be used to determine whether the user is in motor imagery. Significance: Using pupil size and the gaze point positions, we can predict the initial phases of motor imagery, so that we can analyze the EEG signal timely and get more accurate results. References: [1]. Pfurtscheller G, Neuper C, Flotzinger D, et al. EEG-based discrimination between imagination of right and left hand movement[J]. Electroencephalography and clinical Neurophysiology, 1997, 103(6): 642-651. [2]. Graimann B, Huggins J E, Schlogl A, et al. Detection of movement-related patterns in ongoing single-channel electrocorticogram[J]. IEEE Transactions on neural systems and rehabilitation engineering, 2003, 11(3): 276-281.

3-D-28 Towards a single trial fNIRS-based Brain-Computer Interface for communication

Seyyed Bahram Borgheai[1], Mohammadreza Abtahi[1], Kunal Mankodiya[1], Yalda Shahriari[1]

[1]*University of Rhode Island*

Introduction: Brain-computer interface (BCI)-based communication is still a challenge especially for patients lacking voluntary muscle control. Although most of the state-of-the-art BCI-based communication systems mainly rely on electroencephalography (EEG), recent studies have demonstrated the feasibility of using functional near-infrared spectroscopy (fNIRS) for BCI-based communication [Naseer et al., 2014]. Schudlo et al., (2014) developed a system, where subjects were selecting one letter out of three using a mental arithmetic task. However, due to the latency in hemodynamic changes, all these systems are considerably slow. Besides, all these communication tools use binary classification which requires the subject to perform several commands to achieve the spelling of only one letter. To address these issues, inspired by oddball paradigm commonly used for EEG-based P300 speller, this study has further investigated the feasibility of developing a novel oddball-based fNIRS speller. The inherent nature of the oddball paradigm which selects the target based on the intersection of rows and columns can benefit the intrinsically slow fNIRS response. Materials and Methods: Data was recorded from five healthy subjects. fNIRS data was collected using NIRScout system and digitized at 7.8125 Hz. 12 fNIRS channels located on the prefrontal and frontal areas, mainly responsible for the arithmetic tasks, were used in this study [Chau et al., 2014]. Concurrent with fNIRS, EEG data was acquired using g.USBamp and digitized at 256 Hz. Eight electrodes proposed by Krusienski et al., (2008) were used for EEG recordings. A 6x6 matrix of letters was used where each row/column was randomly intensified only once (i.e., single trial) for 300 ms with 6 sec inter-stimulus-interval. The conventional speller matrix was further modified by replacing the "flash" condition with a 2x2 matrix of digits and the subjects were then asked to do a mental arithmetic task. All the stimulation presentations were controlled using BCI2000 software [Schalk et al., 2004]. Within four different window lengths (i.e., 1, 2, 3, and 4 sec), integral, maximum, one temporal sample, and the slopes of oxyhemoglobin (HbO) were used as fNIRS feature, and four temporal features of event-related potential were used as EEG features. Statistical parametric mapping (SPM) and correlation analysis were used to select two and three most optimum channels for fNIRS and EEG respectively. Through a bootstrapping procedure with 10 repetitions, 70% of the data was used for training, the rest for the test, while linear discriminant analysis

(LDA) was employed for further evaluation. Results: Table 1 depicts the average performance across all the participants. Using fNIRS only within 2 sec window length, we could achieve an average accuracy, sensitivity, and specificity of 74.9 ±4.9%, 63.5±13.7%, and 77.3±3.9% respectively. By merging the fNIRS and EEG features together, in our hybrid modality, these values improved to 78.8±5.1%, 70.0±11.9%, and 80.8±4.7% respectively. Discussion: One of the objectives of this study was to develop a novel fNIRS-BCI-based communication modality which can be further applied in patients with various types of neuromuscular disorders. Achieving a satisfactory performance of 74.9% using only 2 frontal channels highlights the superior convenience of fNIRS. Such advantage can facilitate the use of BCI-communication devices in patients whose heads need to rest on their wheelchairs. One explanation for reaching such performance within a short time can be attributed to an initial dip following a mental load task, supporting previous findings reported by Zafar et al., (2016). However, further investigations need to be conducted to evaluate the character recognition and information transfer rate. Significance: Developing a fNIRS-based communication tool can provide a new avenue for the BCI research to further explore such tool for the BCI use in patients who can not use the EEG-based BCIs conveniently and reliably. Besides, the complementing nature of two types of brain responses, electrical and underlying hemodynamic activities, can be further utilized in better understanding the pathological brain.
Acknowledgement: This study was supported by the Institutional Development Award (IDeA) Network for Biomedical Research Excellence from the NIGMS of the NIH (P20GM103430), and National Science Foundation (1565962).

3-D-29 Effects of data sample dependence on the evaluation of BCI performance

Serafeim Perdikis[1], Fabien Bourban[1], Vincent Rouanne[2], José del R. Millán[2], Robert Leeb[3]

[1]Mindmaze SA, [2]École Polytechnique Fédérale de Lausanne (EPFL), [3]MindMaze

Introduction:Pattern Recognition (PR) methodology is nowadays the prevalent design model in Brain-Computer Interface (BCI). Consequently, classification accuracy is the most widely employed metric for BCI performance evaluation, so that best practices like cross-validation or train/test set split to assess generalization capabilities are vital and popular in BCI research. Nevertheless, since BCIs are natively also biosignal time-series processing machines, they are likely to violate common assumptions that otherwise render such PR practices optimal like the independence of training and testing folds. Abstaining from random data shuffling, which is normally a standard step of cross-validation, is shown to be enough to avoid accuracy overestimation arising from autocorrelations of the brain signals and its extracted features. This problem becomes more intense when analysis is done in overlapping sliding windows, as it is often the case. We hereby intend to draw attention on this issue, as well as study the magnitude of accuracy overestimation that can occur with real BCI data when this caveat is overlooked. Material, Methods and Results:We analyzed 64-channel EEG data of 20 able-bodied participants performing a single session of open-loop training with two cue-based BCI paradigms, a 2-class (right and left hand) motor imagery (MI) protocol and a 6-class Steady-State Visually Evoked Potential (SSVEP) protocol (stimuli flickering at 7.5, 9, 10, 12, 15 and 20 Hz). The session consisted of 4 SSVEP and 3 MI runs. In total 45 MI and 24 SSVEP trials, each 5-second long, were collected per task. Data were recorded with a Biosemi ActiveTwo amplifier (BioSemi B.V., Amsterdam, Netherlands) at 2048 Hz sampling rate.

Raw data were pre-processed with linear detrending and DC removal, spatially filtered with a cross Laplacian derivation and high-pass filtered above 1 Hz with a Butterworth filter. For both paradigms, Power Spectral Density (PSD) features are extracted for each channel (8-30 with 2 Hz resolution for MI and 1-30 Hz with 0.5 Hz resolution for SSVEP) in 1-sec long sliding overlapping windows. We repeat the feature extraction increasing the window overlap O from 0 to 875 ms with a step width of 125 ms to control the dependency of consecutive PSD samples. Classification accuracy is then computed by means of linear discriminant analysis (LDA) classifiers using the N best (according to r2 discriminant power) features and 10-fold cross-validation in two conditions: Prior to splitting the dataset in folds, data samples are either randomly shuffled as per regular convention (SampleShuffle), or only trials are shuffled forcing all within-trial samples to be in the same fold (TrialShuffle), thus respecting fold independence given that trials are separated enough in time. The total number of used features N is increased from 10 to 100 with a step of 10. Classification accuracy A is extracted for each paradigm, subject, O and N, by averaging the testing fold accuracy across cross-validation repetitions and then across subjects. Fig. 1a-b illustrate the accuracy difference ASampleShuffle-ATrialShuffle, reflecting the overestimation bias. Fig. 1c demonstrates the effect of N on A for both conditions and all O values using SSVEP data, an ordinary procedure to determine the optimal N. Discussion:Fig. 1a (MI) and Fig. 1b (SSVEP) verify deteriorating bias trends as the amount of data dependence, assessed by O, increases. Interestingly, the bias is considerable even without overlapping (O=0), especially for the multi-class SSVEP paradigm, as consecutive EEG segments are still bound to correlate. Fig. 1c shows that, unlike with TrialShuffle (blue), for SampleShuffle (red) A does not asymptote soundly as N increases, potentially misleading the experimenter to overestimate the number of informative features. This results in greater bias, since the latter is shown to (besides O) also increase with N (Fig.1a-b). These effects extend to train/test set split scenarios and all BCI paradigms. Significance:Sound offline performance evaluation is crucial for establishing optimal methods and parametrization before closed-loop application. Neglecting to address the common, but not highlighted enough, issue of data dependence harms the reliability and online replicability of BCI studies.

3-D-30 Association between RSVP task ERP and P300 speller performance

Kyungho Won[1], Moonyoung Kwon[1], Sunghan Lee[1], Jongmin Lee[2], Minkyu Ahn[2], Sung Chan Jun[1]

[1]Gwangju Institute of Science and Technology, [2]Handong Global University

Introduction: Brain-computer interface (BCI) has been developed in hope that it may provide people with new communication channel by controlling computer or machine with their brain activity. However, some people, called 'BCI illiteracy', cannot use BCI. In that case, people could get frustrated for wasting their time training BCI. Hence predicting BCI aptitude prior to use is important. In this study, we investigated whether P300 speller performance is predictable using a simple cognitive task - rapid serial visual presentation (RSVP). We investigated significant correlation between ERP (P300) amplitude of RSVP task and single trial classification accuracy of P300 speller task (hereinafter referred to as P300 speller accuracy) [1,3]. Material, Methods and Results: Total of 55 healthy subjects participated in this experiment after providing written informed consent. EEG data was recorded during resting state, RSVP task, and P300 speller (Figure1(A,B)). RSVP task consists of 40 trials, and subjects were instructed to input target characters. For P300 speller, 6 by 6 matrix paradigm was used with 6 runs (2 training and 4 test runs) [1,4]. EEG data was collected with 512 HZ sampling rate from the whole head 32-channel system (BioSemi Active 2 system). For P300 speller task, EEG data was band-pass filtered with 0.5 to 10Hz; each epoch (800 ms after stimulus onset) was extracted and preceding 200ms was used as baseline. Epoch was then decimated by replacing 24 time samples with their mean value. Stepwise linear discriminant analysis (SWLDA) was used to solve the binary classification problem, and the single trial offline accuracy was estimated using 10-fold cross validation [1,3]. For RSVP task, EEG data was band-passed with 0.5 to 6Hz. The trial-averaged waveform for both target and non-target was computed to assess P300 properties [2,3]. ERP (P300) amplitude was defined as average of four P300 amplitudes (CP1, CP2, Cz, and Pz), which was computed by the time average of ±50ms with the positive peak within each epoch [2]. Statistical significance between RSVP task ERP and P300 speller accuracy was investigated in order to check the hypothesis that RSVP task ERP may be associated with P300 speller performance by assessing Pearson's correlation coefficients and doing linear regression [1]. P300 speller accuracy was on average of 85.04±2.7%. In RSVP task, the average ERP (P300) amplitude was 2.95±1.7µV, latency was 492±7.0ms, and the average RSVP score was 91.9±5.6%. Significant positive correlation was observed between ERP amplitude of RSVP and P300 speller accuracy ($r = 0.3679$, $p < 0.01$) as shown in Figure1 (C). To estimate the predictive value of ERP amplitude of RSVP on P300 speller accuracy, we did a regression analysis, resulted in an $F=11.27$ with a $p < 0.01$, indicating that the P300 speller accuracy is predictable by ERP amplitude of RSVP with $B=0.82$. Discussion: In the previous study [1], the significant correlation was found between RSVP score and P300 speller accuracy. However, in this study, we investigated whether RSVP task ERP may be another correlate with P300 speller accuracy. We observed the significant correlation between ERP amplitude of RSVP task and P300 speller accuracy. Even though RSVP task ERP latency and RSVP score did not show statistical significance, the same tendencies were observed as the previous researches [1,2]. RSVP task was slightly changed from determining whether the target character was vowel to selecting what the target character was, in order to avoid confusedness since the subjects did not speak English. The modified RSVP task might have reduced the attention and affected the result. For further study, optimal channel selection for computing ERP amplitude and considering functional connectivity is necessary to find better neurophysiological markers [2]. Significance: We showed that RSVP task ERP and P300 speller performance are associated, thus P300 speller performance is predictable by RSVP ERP. Acknowledgements: This work was supported by Institute for Information & Communication Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No. 2017-0-00451). References: 1. Riccio, A. et al., Frontiers in Human Neuroscience, 2013 2. Li, F. et al., Scientific Reports, 2015 3. Blankertz, B. et al., NeuroImage, 2011 4. Farwell L. A., Donchin E., Electroencephalogr. Clin. Neurophysiol., 1988

3-D-31 ERP prevalence and effects of stimulus features and attention on MMN and P300

Matthias Eidel[1], Helena Erlbeck, Ruben Real, Andrea Kübler[2]

[1]University of Würzburg, Germany, [2]University of Würzburg

Introduction: Next to BCI applications, ERPs can also be used for neurological diagnostics, e.g. in

assessing the cognitive state of patients with severe disorders of consciousness (DOC), a state that can result from traumatic brain injury [1]. In current practice however, ERPs are usually not included in the diagnostic process because of a lack of standardization in respect to stimulus presentation, paradigm duration, and instruction. Normative data on the prevalence of MMN and other ERPs from healthy populations have also been requested with other diagnostic applications in mind, e.g. for schizophrenia and disorders of development [2]. New findings on ERPs as diagnostic tools may also serve to design more refined ERP-based BCIs. Methods: N=100 healthy subjects (67 female, ages M=36.36, SD=10.56) underwent EEG-based P300 and MMN acoustic oddball paradigms in several variations: A) MMN multi-feature with several deviant dimensions (see table 1), each in two degrees of deviant-to-standard distance (DSD). B) Two MMN uni-feature paradigms, differing in duration DSD. C) P300: Simple intensity deviation oddball. ERP paradigms were combined with instructional tasks of increasing degree of attention (ignore, passive, focused) toward the deviant, as in Erlbeck et al. [3]. EEG epochs were analyzed with multivariate ANOVAs. ERP prevalence from the present sample was automatically assessed as described in Kotchoubey et al. [4]. (Left) Table 1: Overview of the MMN multi-feature deviants. Standards 75 ms and 65 dB. (Right) Figure 1: Grand averages of the MMN absolute and proportion paradigms at Fz across all subjects (focused condition, standard duration was 75 ms). The difference curve (deviant - standard) delineates the MMN. In the passive and focused tasks, the first of the double peaks was interpreted as MMN, the second as N2b. Peaks were highest in the focused tasks. An additional P300 deflection was only present in the focused task of the proportion paradigm. Results: P300 amplitudes increased with higher attention toward the deviant (focused task), whereas attention effects on MMN were inconsistent. MMN amplitudes mostly increased with higher DSD (see Figure 1). In the multi-feature paradigm, location deviants did not elicit any ERPs and were not included in further analysis. ERP detection rate ranged from 89-100% of participants, depending on the paradigm. Discussion & Significance: Information on the effect of instruction and DSD on ERP amplitudes facilitates the choice of a suitable paradigm for investigating basic and higher cognitive processes in non-responsive patients and allows a more informed ERP-BCI design. The short presentation time for all paradigms accommodates for the potentially short attention span in patients with DOC or other reasons for the non-responsiveness. Prevalence values of MMN and P300 ERPs from a healthy sample help judge the significance of their absence, or presence, in patients. Acknowledgements: This work is supported by the European ICT Programme Project FP7-247919. The text reflects solely the views of its authors. The European Commission is not liable for any use that may be made of the information contained therein.
References: [1] Bernat, J. L. (2006). Chronic disorders of consciousness. The Lancet, 367(9517), 1181-1192. [2] Schall, U. (2016). Is it time to move mismatch negativity into the clinic?. Biological Psychology, 116, 41-46. [3] Erlbeck, H., Kübler, A., Kotchoubey, B., & Veser, S. (2014). Task instructions modulate the attentional mode affecting the auditory MMN and the semantic N400. Frontiers in Human Neuroscience, 8. [4] Kotchoubey, B., Lang, S., Mezger, G., Schmalohr, D., Schneck, M., Semmler, A., ... & Birbaumer, N. (2005). Information processing in severe disorders of consciousness: vegetative state and minimally conscious state. Clinical Neurophysiology, 116(10), 2441-2453.

3-D-32 Towards an EEG-based covert attention Brain-Computer Interface (BCI) training procedure for soccer goalkeepers

Camille Jeunet[1], Luca Tonin[2], Louis Albert[3], Ricardo Chavarriaga[2], Benoît Bideau[4], Ferran Argelaguet[4], José del R. Millán[5], Anatole Lecuyer[4], Richard Kulpa[4]

[1]EPFL / Inria, [2]EPFL, [3]WYSS Center, [4]Univ. Rennes, Inria, IRISA, CNRS, [5]École Polytechnique Fédérale de Lausanne (EPFL)

Introduction:<\i> Current sport-training procedures mostly focus on physiology and biomechanics. We hypothesise that training athletes' cognitive abilities could contribute to further improve their performance. BCIs allow for the design of ElectroEncephaloGraphy (EEG)-based cognitive enhancement training procedures as long as EEG-correlates (C1) specific to the target cognitive ability, (C2) measurable on a single-trial basis and (C3) related to athletes' expertise or performance can be identified. We present preliminary results on the possibility of using BCIs for a cognitive enhancement training procedure aiming to increase soccer goalkeepers' performance through the improvement of their Covert Visuo-Spatial Attention (CVSA) abilities. Indeed, it is essential for these athletes to have high CVSA abilities, i.e., to be able to covertly commit attention to an object located in their peripheral vision field [1]. CVSA has been shown to elicit α-synchronisation over parieto-occipital areas ipsilateral to the attended vision hemi-field [2]. This α-synchronisation reflects an inhibitory process aiming to allocate more resources to the target location. The suitability of this pattern for controlling BCI-based applications [3] and for rehabilitation [4] has been investigated. Here, we aim to assess whether this pattern meets the conditions C1, C2 and C3 and is thereby suitable for a BCI training dedicated to goalkeepers' cognitive enhancement. Material, Methods and Results:<\i> 17 experienced soccer goalkeepers took part in a 2-session study. Each session included 4 runs of 32 trials. Goalkeepers had to look at a central cross and, based on the cue, covertly attend one of the 4 targets located at each corner of the screen (Figure 1A). 500-2000ms after the cue, a '+' or 'x' sign was displayed on the target for 200ms. Participants had to indicate which sign they perceived. Goalkeepers' expertise was set according to the level at which they evolve in the French championship. Their performance was assessed through a multiple-object tracking task completed at both the beginning and end of each session. Data were spatially filtered using a small Laplacian. The Power-Spectral Density (PSD) was computed within 1s sliding windows (62.5ms steps). For each subject, we computed the Individual Alpha Peak (IAP) and extracted the α-power band accordingly (IAP±2Hz). Finally, we identified two Regions of Interest (RoI): Left (P7-P1, PO7, PO3, O1), Right (P8-P2, PO8, PO4, O2); and computed the Lateralisation Index (LI) as: [α-powerLeft - α-powerRight]. Main results: - C1: Consistently with the literature, grand-average analyses revealed that the LI was positive/negative when the target was located on the left/right vision hemi-field, respectively (Figure 1B). A main effect of target location on the LI was revealed [$F(1,16)=11.21$, $p<.0001$]. - C2: A Quadratic Discriminant Analysis classifier was trained using as features the amplitude and latency of the LI during the last 500ms of the trial. Average classification accuracy (n-fold cross-validation) was around chance level. A second classifier was thus trained based on the most discriminant PSD features. It gave significantly higher performances ($p<.05$). - C3: We investigated the relationship between goalkeepers' expertise, CVSA performance and the amplitude and latency of the LI. The different correlation analyses (corrected for multiple comparisons) revealed no significant results, which might be due to the small sample size. Discussion:<\i> Although LI is a main EEG correlate of CVSA, it is seemingly not robust enough to be exploited at a single-trial level. Conversely, subject-specific PSD features (α-band, parieto-occipital channels) seem to be good candidates for online CVSA BCI. This is in line with the strategy currently adopted in motor-imagery based BCIs, where specific channels/frequencies are selected for each subject. These results pave the way for a BCI training procedure dedicated to goalkeepers' cognitive enhancement. Significance:<\i> While BCIs are promising for cognitive enhancement, they are still scarcely explored for improving athletes' performance. Because cognitive abilities greatly influence sport performance, this approach could have a huge impact in sport sciences. References:<\i> [1] Posner (1980), Q. J. of Exp. Psycholo. [2] Rihs et al. (2007), Eur. J. of Neurosc. [3] Schmidt et al. (2010), IEEE SMC [4] Tonin et al. (2017), Front. Hum. Neurosc.

3-D-33 Gaze versus EEG-based control of a visual P300 BCI in healthy children

Mélodie FOUILLEN[1], Emmanuel MABY[2], Lucie LE CARRER[3], Jérémie MATTOUT[2]

[1]Centre de Recherche en Neurosciences de Lyon, [2]Lyon Neuroscience Research Center, [3]Hospices Civils de Lyon

Introduction: The well-known P300-speller and other visual P300 based interfaces following the same principle are based on covert attention to infer the user's choices. However, they are known to require overt attention, i.e. gaze orientation towards the targets, in order to reach high enough performance [1]. While focusing the target is hence mandatory, it is not clear so far, beyond first person's verbal reports, whether it is conversely indeed not sufficient to produce the expected and (discriminant) control signal. In other words, as attention and gaze direction are partly dissociated, what remains elusive is the contribution of (covert) attention to P300 BCI performance, independently of eye gaze. This question is essential for future applications of P300-based BCI, namely for the training of attention, e.g. in children with ADHD [2]. We here tested this hypothesis in healthy children who played a connect-four game [3], either controlled by eye gaze or controlled by EEG. Material, Methods and Results: 32 healthy children (6-15 years old; 15 girls) were included. After a short calibration phase, children performed two blocks made of several games of a connect-four where they were applying against an AI. Importantly, during one block, participants received feedback based on their EEG signal, while during the other block the feedback was based on eye-gaze as measured with a remote eye-tracking system (ET). Half of the children started playing based on EEG (Group 1), while the other half started based on ET (Group 2). Nevertheless, both EEG and ET were monitored along both blocks, for the two groups. Children were initially told that control was only and always based on EEG. This means that they were instructed to pay a substantial attentional effort to control the game (e.g. by counting the number of times their target column was flashed). Signal processing was based on Riemannian geometry for feature extraction and subsequent classification of target and non-target EEG responses, respectively. We computed the accuracy of EEG-based control, taking the ET output as the reference (i.e. true targets were indicated by eye gaze). We predicted that eye gaze focusing would not be sufficient to obtain reliable target EEG signals and high accuracy. We thus expected that during ET based control, subjects would gradually reduce their attentional effort, which would impair EEG-based classification. Figure 1 shows the averaged accuracies obtained with EEG, for each group and block. A 2x2 repeated measure ANOVA (Time * Control mode) revealed a significant interaction. This is mostly driven by a drop of performance of participants in Group 1 during the second block (i.e. during ET-based control). Discussion: A likely explanation for the observed effect is that, at the beginning, all children do their best to follow the instruction to carefully pay attention to the target and the target only. However, over time and particularly in block 2, this effort becomes more difficult to produce and actually vanished in the group whose feedback/performance was not relying on this effort anymore. Indeed, participants in Group 2 who needed to maintain such an effort in order to maintain their performance, did so. Conversely, participants in Group 1 who could simply rely on eye gaze to perform well in the second block, did alleviate their attentional effort, yielding a drop in EEG classification accuracy. Significance: It seems that when children are playing based on ET, they gradually diminish their attentional effort, even if they think that they are controlling the game with their EEG. This highlights the important role of covert attention for achieving a good control of visual P300 based interfaces. This speaks in favor of the specificity of the P300 response to reflect the attentional effort, beyond eye gaze orientation. This also suggests that an EEG-based training of attention should be more effective than a solely ET-based one [2]. [1] Brunner et al., J. Neural Eng., vol. 7, no. 5, p. 56013, Oct. 2010. [2] Fouillen et al., 7th Graz Brain-Comput. Interface Conf. 2017. DOI : 10.3217/978-3-85125-533-1-26 (Best poster Award) [3] Maby et al., Adv. Hum.-Comput. Interact., 1-8, 2012.

3-D-34 Automated EEG enhancement and recurrent neural networks for lane change prediction during driving

Marc-Antoine Moinnereau[1], Sam Karimian-Azari[1], Tsuyoshi Sakuma[2], Hidenori Boutani[2], Lucian Gheorghe[2], Tiago H. Falk[1]

[1]Institut national de la recherche scientifique (INRS - MuSAE Lab), [2]Nissan Motor Corp, Nissan Research Center, Mobility Service Lab

Introduction: In the last years, brain computer interfaces (BCI) are gaining popularity to predict the user's intention. In this study, we are specially interested in interfaces that extract movement related cortical potentials (MRCP), a low negative frequency (0-5 Hz), in the electroencephalogram (EEG) signal and more specifically in the task of classifying when a driver attends to do a lane change to the left or right. Therefore, we suggest to compare three automated artifacts removal for MRCP detection (accelerometer-based independent component analysis - acc-ICA, constrained ICA - cICA and empirical mode decomposition - EMD) and use machine learning approaches to automatically extract their meaningful characteristics. More specifically, we use a recurrent neural network (RNN) reservoir, which has been proved to give better accuracy for spatio- and spectro-temporal signals than some classic machine learning approaches. In this work, we compare the RNN results with a support vector machine (SVM) approach. Moreover, we also investigate the classification performance as a function of the length of MRCP windows. Thus, we explore ways of reducing the delay of the enhancement algorithms to get as close as possible to real-time. Furthermore, we show that the RNN greatly outperforms the SVM approach and obtains superior classification results with an average classification rates of 91.8%, 94.52% and 92.96% for respectively acc-ICA, cICA and EMD. Finally, we observe that, indeed, the classification results improve with the increasing of the window length. Material, Method and Results: The experiment was made in a driving simulator in Atsugi, Japan at Nissan's research center. EEG recording were performed with an 64 EEG channels placed according to the 10/20 extended standard using the Active Two Biosemi recording device. The subjects were instructed to do a changing lane on the highway. The first aim of this study was to detect MRCP signals using the three EEG enhancement algorithms : acc-ICA [1], cICA [2] and EMD [3]. Then, it was to classify if the user attempted to do a changing lane to the left or right. To do so, we compared the classification obtained with RNN reservoir [4] with a SVM approach. The results showed classification rates below 60% using SVM, whereas RNN reported significantly higher averaged classifications of 91.8%, 94.52% and 92.96% for respectively acc-ICA, cICA and EMD approaches when considering only 6 electrodes and a window of 8 second (where the turning appears at 4 second). Furthermore, with a window of 4 second before the changing lane, we obtained satisfying averaged classifications of 78.20%, 83.89% and 84.80%. Discussion: Our results showed that the classification rates obtained with the RNN highly exceeds those of the SVM. Acc-ICA accuracy is lower than cICA and EMD because it has a risk that EEG components are removed. Moreover, the recognition rates should improve by increasing the length of the window. We showed that a window of 4 second is sufficient to achieve reliable classification. Significance: The detection of MRCP in EEG signals is very relevant to predict the user's intention. In our case, it might be very useful for supporting and helping the driver when he attends to change lane. References [1] I. Daly, M. Billinger, R. Scherer, G. Muller-Putz, "On the automated removal of artifacts related to head movement from the EEG", IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society, vol. 21, pp. 427-434, 2013. [2] F. Karimi, J. Kofman, N. Mrachacz-Kersting, D. Farina, and N. Jiang, "Detection of Movement Related Cortical Potentials from EEG Using Constrained ICA for Brain-Computer Interface Applications". Frontiers in Neuroscience, vol. 11, pp. 356, 2017. [3] F. Riaz, A. Hassan, S. Rehman, I. Niazi, M. Jochumsen, K. and Dremstrup, "Processing movement related cortical potentials in EEG signals for identification of slow and fast movements. 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, pp. 4908-4911, 2014. [4] S. Brodeur, and J. Rouat, "Regulation toward self-organized criticality in a recurrent spiking neural reservoir", Artificial Neural Networks and Machine Learning - ICANN 2012, pp. 547 554, 2012.

3-D-35 Error potentials for identifying auto-correction errors during tablet-based text entry

Felix Putze[1], Tanja Schultz[1], Wolfgang Stuerzlinger[2]

[1]University of Bremen, [2]Simon Fraser University

Introduction: Today, predictive text entry systems are omnipresent on mobile phones and tablet computers. They provide auto-correction mechanisms to automatically replace mistyped words. However, even sophisticated state-of-the-art auto-correction approaches have noticeable error rates. In recent work [1], we recorded an EEG data corpus of participants typing with such a text entry system and try to detect errors of the auto-correction by classifying EEG error potentials. Material, Methods and Results: For data collection, participants were asked to type short sentences presented to them on a virtual keyboard of a tablet computer. The keyboard contained a simple auto-correction mechanism which replaced non-dictionary words with dictionary entries based on Levenshtein edit distance. Due to ambiguity in the dictionary, the auto-corrections contain errors and our hypothesis was that these auto-correction errors could be classified based on error potentials in the EEG signal. EEG was recorded via a BrainProducts actiCAP with 32 active electrodes. By visual, auditory, and tactile cues, the keyboard directed the participant's attention towards the auto-corrections. Using the described experimental setup, we collected a total of 12 data sets. Each data set contained 120 sentences with a mean total

number of 474 words. Of all typed words, 26% were corrected. Of those corrections, 74% yielded the correct word. This indicates that the system must deal with an imbalanced classification problem, in which the error case manifests the minority class. As basis for classification of error potentials induced by erroneous auto-corrections, we combine EEG features and context features. We calculate two types of EEG features: 1) Time-domain features consisting of signal means for segments of 50ms length, filtered between 4 and 13Hz. 2) Frequency-based features, consisting of the frequency power spectrum between 4 and 13Hz. As context features, we used: Typing speed for replaced word, Length of the replaced word, time before user continues typing during evaluated EEG window, and 1/N, where N = number of candidate words of minimal Levenshtein distance to typed word. To control the number of features, Fisher-score based feature selection was performed. For classification, we employed a person-dependent regularized Linear Discriminant Analysis (LDA). To avoid a bias towards the "no error" result, we combined oversampling of the minority class with undersampling of the majority class. For oversampling, we employ the ADASYN algorithm. For undersampling, we used a bagging approach in which we trained several classifiers on randomly selected subsets of the majority class data (and all data of the minority class). A person-dependent 10-fold cross-validation estimated an average accuracy of 85% for the described classification setup. A paired, one-sided t-test showed that the classifier exhibits a performance which is significantly better than the baseline accuracy of 76% ($p < 0.05$). We also employed paired, one-sided t-tests showing that the classifier combining EEG and context features performs significantly better than variants using only one type of features ($p < 0.05$ in both cases). Inspection of selected feature revealed a preference for features linked to error potentials, dominantly selected from Fz. Discussion: The present study has shown the feasibility of detecting erroneous auto-corrections from EEG error potentials. For successful classification, it is necessary to handle imbalanced classes and to combine the EEG features with additional context information. Model-based simulation and a preliminary user study have shown the potential to achieve practical benefits for text entry efficiency. Further investigations have commenced which employ an online BCI for a full user study. Furthermore, we will use eye tracking to improve the temporal alignment of windows and to provide additional features. Significance: The presented study shows the potential for classification of error potentials in an ecologically valid setting for an application which is used by billions of people every day.
[1] Putze, F., Schünemann, M., Schultz, T., & Stuerzlinger, W. (2017). Automatic classification of auto-correction errors in predictive text entry based on EEG and context information. In Proceedings of the 19th ACM International Conference on Multimodal Interaction.

3-D-36 The factors causing the unstable visual stimulus in portable devices

Kuan-Jung Chiang[1], Wen-Hsuan Chan[2], Masaki Nakanishi[3], Yu-Te Wang[3], Tzyy-Ping Jung[4]

[1]SCCN / UCSD, [2]UCSD, [3]University of California San Diego, [4]University of California, San Diego

Introduction: Our previous studies demonstrated a steady-state visual evoked potential (SSVEP) brain-computer interface (BCI) that rendered visual stimuli and implemented conventional electroencephalogram (EEG)-decoding algorithms on mobile devices [1]. However, the ITR of the BCI implemented on mobile devices was considerably lower than that on a high-end but bulky PC because more advanced decoding algorithms require precise synchronization between stimulus presentation and

EEG acquisition [2]. It is difficult to realize on mobile devices because of the variable latency between the event marker and the true onset of the visual stimulus, hindering the feasibility and practicability of deploying SSVEP-based BCI systems to real-life situations. This study aims to identify and resolve the technical issue associated with the imprecision of the stimulus presentation on mobile devices. If this study can solve the technical issue, it will considerably improve the performance and practicality of BCIs in real-world environments. Method: The entire testing system consisted of an Android-powered Tablet, a dry and wireless EEG headset with a trigger receiver, and a light sensor receiver. After the App was launched, a steady-state visual stimulus flickering at 9.25 Hz and a flicker presented only at the first black-to-white frame of a 4-sec sequence [3] would appear on the screen with two light sensors attached. One of the light sensors was attached to the 9.25 Hz stimulus and connected to the wireless EEG headset so that the stimulus would be digitalized and recorded. The other light sensor was connected to the StimTracker, whose output was connected to the wireless trigger receiver through a parallel port. Therefore, both the 9.25 Hz visual stimulus and first black-to-white frame were recorded and synchronized by the wireless EEG headset. Note that, the App also sent an event marker at the onset of each visual stimulus via Labstreaminglayer (LSL) right before the first drawing command in the OpenGL ES. Results: Figure 1a shows a graphic command pipeline when the Tablet draws the visual stimuli. The graphic driver breaks down the onDraw command into several sub-commands, including eglSwapBuffers and glClear. The completion time for each sub-command varies. For instance, the glClear command of a Frame (#78 in Figure 1a) takes around 13 ms to complete, and the glClear completion time for another Frame (#79) is much shorter (see Figure 1a). Figures 1b and 1c show the epoched and over-plotted 4-second trials time-locked to the event markers generated by the LSL (Figure 1b) and the event markers generated at the first black-to-white frame captured from the screen (Figure 1c). The onset and completion times of trials vary across trials in Figure 1b, but relatively stable in Figure 1c. Furthermore, some 4-second trials in Figure 1b have 37 cycles, while others have only 36 cycles. In contrast, all of the trials in Figure 1c have exactly 37 cycles. Conclusion: This study directly measured the time courses of the graphic command pipeline and the first black-to-white frame from the screen. By doing so, we are able to find the sources of the variable latencies between the drawing command and its actual drawing. Results showed that the single draw command written in OpenGL ES was broken down into several sub-commands, queued and executed in a certain order by the graphic driver. This leads to variable delays between the drawing command and the actual drawing, severely affecting the accuracy of time-domain-based analysis, such as Task-related Component Analysis (TRCA) [2] and template-based canonical correlation analysis [4]. Using the first black-to-white switching as the true event-onset marker, a high-speed (one second per number) SSVEP-BCI system using TRCA can be implemented on mobile devices. References: [1] Y-T. Wang et al, "Developing stimulus presentation on mobile devices for a truly portable SSVEP-based BCI," IEEE EMBC, pp. 5271-4, 2013. [2] M. Nakanishi et al, "Enhancing Detection of SSVEPs for a High-Speed Brain Speller Using Task-Related Component Analysis," IEEE Trans. on Biomedical Eng., 65:104-12, 2018. [3] Y. Wang et al, "Visual stimulus design for high-rate SSVEP BCI," Electron. Lett., 46(15): 1-2, 2010. [4] M. Nakanishi et al, "A high-speed brain speller using steady-state visual evoked potentials," IJNS, 24, 1450019, 2014.

3-D-37 High-temporal-resolution estimation of alertness using an EEG-based brain-computer interface

Chun-Shu Wei[1], Kritin Karkare[1], Tzyy-Ping Jung[2]

[1]University of California San Diego, [2]University of California, San Diego

Introduction: Brain-computer interfaces (BCIs) based on electroencephalogram (EEG) have been shown capable of not only enabling communication between the human brain and external environments but also recognizing and monitoring internal brain states [1]. In particular, studies have shown that EEG can be applied to tracking alertness [2], assessed by response time (RT) measurements [3]. A quantitative measurement that has been commonly used to index alertness is the frequency of lapses (non-responses), or the lapse rate. However, conventional approaches to estimate the lapse rate using the RT measurement require a prolonged time window, limiting the sampling resolution of the lapse rate. We herein propose a new alertness index (AI) derived from the RT data in a sustained attention task, featuring a high-temporal resolution and relating to prospective lapse rate (PLR), the lapse rate within an upcoming period. However, the caveat is that the RT-based AI requires behavioral responses to frequent driving events, which is not practical in real-world use. This study thus develops and validates an EEG-based AI monitoring with high temporal resolution. Material, Methods and Results: To develop a method to continuously monitor AI without relying on frequent behavioral responses, we first modeled the associations between EEG and the RT-based AI. Thirty-seven healthy volunteers participated in a lane-keeping driving task in a virtual-reality driving simulator [4]. Thirty-channel EEG signals and behavioral data were simultaneously recorded during the experiments. The RT-based AI was derived from the RT measurements across time by using the transformation and estimation developed in [5], where a modified hyperbolic tangent function transforms the RT measurements into a bounded (between zero and one) normalized RT. Next, the AI is estimated by a 90-s moving average of the normalized RT. In the driving task, the RT-based AI is sampled at each onset of a lane-departure event (every 6-10s). The PLR at different AI levels was estimated by an off-line statistical analysis on the RT data across sessions from multiple subjects. The EEG features related to alertness were extracted as described in our previous work [6]. To obviate the inter- and intra-subject variability in the EEG-alertness association, we adopt a subject-transfer framework [6] to minimize the calibration effort in the proposed EEG-based BCI. The efficacies of these AIs are inferred from their relationships with PLR, the probability of having a slow or no response within an upcoming period, herein proposed as the ground truth of alertness. Figure 1 compares the PLRs given the RT-based AI and the EEG-based AI, where both RT- and EEG-based AIs show inversely proportional relationships with the PLR. Discussion: Using the newly defined PLR as the ground truth of alertness, the proposed RT-based AI, and the simultaneous behavioral and EEG data acquisition in the driving experiment, we are able to develop a framework of an EEG-based BCI for high-temporal-resolution alertness assessment. Significance: 1) This study re-defined the ground truth of alertness by the PLR and proposes the behavioral AI as an associated quantitative measurement. 2) This study also developed an EEG-based BCI for high-temporal-resolution alertness monitoring based on a subject-transfer framework to improve its practicality for real-world use.
References: [1] JR Millan & J Mourino, "Asynchronous BCI and local neural classifiers: an overview of the adaptive brain interface project," IEEE TNSRE, 11(2): 159-61, 2003. [2] T-P Jung et al. , "Estimating alertness from the EEG power spectrum," IEEE TBME, 44(1): 60-9, 1997. [3] W. Sturm and K. Willmes, "On the functional neuroanatomy of intrinsic and phasic alertness," NeuroImage, 14, 1.2, S76-84, 2001. [4] R-S Huang et al., "Tonic Changes in EEG Power Spectra during Simulated Driving," LNCS, 394-403, 2009. [5] C-S Wei et al., "Exploring the EEG Correlates of Neurocognitive Lapse with Robust Principal

Component Analysis," Foundations of Augmented Cognition: Neuroergonomics and Operational Neuroscience, 113-20, 2015. [6] C-S Wei et al., "Transfer learning with large-scale data in brain-computer interfaces," IEEE EMBC, 4666-9, 2016.

3-D-38 WOMBATS: Wearable mOdular Multi-modal Bio-sensing Acquisition and Tracking System

Siddharth Siddharth[1], Aashish Patel, Tzyy-Ping Jung[1], Terrence Sejnowski

[1]*University of California, San Diego*

Introduction: The goal of our work is to take the bio-signal applications out into the wild with multi-modality in a wearable device framework, real-time capability, and automatic visual stimulus tagging. We designed a state-of-the-art multi-modal bio-sensing system capable of acquisition and recording Electroencephalogram (EEG), Photoplethysmogram (PPG), and eye-gaze using sensors we developed. In addition, it can also detect objects in real time from user's perspective to pinpoint the stimulus in real-world experiments. Furthermore, using other sensors from industry, it can be used to measure Galvanic Skin Response (GSR), human body motion, body temperature etc. By integrating multi-modal measurements into an accessible package, we are able to explore previously unanswerable questions ranging from open-environment interactions to emotional response studies. System Overview: The system is composed of a central compute module and a companion headset. The compute node collects, time-stamps and transmits the data while also providing an interface for a wide range of sensors including EEG, PPG, GSR, and eye gaze among others. The companion headset contains the gaze tracking cameras. EEG Sensors and Acquisition: We developed novel dry EEG sensors along with filtering and digitizing circuitry. The conducting element of the sensors is made of Silver (Ag) while the small sensor itself houses the circuitry for noise filtering to increase the signal to noise ratio (SNR). The sensors also have another layer of conductive material over them to act as a Faraday cage and shield the sensor from outside noise. PPG Sensor: We developed a small PPG sensor capable of attaching behind the earlobe. The PPG sensor is Infra-Red (IR) based and also houses a three-stage band-pass filter to filter the PPG signal as soon as it is acquired. It also houses a 3-axis accelerometer to remove the noise from the PPG due to motion by modeling the noise and using an Adaptive Noise Cancellation (ANC) filter. Eye-Gaze headset: The eye-gaze headset comprises of two small cameras. The world camera is a color camera which points away from the subject to record the world from subject's perspective. The eye-camera is an IR-based camera which is used to detect the pupil of the eye using computer vision algorithms. After a fast and easy calibration between the two cameras, subject's eye-gaze is mapped on to the world view in front of him/her. RaspberryPi Compute Module 3 is then used for data acquisition and transmission from all the sensors which can either be saved on the module or can be sent after synchronizing using Wi-Fi. We also use an external GPU on the feed from the world camera to detect up to 20 different classes of objects in the world view and tag them in real-time. In addition, we also used Biovotion armband sensor module to get various physiological signals out of the box and synchronized them with the modules mentioned above. The system is also compatible with Notch motion sensors to get full body motion model in real-time. Results: We evaluated our PPG sensor against an electrocardiogram (ECG) sensor on 6 subjects to evaluate the deviation in computing average heart rates between the two sensors. We found that in almost all the cases the deviation was inside the 95%

conformation threshold i.e. under Mean ± 1.96Std on the Bland-Altman plot. The accuracy was further increased for both while the subject was sitting and while walking using ANC filtering described above. We then evaluated the accuracy and precision of our eye-gaze system and found the mean values to be 1.03 degrees for error in accuracy and 0.16 in angular precision. Even after head movements, the changes in the error for these measures was negligible. Discussion and Significance: By developing a low-cost, portable, multi-modal bio-sensing platform that is capable of interfacing with numerous different sensors, we are able to explore richer experimental questions that have previously been unable to be accessed due to the constrained nature of the measurement hardware. References:
Siddharth S, Patel A, Jung TP, Sejnowski T, An affordable bio-sensing and activity tagging platform for HCI research. HCI International 2017. Siddharth, Tzyy-Ping Jung, and Terrence J. Sejnowski, "How about taking a Low-cost Multi-modal Bio-sensing and Eye-gaze Tracking System into the "Wild"?", The 38th IEEE EMBC, 2016.

3-D-39 STRUM: A task battery for neuroergonomics research

Tim Mullen[1], Scott Makeig[2]

[1]Intheon, [2]University of California San Diego

Introduction: In recent years, real-time EEG analysis and brain-computer interface (BCI) methodology have reached a level of maturity, fueled in part by widespread adoption of machine learning, that allowed these methods to be increasingly applied outside the realm of clinical care, and to expand into general-purpose user-state tracking of non-clinical user populations, for instance for human-computer interaction (HCI) applications. However, many of these applications have not yet materialized, among others for reasons not previously seen in controlled laboratory experiments, including: increased artifacts due to unrestricted movement, reduced signal quality due to divided attention between multiple task activities, increased signal variability due to a richer variety of tasks performed by the user, and a shortage of labeled training data. The STRUM task was designed to help benchmark methods in this setting. Material, Methods and Results: The STRUM (Small Team Reconnaissance Urban Missions) task mimics a spectrum of tasks encountered by operators of vehicle crew stations, that is, a multi-screen display featuring side tasks organized around a central driving simulator task (Fig. 1). The STRUM task includes side tasks modeled after diverse well-known experimental paradigms such as N-Back, visual search, language comprehension, two-alternative forced choice (2AFC) tasks with skip, as well as multimodal stimulus presentation, including visual and auditory stimuli with both sharp onset and soft onset. Multiple side tasks can be active at the same time, and the task mix varies throughout the session. To maintain levels of engagement and distraction typical of real-world tasks, STRUM includes multiple 'missions' that the user is asked to perform while solving the side tasks. We have collected and analyzed a dataset of 56 subjects performing the task in a two-person configuration using two 206ch EEG systems, plus additional sensors not analyzed in the evaluation. For each session and subject, we have extracted EEG segments around correct/incorrect button presses, stimulus presentations of target/distractor stimuli, during periods of high/low workload, and during mainly visual/primarily auditory task loads. For each of these two-class contrasts, we have performed a separate within-subject cross-validation using a range of standard BCI methods and some more recent approaches to quantify the accuracy with which these conditions can be separated based on the EEG information alone. Most of the machine learning implementations had previously been validated in a separate article on benchmark datasets [1], and were applied here with minor adjustments in parameters. In summary, we found that many methods known from the literature, including shrinkage LDA, Hierarchical Discriminant Component Analysis (HDCA), and various regularized and/or spectrally extended versions of the Common Spatial Pattern algorithm performed significantly at above chance level across most of the tested conditions. However, at the same time, we found that the achieved performance of these algorithms, with AUC scores between 0.55 and 0.65 across the entire matrix (only exceeded in a handful of combinations of task and method, specifically for response-error detection using regularized linear methods) Discussion: While the scores attained with these methods in the intentionally punishing STRUM task are encouraging, the results clearly fall short of the performance seen in more constrained laboratory experiments on similar tasks (e.g., [2], [3]). This demonstrates a broad opportunity for further improvements in order to meaningfully augment HCI. Significance: We hope the STRUM paradigm and dataset will serve as a useful testbench for innovation in methods for outside-the-lab deployment, particular with regards to robustness to artifacts, and learning from small amounts of labeled data in settings that closely reflect real-world BCI use. References [1] Kothe, C. A., & Makeig, S. (2013). BCILAB: a platform for brain-computer interface development. Journal of neural engineering, 10(5), 056014. [2] Zander, T. O., & Kothe, C. (2011). Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general. Journal of neural engineering, 8(2), 025005. [3] Brouwer, A. M. et al. (2012). Estimating workload using EEG spectral power and ERPs in the n-back task. Journal of neural engineering, 9(4), 045008.

E- Signal Analysis

3-F-40 Towards reducing calibration in BCI: Artificial EEGs generation by deep learning

Wonjun Ko[1], Jee Seok Yoon[1], Heung-Il Suk[1]

[1]Korea University

Introduction:
 In BCIs, the so-called calibration stage has always been one of the main concerns in their practical use in real. In early work, Lotte [1] presented the potential of using artificial EEG generated by mixing real signals in different ways and achieving promising results. In this work, inspired by his work, we introduce our recent project of generating artificial brain signals by deep learning, and thus can reduce the time of calibration without sacrificing performance.
 Material, Methods & Results:
 In our work, we used the BCI Competition IV - dataset IIa that consists of 4 motor imagery tasks acquired from 9 subjects. As for motor-imagery related EEG generation, we designed our own architecture in the framework of the Conditional Generative Adversarial Network (C-GAN) [2]. Specifically, we designed a generator with LSTM-RNN and a discriminator with a Shallow FBCSP ConvNet [3]. Basically, we considered a subject-wise BCI, but to make our network robust in generating EEG signals, we first pretrained our C-GAN with samples of all subject in a training session, and then fine-tuned with the samples of the target specific, separately. Regarding the quality of the C-GAN training,

we inspected the spectral power density of the generated signals by comparing with the corresponding 1/f curve.
 For a quantitative analysis, we measured classification accuracies of competing methods trained with different numbers of EEG samples. Further, we also investigated how the performance changes according to the ratio between the number of real EEGs (12.5%, 25%, 50% of the whole training data) and the number of generated EEGs. As an preliminary experiment, we considered left-hand vs. right-hand classification to sure the effectiveness of the proposed method. For feature extraction and classification, we used the standard CSP algorithm and a LDA classifier, respectively. We achieved an accuracy improvement by 5% on average when using the generated EEGs compared to using only real EEGs.
 Discussion & Significance:
 In this project, we proposed a novel framework for artificial EEG generation and its use for BCI with a limited number of real calibration samples without losing the classification power. In the meantime, it is of great interests to use deep models with an expectation of enhancing BCI performance as other fields such as computer vision, speech recognition, natural language understanding. However, due to its requirement of a large dataset, it has been relatively limited to apply deep models in BCI. With the idea of generating realistic EEG signals, it would be beneficiary to utilize generated EEG signals and thus take advantage of the high power of deep learning in feature representations and class discrimination.
 Acknowledgement:
 This work was supported by Institute for Information & Communications Technology Promotion (IITP) grant funded by the Korea government (No. 2017-0-00451). All correspondence should be directed to Heung-Il Suk.
Reference:
 [1] F. Lotte, "Signal processing approaches to minimize or suppress calibration time in oscillatory activity-based brain- computer interfaces," Proceedings of the IEEE, vol. 103, no. 6, pp. 871-890, 2015.
 [2] M. Mirza and S. Osindero, "Conditional generative adversarial nets," CoRR, vol. abs/1411.1784, 2014.
 [3] J. Pan, E. Sayrol, X. Giro-i Nieto, K. McGuinness, and N. E. O'Connor, "Shallow and deep convolutional networks for saliency prediction," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 598-606, 2016.

3-F-41 EEG-derived Interhemispheric connectivity as a neurophysiological indicator of post-stroke recovery outcome

Donatella Mattia[1], Manuela Petti[2], Jlenia Toppi[2], Laura Astolfi[2], Febo Cincotti[3], Floriana Pichiorri[4]

[1]Fondazione Santa Lucia IRCCS, [2]Sapienza University of Rome, [3]Sapienza University of Rome; Second affiliation: NeuroElectrical Imaging and BCI Lab, Fondazione San, [4]Fondazione Santa Lucia- IRCCS

Introduction: Brain connectivity has been employed to investigate on post-stroke recovery mechanisms and to assess the effect of specific rehabilitation interventions. We already provided evidence that interhemispheric connectivity (IHC) in subacute stroke patients is modulated by different rehabilitation interventions: specifically, a Brain-Computer Interface (BCI)-based motor imagery training of the paretic upper limb in which ipsilesional electroencephalograpic (EEG) sensorimotor rhythms were reinforced, lead to an increase in IHC at rest specific to the EEG frequency ranges engaged in the training (1). In the present study we aim to define an index of IHC derived from EEG, correlated with corticospinal tract (CST) integrity and clinical impairment. Such index could be employed as a marker to evaluate the effects of training aimed at re-establishing interhemispheric balance and eventually drive the design of future BCI-based rehabilitation interventions. Material, Methods and Results: Thirty sub-acute stroke

patients underwent clinical and neurophysiological evaluation, including the upper limb section of Fugl-Meyer Assessment (FMA). CST integrity was assessed by Transcranial Magnetic Stimulation (TMS). According to TMS results, patients were divided into two groups with preserved/impaired CST (presence/absence of motor evoked potential on the affected upper limb). High-density EEG was recorded at rest and EEG-derived connectivity was assessed by means of Partial Directed Coherence. The normalized Inter-Hemispheric Strength (nIHS) was calculated for each patient and frequency band on the whole network and in three sub-networks relative to the frontal, central (sensorimotor) and occipital areas. Between group differences in nIHS were analyzed by unpaired two-tailed Welch t-tests for the whole scalp, each scalp area and frequency band. Two-tailed Spearman correlation between nIHS and FMA was performed to investigate the potential of the proposed connectivity index as a neurophysiological descriptor of stroke derived impairment. Significance level was set at $p<0.05$, False Discovery Rate correction for multiple comparisons was applied. IHC as expressed by nIHS on the whole network was significantly higher in patients with preserved CST integrity in beta and gamma bands. The same index estimated for the 3 sub-networks showed significant differences only in the sensorimotor area in lower beta, with higher values in patients with preserved CST integrity. The sensorimotor lower beta nIHS showed a significant positive correlation with clinical impairment (FMA). Discussion: We found that the CST integrity as defined by TMS in a sample of subacute stroke patients was associated with a significant difference in EEG-derived IHC (in favor of the group with preserved CST integrity). As such, this difference was topographically and spectrally specific, involving scalp electrodes relative to the sensorimotor area in a motor related EEG frequency range (lower beta). The lower beta sensorimotor nIHS index correlated positively with upper limb motor impairment. EEG with its non-invasiveness, portability and high temporal resolution can be recorded during rehabilitation interventions allowing the monitoring of brain activity (and connectivity) along the recovery process: an initial step was taken in our previous work in which an EEG-based BCI was used to monitor motor imagery practice after stroke (1). Advancements in signal processing methods may allow to estimate connections in real-time and eventually reinforce specific connectivity patterns in a BCI setting (2). Significance: Our study provides initial evidence for an EEG-based index which is a measure of the IHC and correlates with functional motor impairment in subacute stroke patients. The identified index could be employed to evaluate the effects of training aimed at re-establishing interhemispheric balance and eventually drive the design of future connectivity-driven rehabilitation interventions (3). We already showed that IHC could be modulated in response to BCI-training leading to significantly better recovery outcome(1). The present study corroborates the possible role of EEG-derived connectivity indices as neurophysiological markers of rehabilitation outcome, and possible predictors of response to BCI-based rehabilitation approaches.
References: (1) Pichiorri et al., Ann Neurol, 2015 (2) Billinger et al., Biomed Tech, 2013 (3) Pichiorri et al., EJN, 2017.

3-F-42 A fast classifier for somatosensory Brain-computer Interface

Jiangbo Pu[1], Jianing Li[1], Yong Hu[2]

[1]Institute of Biomedical Engineering,Chinese Academy of Medical Sciences & Peking Union Medical Colle, [2]The University of Hong Kong

Currently, most of non-invasive brain computer interface (BCI) systems are based on visual or auditory modality, which occupies eyes or ears of users during the use of BCI. Somatosensory stimulation can also be an interesting alternative, which is an alternative for BCI applications. Therefore, analysis of somatosensory ERP features and its classification are necessary to build a somatosensory BCI. This paper developed a fast classifier by using sliding windows and moving averages, creating a classification scheme for somatosensory brain-computer interface. By far the most used classifiers in BCI are Linear Discriminant Analysis (LDA), Support Vector Machines (SVM), and Neural Networks. Linear discriminant analysis discriminates between two data classes based on a hyperplane, and is best used in binary cases. Support Vector Machines are a stable discriminative classifier with a prescribed margin of error, and are commonly used, while Neural Networks are unstable, non-linear classification techniques used for classification. The most widely used classifier in P300-BCI among them is LDA, and has achieved a good result. However, the accuracy percentages and bitrates of BCI based on somatosensory stimuli were not as satisfactory enough as in visual stimuli. The use of sliding window averages is a commonly used technique of artifact reduction. It has been experimented as a classification technique with electromyography (EMG) data, with generally superior result to traditional classification methods. we aim at investigating whether such classification improve the somatosensory P300 BCI performance. In this paper, an electrical somatosensory based P300 BCI was built to obtain electroencephalogram(EEG) data, since previous studies has shown that electrical stimuli can elicit P300. The Sliding Windows, LDA and SVM were used as classifier separately. This study recruited 5 healthy subjects from college students aging between 18 and 28 years old. Each of the participants was right-handed and had normal sensorimotor functions. All participants offered their written informed approved by the local ethical committee. The performance of the developed classifier was compared to commonly used classifiers for BCI, i.e. Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA). Results presented that the present classifier has superior performance to both SVM and LDA in sensitivity, specificity and accuracy. In the same dataset, average accuracy with SVM showed 0.768±0.054, and LDA showed 0.774±0.053, while the sliding windows averages showed 0.849±0.031. In considering sensitivity and specificity of SVM and LDA, both of them showed lower than the proposed classifier. To make a comprehensive comparison, ROC curves of three classifiers are constructed as attached Figure. The speed of classification is another important parameter to be considered. In our Dell workstation with Intel Xeon processors, the Sliding Window requires 268ms, LDA requires 107ms, while SVM requires 6489ms. The Sliding Window has by far the best performance, and it is fast enough to use in real-time and online applications, as opposed to the SVM. The LDA is faster, however the performance is not good enough. Therefore the Sliding Window method is the best method for this type of classification. This is a preliminary study to demonstrate the usefulness of classifier of sliding window in somatosensory BCI. It is noted that the preliminary results were collected from 5 subjects. However, the comparison among different classifiers has already showed a clear and discriminant outcomes. Further study in a large scale application should further improve this classification method. A signal processing and classification method was experimented for multi-target online brain computer interface P300 classification, based on sliding windows. This method was found to be more accurate than traditionally used Linear Discriminant Analysis and Support Vector Machines, and faster than the Support Vector Machines.

3-F-43 Real time classification between uni- and bimanual motor imagery task for BCI controlled functional electrical stimulation

Aleksandra Vuckovic[1], Sara Pangaro[2]

[1]University of Glasgow, [2]2University Campus Bio-Medico di Roma

Introduction Most Brain Computer Interface (BCI) systems based on EEG, used for rehabilitation, are designed to classify motor imagery (MI) of the left and right hand or between one hand and the resting state. However, lots of activities or daily living require combination of uni and bimanual tasks. Therapies based on bimanual practice after stroke have positive therapeutic effect [1]. Bimanual control of BCI operated orthoses would increase their usability. A challenging aspect in creating a uni vs bimanual classifier is that bimanual movements do not necessarily result in a distinctive pattern of neural activity [2]. Materials, Methods and Results Ten adult, right handed able bodied volunteers took part in the study. On the first day they participated in a cue-based off-line imagery task. Those whose off-classification accuracy exceeded 70% took part in a subsequent on-line BCI task about a week later. Off-line session: Participants sit comfortably 1 m from a computer screen. At t=0s a warning sign appeared on the computer screen and stayed there until t=4s. At t=1s a warning sign was overlaid by an execution cue (⍰ for MI of the right hand, ⍰ for the left hand and ⍰ for both hands) which remained on the screen for 1.25s. Depending on a cue, participants imagined waving with one or both hands from t=1s till t=4s. Cues appeared in a semi random order. One hundred trials of each of three types of MI were performed, divided into 10 shorter sub-sessions. EEG was recorded with linked ear reference using usbamp (Guger technologies, Austria) with 31 electrodes placed over the sensory-motor cortex and one for EOG. Noise, primarily EOG, was removed by calculating independent components and removing noisy components before returing back to EEG domain. Following this, event-related spectral perturbation was calculated in EEGlab [3] for each task and each participant separately to determine one or two frequency bands with strongest event related desynchronization , in pre-defined frequency bands: 8-12, 16-24, 16-30 and 30-35 Hz. Common spatial patterns (CSP), ranging from 2 to 32, were calculated for either full band 8-40 Hz or for CSP in selected bands (CSPb) for the left and right, left and both hands and right and both hands. Linear discriminant analysis classifier (leave-one out procedure) was implemented in Biosig [4]. The average classification accuracy for CSP and CSPb respectively was 74%±9%, and 74±10% for left vs right hand; 69±8% and 73±7% for right vs both hands; 70 ±8% and 71±7% for left vs both hands. For CSP only 3 participants achieved a classification accuracy higher than 70% as opposed to 6 participants for CSPb, which was used for on-line classification. On-line sessions: The experimental procedure was similar to the off-line but a bar proportional to the on-line accuracy overplayed the execution cues on the computer screen. Unmodified classifier from the off-line session was used. Functional electrical stimulation (frequency 33 Hz, pulse duration 250 ⍰s, amplitude 6-11 mA, duration 2s) was delivered through bipolar pair of electrodes to right or to the left and right hand extensor muscles with intensity sufficient to produce visible muscle contraction. In one sub-session participants were asked to perform left and right MI (40 trials per condition) and in the other sub-session on the day same day they performed right or bimanual MI (40 trials per condition).The order of sub-sessions varied between participants to counterbalance fatigue. The average accuracy was 69±3% and 66±3% for the left vs right and right vs both MI respectively, which was above chance level of 60% [5]. Discussion: This study shows that using CSPb it is possible to classify between uni and bimanual task above chance level. The same classification parameters were used in off and on-line sessions organised a week apart. Significance: Novel rehabilitation protocols and more natural assistive BCI can be created by combining un and bimanual tasks. Conflict of interest: none References: 1. Stewart KC et al. J Neurol Sci. 2006;244:89-95. 2. Szameitat AJ et al. PLoS One. 2012;7:e38506. 3. Onton and Makeig Progress in Brain Research 2006;159:99-120 4. Viddaure et al. Comput Intell Neurosci. 2011; 2011: 935364. 5. Mueller-Putz et al. Int J Bioelectrom. 2008;10:52-55

3-F-44 Steps towards sensitizing EEG feature identification in paediatric brain signals for use in BCIs

Eli Kinney-Lang[1], Loukianos Spyrou[1], Ephrem Zewdie[2], Abdullah Azeem[3], Adam Kirton[2], Javier Escudero[1]

[1]University of Edinburgh, [2]Cumming School of Medicine, University of Calgary, [3]University of Calgary

Introduction: Brain-computer interfaces (BCIs) designed for paediatrics have yet to be fully realized [1,2]. One hurdle facing paediatric BCIs is the dynamic progression of elctrophysiological states of a child throughout development [3]. Variations in development may be further pronounced in children facing motor or other impairments. One potential solution is to sensitize feature identification to the unique developmental state of a child while accounting for shared patterns across typical development [3]. A proof-of-concept was previously demonstrated on resting-state EEG in paediatric epileptic populations ([4], under review), where EEG signal analysis incorporated tensor (i.e. multi-way) methods in identifying age-specific features. This ongoing proposal aims to replicate our resting-state findings in a paediatric stroke population and to adapt the proposed methods to task-driven EEG, including steady-state visual evoked potentials (SSVEP) and movement-related cortical potentials (MRCPs). Together, these steps could provide critical improvements in signal analysis for EEG BCIs tailored towards paediatrics. Materials, Methods and Results: Two paediatric EEG datasets are used for analysis. First, approximately 30 EEGs from paediatric stroke patients at the Alberta Children's Hospital provides validation of our previous findings in a population ideal for BCI rehabilitation. The goal is to replicate discerning age-specific features in EEGs using tensor analysis methods [4]. Second, publicly available EEG data on healthy participants from the Child Mind Institute (CMI) [5] is explored. Data comprising the high-density 129-channel `Contrast-Change Paradigm' (CCP) of pre-adolescent subjects (approx. 6-11 y.o., n=44) is the focus. The CCP provides a simple motor task, in which users select between left/right images flickering at 20/25 Hz changing in contrast from 50%/50% to 0%/100% (or vice versa) [5]. Due to the CCP design, both SSVEP and MRCP potentials can be isolated, and used as 'simulated-BCI' signals. Tensor analysis exploits the high dimensionality of EEG data to uncover latent relationships in signals, such as age-related features common across subjects. Tensors were constructed with dimensions [Trial]x[Channels]x[Frequency]x[Subject]. Combinations of tensor model decompositions will be explored, including variations on the Parallel Factor (PARAFAC) and Tucker models, to identify dominant underlying factors. Non-negativity and unimodal constraints on different dimensions can improve model stability, interpretation, and help illicit prominent factors across ages. Figure 1 illustrates a PARAFAC decomposition of the CMI SSVEP data, showing the [Channels]x[Frequency]x[Subject] dimensions for left-select (top row,20 Hz) and right-select (mid row, 25 Hz) triggers and their differences (bottom row) at occipital channels. These results are similar in approach to the BCI tensor analysis in [6]. Discussion: The results demonstrate simple tensor analysis, like PARAFAC, is capable of extracting underlying factors associated with signals of interest (yellow), i.e. SSVEP frequencies at 20/25 Hz, while separating out erroneous data (red) and background noise (blue). These separated factors account for properties from each dimensions, including the age-ordered [Subject] dimension, since PARAFAC requires strict 1-to-1 interactions between factors across dimensions [7]. Exploring tensor decompositions across the acquired datasets, along with integrating age-weighted probabilities to the extracted feature profiles, could offer solutions for incorporating age-related features and properties into the signal analysis stage of BCIs. Significance: The details presented here are a work in progress. Adapting the powerful tools of tensor analysis to incorporate developmental information into EEG feature identification lays a framework which could improve BCI signal analysis for children. Replication of this work in both healthy and afflicted paediatric populations will further validate its potential for BCI systems. Acknowledgments: Funding was provided by Edinburgh Neuroscience NeuroResearchers Fund. References: [1]DOI:10.2478/s11536-013-0249-3 [2]DOI:10.1088/1741-2560/13/6/061002 [3]DOI:10.1109/EMBC.2017.8037684 [4]ArXivID:1712.07443 [5]DOI:10.1038/sdata.2017.40 [6]DOI:10.1088/1741-2560/13/2/026005 [7]DOI:10.1016/S0169-7439(02)00089-8

3-F-45 Enhancing the BCI performances for steady-state visual evoked potentials around ear

No-Sang Kwak[1], Seong-Whan Lee[1]

[1]*Korea University*

Introduction: In recent brain-computer interfaces (BCIs), the versatile applicability of ear-electroencephalography (EEG) electrodes has been researched for convenient BCIs [1, 2]. In particular, ear-EEG BCIs have shown reliable performance in auditory steady state response, auditory event related potential and sleep detection paradigms. Also, a steady-state visual evoked potential (SSVEP), one of the wildly used paradigms in BCI, could be detected using ear-EEG [1]. However, the performance is still lower than conventional scalp EEG devices because ear-EEG generally provides restrictive channel location around (or in) the ear with few number of electrodes. Hence, in this abstract, we introduce a method that can enhance ear-EEG based SSVEP performances using regression analysis between EEG signals in the occipital area and around the ear. Our experimental results showed a feasibility of a reliable, stable SSVEP decoding of ear-EEG BCI. Material, Methods and Results: We collected EEG data using scalp EEG devices with channels around the ear (i.e., FT9-10, FTT9h-10h, T7-8, TPP9h-10h, TP9-10) and occipital lobe (PO7, PO3, PO, PO4, PO8, O1, Oz, O2). We designed an SSVEP experimental paradigm using five LEDs which have flickering frequencies of 9, 11, 13, 15 and 17 Hz respectively. Subjects were asked to concentrate their gaze on the visual stimuli during 5 s following auditory cues that were randomly given (70 trials in total; similar to [3]). In training session, we build regression models between occipital (dependent variables) and around-ear EEG signals (independent variables); we validated three regression models using multivariable linear regression (MLR), ridge regression (RR) and kernel ridge regression (KRR) analysis. In test session, we estimated occipital EEG signals using only around-ear EEG signals based on the regression models. For classification, we employed canonical correlation analysis (CCA) with acquired around-ear EEG signals and estimated occipital EEG signals. As results, the grand averaged estimation performances of occipital EEG signals (correlation coefficient) were 0.7763, 0.7786, and 0.7463 in MLR, RR and KRR respectively. In the case of RR, the best classification accuracy recorded 80% (c.f., 93.33% for actual occipital EEG signals, 53.33% for only actual around-ear EEG signals). Discussion: The study in [4] reported that high mutual information exists between ear and scalp EEG signals. In our study, we designed and validated three regression models for predicting occipital EEG signals using around-ear EEG signals based on linear- and nonlinear regression analysis. The linear regression methods (i.e. MLR and RR) showed a better performance than nonlinear method. We surmise occipital EEG signals and around-ear EEG signals have a prominent linear relationship in the low frequency band. Also, we analyzed functional connectivity (FC); we found strong connectivity during SSVEP in both actual and estimated EEG signals (Figure 1). Significance: Our study demonstrates SSVEP BCI based on ear-EEG could achieve reliable performances by using the regression model. However, a more sophisticated regression framework for the prediction may improve the presented results. Future work will target the evaluation of the proposed method with an ear-EEG device. Acknowledgements: This work was supported by Samsung Research Funding Center of Samsung Electronics under Project Number SRFC-TC1603-02. References [1] D. Looney, P. Kidmose, C.-S. Park, M. Ungstrup, M. Rank, K. Rosenkranz, and D. Mandic, "The In-The-Ear Recording Concept: User-centered and Wearable Brain Monitoring," IEEE Pulse, Vol. 3, No. 6, 2012, pp. 32-42. [2] S. Debener, R. Emkes, M. Vos, and M. Bleichner, "Unobtrusive Ambulatory EEG using a Smartphone and Flexible Printed Electrodes Around the Ear," Scientific Reports, Vol. 5, 2015, Article 16743. [3] N.-S. Kwak, K.-R. Müller, and S.-W. Lee, "A Convolutional Neural Network for Steady State Visual Evoked Potential Classification under Ambulatory Environment," PloS one, Vol. 12, No. 2, 2017, e0172578. [4] K. B. Mikkelsen, P. Kidmose, and L. K. Hansen, "On the Keyhole Hypothesis: High Mutual Information between Ear and Scalp EEG," Frontiers in Human Neuroscience, Vol. 11, 2017, Article 341.

3-F-46 EEG data evaluation based on fuzzy clustering for improving classification accuracy

Jianguo Wang[1], Zhifu Deng[1], Zhiduo Cao[1], Banghua Yang[1]

[1]Shanghai University

Introduction: Electroencephalography (EEG) signal classification is a key part of the BCI in motor imagery. However, the acquisition of EEG is susceptible to other bioelectricity of the body such as EOG and EMG, which contaminates the EEG data and leads to poor performance of the modeling accuracy. Therefore, the EEG denoising methods such as PCA, ICA and Fast Fourier Transform were introduced and have achieved some promising results[1]. While those methods can help improve the classification results, they cannot be used to evaluate the quality of the EEG data, which means the classification results is not able to tell whether the dataset is good or bad. This triggers our thinking to find a way of detecting and removing the part of the dataset, which is severely contaminated before conducting the classification. A methodology based on fuzzy c-means clustering is proposed to evaluate the quality of our EEG data. The goal is to discover the bad part of the data severely contaminated in our dataset and to remove it, and therefore the classification result becomes more accurate with better train data. In this way, the outline or noise can be removed before modeling and classification. The whole procedure is shown in Figure 1. Material: The data comes from the BCI competition IV dataset I. Clustering algorithm is applied to evaluate the quality of the EEG data. The contaminated data is selected and removed so that the retained data is of high quality. Therefore, the classification performance is further. The process of our method is shown in figure 1. Firstly, some data preprocessing process such as Fourier filtering is performed. Next and most importantly, fuzzy c-means clustering algorithm is applied to the preprocessed data. Only 16 channels (FC5, FC1, FC2, FC6, T7, C5, C3, CZ, C4, C6, T8, CP5, CP1, CPZ, CP2, CP6) are chosen from the original dataset which contains 59 channels to speed up the computation. Methods: The denoised data is classified by the fuzzy c-means clustering algorithm mentioned above. It is divided into 10 categories, in which every 4000 groups of data (data in 4s with frequency as 1000Hz and each data contains 16 channels, every 16 channels is called a group) represent a motion imagery process. The information of which category each group of data should belong to is got based on the membership rules. How many groups of data are included in each class is calculated, the data obtained from 100 left-hand experiments in 200 experiments should be roughly equal in each type of distribution in ideal state. In the same way, the experiments on both right hand and legs should be roughly equal. Influenced by noise, the distribution of experimental data is not uniform. We have counted the number of data in each of the 10 categories. Smaller number indicates the less data containing the class. When the number is smaller than 10 or less, it means that only less than or equal to one-tenth of the total data contains the class. Data contained in this class is obviously different from the others. Based on this, we can come to the conclusion that data contained in these categories is more severely contaminated by noise, ie, bad data which should be removed to improve the modeling accuracy. As shown in Table 1 and Table 2, the 2nd 9th 10th only contains 2, 2 and 3 data. Which indicates that data contained in these three categories is bad and should be removed. In the same way, in Table 2, the first category only contains 5 data, which means these 5 data should be removed. Finally, 7 data of left hand and 5 data as shown in Table 1 and Table 2 are removed, the remained 188 data are used to build a classification model. Result: Traditional CSP is used for feature extraction and SVM is used as the classification method. The result is compared with the original data and the data processed by the proposed method. The classification results are 90% and 94% respectively, which shows a 4% accuracy improvement can be achieved using the proposed methodology in data evaluation, which finally helps in classification performance. Conclusion and discussion: In our study, a clustering method to evaluate the EEG data is proposed, which can remove the bad data severely contaminated by noise such as EOG. As a result, the meaningful critical data is reserved, which lead to the improvement of the performance for classification. However, there are some problems worth to further investigate, for example, how many categories should be adopt

3-F-47 A study of the role of attention in classifying covert and overt motor activities

Banghua Yang[1], Jinlong Wang[1], Cuntai Guan[2], Chenxiao Hu[1], Jianguo Wang[1]

[1]Shanghai University, [2]Nanyang Technological University

Introduction: The existing motor imagery of brain-computer interface focuses more on the aspect of motor imagery and less on the experimental ways of combining other motion and imagination. In this paper, aiming at studying the role of attention in the context of classifying covert and overt motor activities, we designed different experiments to explore it in different modes. In our experiments, covert is only motor imagery. Overt motor activities are divided into two types--attention to the screen and attention to intended hand. These EEG data in different modes are analyzed by wavelet packet decomposition-Common Spatial Patterns（WPD-CSP） and certain meaningful results are found. Materials and methods: We selected six healthy volunteers as experimental subjects, respectively, carried on the experiment. Figure 1 represents a single trial flow diagram. We divide a single trial into three stages, rest, pre-demo and execution. We only record the EEG data in the third stage. The three experimental modes are as follows: a. Covert motor activity (Motor Imagery Only, MIO): In the third stage, the subjects start motor imagery of corresponding side of the hand-fist movement when the green arrow shows and always pay attention to their intended hand. b. Overt motor activity Ⅰ (Movement Execution Only, MEO, attention to the screen): In the third stage, the subjects only perform hand-fist movement on the corresponding side, and the brain tried not to imagine the hand movement as much as possible. In practice, in order to reduce the imagination of the brain, a calm beautiful sea picture appears in the video of the recording stage. The subjects relax on themselves with their attention focused on the picture instead of their hand movement, and only their hands make a fist movement mechanically. c. Overt motor activity Ⅱ (Motor Imagery and Movement Execution, MI&ME, attention to intended hand): In the third stage, the subjects are required to start motor imagery and actual movement simultaneously. Figure 2 indicates flow chart of our experiment framework. The WPD-CSP algorithm was used to extract the features of the data under different modes and classified by SVM algorithm to get the corresponding classification accuracy. Figure 3 shows specific process. Results: Based on the results of EEG analysis of six subjects, as Figure 4 shows, it can be concluded that under the experimental conditions of the three different modes, the effect of MI&ME is the best, the second is the MIO, and the effect of MEO is the worst of the three modes. The average accuracy of MI&ME is more than 5% higher than that of MEO, and an average of 3% higher than the accuracy of MIO. The accuracy difference between MI&ME and MEO is statistically significant (p-value is 0.003). On the other hand, from the Figure 5, it is clear that some related areas of brain are more active when subjects are in MI&ME mode. Discussion and significance: In this study, we present three different modes of motor imagery experiments for the existing brain imaging experiments. Self-designed experiments to obtain EEG data under different modes and conduct the corresponding analysis. From the study, we hypothesize that (1) attention plays an important role in overt and covert motor activities, which may imply that simultaneously overt and covert motor activities may provide better activations in stroke rehabilitation; (2) pure overt movement (like those in robotic rehabilitation) without focusing on the affected limbs may compromised its effect in rehabilitation. That is, while the robot mechanically drives the affected side for rehabilitation training, the patient should also actively carries out the imagery of the affected limbs. In order to stimulate the patient's nerves, the patient's nervous system should directly involve in the training to motivate the rehabilitation of neurological function. Compared with traditional mechanical arm movement or pure motor imagery, MI&ME should have a better rehabilitation effect. Reference: [1]Banghua Yang, Huarong Li, Qian Wang and Yunyuan Zhang. Subject-based feature extraction by using fisher WPD-CSP in brain-computer interfaces. Computer Methods and Programs in Biomedicine, 129 (2016) 21-28

3-F-48 Decoding lip movements during continuous speech using ECoG

Srdjan Lesaja[1], Christian Herff[2], Garett Johnson[1], Jerry Shih[3], Tanja Schultz[2], Dean Krusienski[1]

[1]Old Dominion University, [2]University of Bremen, [3]University of California San Diego

Introduction: Recent work has shown that it is possible to decode aspects of continuously-spoken speech from electrocorticographic (ECoG) signals recorded on the cortical surface [1]. The ultimate objective is to develop a speech neuroprosthetic that can provide seamless, real-time synthesis of continuous speech directly from brain activity. The aim of this work is to investigate the neural correlates of speech-related lip movements from video recordings, and to utilize this information in the development of improved decoding models. Material, Methods and Results: ECoG data have been collected from subjects undergoing clinical monitoring for epilepsy. The subjects performed a battery of speech tasks including modal and imagined continuous speech, as well as spontaneous modal and imagined speech via standard picture description and directed conversation tasks. From the ECoG signal, the high gamma-band (70-170 Hz), with a notch filter to remove 120 Hz harmonic, was used for analysis. For each electrode, the average power across the band was calculated using the FFT on 50 ms windows with a 25 ms overlap. In addition, the instantaneous amplitude of the band was calculated using the Hilbert transform and the offset bias described in [2]. These were the two brain signal measures used. From simultaneous video recordings, lip movement features were extracted using Python and Dlib [3], an open source computer vision algorithm library. The video frames were synchronized to the ECoG signal during acquisition by BCI2000 [4]. For each frame, we used Dlib to automatically detect facial landmarks. Of 68 facial landmark points, 20 were used to outline the inner and outer lines of the lips. These 20 points were used to calculate four lip features: area of outer lip perimeter, area of inner lip perimeter, distance between outer top and bottom lips, distance between inner top and bottom lips. The spatio-temporal relationships between brain activity and lip movement features were computed. Features were correlated to the gamma-band activity at multiple time-lags to characterize brain activity in relevant areas during the process of speech production. To ensure the correlations were significant, a randomization test was performed. Normal distribution maximum likelihood parameters were fit for each electrode signal. One thousand simulated random electrode signals were generated and correlated to the video features. These simulated correlations were used to construct an empirical distribution. Real electrode correlation measurements were compared to this distribution, and their p-value calculated to ensure the correlations were greater than those that would be seen by random chance. The results of the time-lag analysis are shown in Figure 1. Additionally, several other analyses were explored. The brain signal measures were used to train a classifier to distinguish open-mouth and closed-mouth states based on a threshold of the mouth perimeter area. Brain signals were also used to attempt to predict the dynamic lip contours. Figure 1: Activation index [-log(p-value)] at different time lags Discussion: The maximum correlation across channels was 0.21, with no simulated electrode reaching above 0.03. An analysis of the facial feature performance showed that the area-based features had both the highest absolute correlation, as well as a greater number of electrodes with high correlation. Of the two area features, the outer lip area performed slightly better than the inner lip area. The band power and instantaneous amplitude had very comparable correlations, with the power having slightly higher maximum correlations per electrode. Significance: The analysis indicates that there is a distinct spatio-temporal progression of brain activity during the lip movements of continuous speech. These results provide important insights about the brain dynamics of these isolated speech articulators. Through the characterization of brain activity related to these and other speech articulators, improved speech decoding schemes can be developed for brain-computer interfaces and neuroprosthetics. Acknowledgements: This work was supported 01GQ1602 (BMBF) and 1608140 (NSF). References: [1] Herff, C., & Schultz, T. (2016). Automatic Speech Recognition from Neural Signals: A Focused Review. Frontiers in Neuroscience, 10, 429. [2] Schalk, G. (2015). A general framework for dynamic cortical function: the function-through-biased-oscillations (FBO

3-F-49 Boosting Communication speed and accuracy for P300 BCI spellers

Luigi Bianchi[1], Matteo Cosmi[2], Chiara Liti[1], Veronica Piccialli[1]

[1]University of Rome "Tor Vergata", [2]"Roma Tre" University

Introduction: In this work, we present a new procedure to carry out the classification phase in a P300 brain computer interface (BCI), or more in general, to solve any binary classification problem where the dataset is made of repetitions. Our procedure, based on the use of the protocol's information and the classifier's properties, allows us to increase dramatically both the communication speed and the accuracy. Material, Methods and Results: We test our strategy on the P300 speller with ALS patients (008-2014) dataset of the BNCI Horizon 2020 database. Eight patients are required to copy-spell seven predefined words of five characters each, by controlling a P300 6x6 matrix speller. A single stimulus repetition consists in 12 successive and random intensifications of all rows and columns. Two of them contain the desired character (target stimulus). For each character, 10 stimulus repetitions are performed. We split the dataset by using the first three words as training (15 characters), and the last four as test set (20 characters). We consider decimated EEG data resampled in the time domain by replacing each sequence of 12 consecutive samples with their mean value. A 4200x137 matrix represents the final dataset for each patient. No artefact rejection strategy is used. A standard P300-Speller BCI uses the hyperplane computed by a linear classifier and certain information on the protocol to discriminate the trials. Typically, due to the existence of exactly one target stimulus every six instances, the target label is assigned to the column (row) having the maximum decision value (obtained by inserting the trial into the hyperplane). Our method is based on a standard linear classifier, but we exploit in an innovative way the produced hyperplane considering that the patient has to recognize the same character ten times and the target column (row) is always the same. In our training strategy, for each set of column (row) trials in a stimulus repetition, we order in decreasing way the decision values and we assign a score to each column (row) according to different strategies based on the trials distribution with respect to the hyperplane. The scores are then summed up on the ten repetitions and the target label is assigned to the trial having the highest total score. In the test phase, the scores are summed up step by step and if the gap between the first best and the second best partial score exceeds a certain threshold it is possible to simulate the interruption of the stimulus repetitions. This results in a fundamental advantage: a suitable choice of the threshold dramatically reduces the time to perform a classification boosting the communication speed, controlling the accuracy loss (if any). Our approach, then, leads to a huge benefit for the patients, and potentially to a new dynamically adjusted protocol. In Table 1 we report the results obtained by SWLDA for increasing values of the threshold and for four different decision functions: in the first three the strategy used to assign the score to each columns (row) trial changes, whereas the fourth is obtained by a voting system based on the first three functions. We report the number of correctly classified characters and the percentage of saved stimulations (in brackets) on the test set. Discussion: The effectiveness of our strategy is shown by the comparison with the standard decision function (max function), that we outperform, and by the high accuracy obtained without removing artefacts. We get better results in terms of accuracy than the ones obtained by averaging for each column (row) the ten trials corresponding to the ten stimuli repetitions (Dec12Med10), showing the effectiveness of the score assignment strategy. Furthermore, we have a tool (the threshold choice) that allows us to balance the two main goals: communication speed and accuracy. Indeed, considering the overall bitrate, our strategy allows to boost the bitrate from 7.083 bpm as in the ideal case of 100% accuracy using all the repetitions, to 11.135 bpm, with an increment of the communication speed of 57.2%. Significance: Our approach leads to the definition of an innovative dynamically adjusted communication protocol that can achieve both high accuracy and high speed. Furthermore, tuning the threshold parameter it is possible to privilege speed or accuracy depending on the application.

3-F-50 Single-trial target detection with magnetoencephalography with multiple difficulty levels

Hubert Cecotti[1]

[1]California State University, Fresno

Introduction: Brain-Computer Interfaces (BCIs) are mainly based on electroencephalography (EEG) recordings as EEG amplifier can be portable and it represents one of the less expensive solution to provide BCI systems outside of the laboratories. In some situations, where brain monitoring is used as a regular tool for assessing some brain functions, the portability is not a problem and a high signal quality can be obtained with other types of brain imaging techniques like magneto-encephalography (MEG). This study deals with the detection of facial expressions during a serial visual presentation task at the single-trial level with MEG recordings, where different images of faces with particular facial expressions are presented to the user. We focus on the links between single-trial detection and behavioral performance. The challenge is to extract relevant features to differentiate between target images from non-target images and to associate single-trial detection with the difficulty level. Single-trial detection provides an efficient way to measure the detection a short time scale during the experiment and to follow the evolution of the accuracy over time. Material, Methods, and Results: Ten healthy adult participants (mean age=26.2) had to pay attention to a stream of images (presentation rate=1 Hz (stimulus onset asynchrony=1000ms, stimulus duration=333ms)) (40 blocks of 12 images, each block contains faces from the same person, but with different facial expressions corresponding to 6 different classes: anger, disgust, fear, neutrality, sadness, and happiness). The goal of the task was to detect the presence of images with a specific facial expression (one among the six available), by pressing a button. Six sessions were recorded for each participant, one session per type of target. The goal of the data analysis is to detect the presence of a target by using only the MEG signal and the stimulus onsets. The MEG signal was recorded with an Elekta Neuromag 306-channel MEG system in the NIFBM Facility of the Intelligent Systems Research Centre at Ulster University, Derry, UK. The signal was recorded with a sampling rate of 1kHz. The signal was bandpass-filtered between 0.1Hz and 41.66Hz, and downsampled to 125Hz. Single-trial detection was achieved by using xDAWN for spatial filtering and BLDA for the binary classification. For the behavioral performance, the reaction time (RT) across participants (in ms) was 606±56, 588±72, 548±68, 541±47, 564±36, and 609±57 for anger, disgust, fear, happy, neutral, and sad. The hit rate and the prevision (in %) was 54, 55, 70, 86, 72, and 47 ; 57, 53, 70, 86, 80, and 55. The performance was assessed by using a five-fold cross validation by classifying targets from non-targets using a time segment of 1s post stimulus. The area under the ROC (AUC) curve across participants for the six conditions is 0.763, 0.778, 0.835, 0.898, 0.847, and 0.685 for the six types of targets. The results indicate a negative correlation between single-trial detection and RT (-0.54), a strong correlation between AUC and the hit-rate (0.85), and a low correlation between AUC and Precision (0.37). Discussion: The results support the conclusion that single-trial detection using MEG recordings provide high performance with some types of targets with a low difficulty, which could be suitable for an efficient online neurofeedback while patients identify target images of a particular class. The difficulty level as represented by the type of facial expressions has a key impact on the performance, both at the behavioral level and the single-trial detection level. Significance: Patients who sustain moderate-severe traumatic brain injury have a low performance at recognizing emotional expressions. There exists a greater impairment in recognizing negative emotions such as fear, disgust, sadness, and anger as compared to positive emotions such as happiness and surprise. The research literature indicates that there exists a clear link between the recognition of facial expressions and TBI. The proposed study provides baseline results using single-trial detection with healthy people processing images representing faces. Further study will include patients with TBI to establish difference of performances between healthy and TBI patients.

3-F-51 Nine automatic artifact rejection algorithms all decrease P3 speller accuracy

Katie Dhuyvetter[1], Jane Huggins[2], David Thompson[1]

[1]Kansas State University, [2]Direct Brain Interface Laboratory, University of Michigan

Introduction:<\i> BCI systems are susceptible to blinking artifacts. One method of removal is to use an automatic artifact rejection (AAR) algorithm on the data. Our previous results [1] indicated that one removal method, FORCe [2], resulted in decreased P3Speller BCI performance. This work extends that result to a larger set of algorithms. Material, Methods and Results:<\i> In the original study [3], [4] the participants were tested on three days with a 16-channel EEG cap. The study used a Farwell/Donchin row-column P3Speller. Subjects wrote three sentences on the P3Speller each day, with an extra training file on the first day. Data from 34 participants who completed the protocol were included in this study. However, participants were excluded if any method experienced errors during processing. The final participant count was 21, including 7 people with Amyotrophic Lateral Sclerosis and a person with Muscular Dystrophy. The AAR algorithms used are implemented within the EEGLAB software [5] and two artifact rejection plugins. The first plugin tested, "AAR plug-in for EEGLAB," [6] had the following methods: bsscca, efica, fcombi, iwasobi, jader, multicombi, pca, and sobi. An additional plugin, "MARA" [7], was also tested. After these algorithms were applied, Least Squares regression was used for classification. Step-wise Linear Discriminant Analysis was investigated, but not reported for brevity. Regardless of method, the overall impact on performance was negative for most users. Of the 1701 file/method combinations investigated, 1378 (81%) had lower than online performance. Performance was unchanged in 209 cases, and increased in 323. Each of the nine methods was statistically significantly more likely to harm performance than any other outcome. This remains true after Bonferroni correction for number of methods. Discussion:<\i> Overall, the automatic artifact rejection algorithms used reduced BCI performance. Initial investigations indicate that multiple factors led to the decrease in performance. Three potential factors were identified: 1) a subset of participants blinking with consistent timing, resulting in artificially-inflated performance which AAR properly removed, 2) algorithms reducing amplitude of the P300 response, and 3) algorithms making the regression matrix more linearly dependent, leading to inaccurate weight vectors. Significance:<\i> This investigation implies that AAR algorithms, at least the ones tested here, can harm P3Speller performance. Other classification approaches may be less sensitive to the issues caused by these AAR algorithms. Still, the widespread pattern of decreased performance may be a caution for other investigators to carefully consider their choice of AAR algorithm. Further study is required. Acknowledgements:<\i> The data were collected under NIDRR grant H133G090005 and award number H133P090008, and NIH award R21HD54697. The opinions and conclusions are those of the authors, not the respective funding agencies. References:<\i> [1] J. Tillman, J. E. Huggins, and D. E. Thompson, "Blink artifact rejection reduces P3 speller accuracy but may prevent unintended blink-based control," in 6th Inter. BCI Meeting<\i>, Jun. 2016. [2] I. Daly, R. Scherer, M. Bilinger, and G. Muller-Putz, "FORCe: Fully Online and Automated Artifact Removal for Brain-Computer Interfacing," IEEE Trans. Neural Syst. Rehabil. Eng. Publ. IEEE Eng. Med. Biol. Soc.<\i>, vol. 23, no. 5, pp. 725-736, Sep. 2015. [3] D. E. Thompson, K. L. Gruis, and J. E. Huggins, "A plug-and-play brain-computer interface to operate commercial assistive technology," Disabil. Rehabil. Assist. Technol.<\i>, vol. 9, no. 2, pp. 144-150, Apr. 2013. [4] D. E. Thompson, S. Warschausky, and J. E. Huggins, "Classifier-based latency estimation: a novel way to estimate and predict BCI accuracy," J. Neural Eng.<\i>, vol. 10, no. 1, p. 016006, Feb. 2013. [5] O. A. Padierna Sosa, Y. Quijano, M. Doniz, and J. E. Chong Quero, "Development of an EEG signal processing program based on EEGLAB," in Pan Amer. Health Care Exch.<\i>, Mar. 2011. [6] G. Gomez-Herrero, "Automatic removal of ocular artifacts in the EEG without an EOG reference channel," in Nordic Sig. Proc. Symp.<\i>, Jun. 2006. [7] I. Winkler, S. Haufe, and M. Tangermann, "Automatic classification of artifactual ICA-components for artifact removal in EEG signals," Behav. and Brain Func.<\i>, vol. 7, no. 30, Aug. 2011.

3-F-52 BCPy, an open-source python platform for offline EEG signals decoding and analysis

Aurélien Appriou[1], Léa Pillette[1], Andrzej Cichocki[2], Fabien Lotte[1]

[1]Inria, LaBRI (Univ. Bordeaux, CNRS, Bordeaux-INP), France / RIKEN BSI, Wakoshi, Japan, [2]RIKEN BSI, Wakoshi, Japan / SKOLTECH, Moscow, Russia

Introduction Although promising, BCIs are still barely used outside laboratories due to their poor robustness. Moreover, they are sensitive to noise, outliers and the non-stationarity of electroencephalographic (EEG) signals. Many algorithms have been developed for EEG signals processing and classification. The current major platforms (BCI2000, BBCI, OpenVIBE, BCILAB, BCI++, BF++) provide modules going along the BCI process: data acquisition, signal processing, classification, statistical modelling and visualization [3]. Each platform has specific strengths, e.g., numerous data acquisition methods for BCI2000, extensive Machine Learning (ML) algorithms for BCILAB, or real time graphical-user interface (GUI) for BCI++ and OpenViBE. However, all comprise classification tools, more or less developed. For example, BCI2000, BBCI or OpenVIBE propose the Common Spatial Pattern (CSP) filter and the Linear Discriminant Analysis (LDA) classifier, which are very popular BCI ML tools [5]. Most of these platforms are open source and implemented in C++ or Matlab. We propose BCPy, an open-source, easy-to-use python BCI platform for off-line EEG signal analysis. Using Python makes it simple and extendable by non-computer scientists. Python is free, whereas Matlab is not, and contains good scalable libraries for scientific computing, such as numpy (https://www.numpy.org) or scipy (https://www.scipy.org). Moreover, Python is the major language used to implement recent advances in ML and Deep Learning ([6], https://www.tensorflow.org/, http://scikit-learn.org/), thus making them easily available for BCI research. Material, Methods and Results BCPy comprises four main modules: 1) reading different EEG data format, e.g. ".gdf", ".mat" and ".pkl"; 2) filtering and representing EEG signals, e.g., CSP or Filter Bank CSP (FBCSP), mutual information feature selection; 3) classifying EEG signals, e.g. LDA, Riemannian Geometry or Convolutional Neural Network (CNN); 4) visualizing statistics on the analysis results. All algorithm examples mentioned above are already implemented. Each module can be used independently. Moreover, BCPy has a jupyter notebook GUI (see Figure 1), allowing users to test and compare algorithms with various parameters on their data, without any programming. BCPy has already been used to analyze 3 types of BCI data. First, we used algorithms for classification of Motor-Imagery EEG signals and compared results to the literature. For example, the FBCSP results were compared to [1]. The second study compared algorithms performances for EEG classification of workload levels (high vs low) [2]. This revealed that CNN obtained significantly better classification accuracy (user-specific mean = 72.7%) than CSP+LDA (67.0%), with both user-specific and user-independent ML calibration. Moreover, CNN also outperformed FBCSP and Riemannian Geometry. Each of these algorithms has proved efficient either in recent active BCI classification competition [1,7] or in other independent studies [6]. The third study classifies four types of attention (Alertness, Sustained, Selective and Divided attention) [9], two by two, using CSP+LDA in the alpha band (8-12 Hz). Results indicate that each of the four types of attention is distinguishable from the others, with accuracies ranging from 74% to 83%. Next, we will look at the other frequency pass-bands by using FBCSP. Discussion BCPy accelerated EEG signals analysis for three studies. More tools will be implemented rapidly, e.g. statistical analysis and data visualization, to make BCPy more versatile. New ML tools will be added, notably Recurrent Neural Networks, which showed promising results in many areas [8]. Finally, we aim at making BCPy available online, using jupyter notebook. Significance We propose BCPy, a free, open-source EEG analysis platform based on Python, usable by anyone without programming knowledge, hopefully bridging gaps between engineering and neuroscience/psychology researchers and accelerating BCI research. We acknowledge support from the Japanese Society for the Promotion of Science and the European Research Council (grant ERC-2016-STG-714567). References 1. Ang et al, Frontiers in Neuroscience, 2012 2. Appriou et al, ACM CHI, submitted 3. Brunner et al, Towards Practical BCI, 2013 5. Lotte et al, JNE, 2007 6. Schirrmeister et al, HBM, 2017 7. Yger et al, IEEE TNSRE, 2016 8. Yang et al, http://arxiv.org/abs/1707.01786 9. Pillette et al, BCI meeting, submitted

3-F-53 Area-to-area transfer improves single-Channel SSVEP classification

Chi Man Wong[1], Ze Wang[1], Ka Fai Lao[1], Feng Wan[1]

[1]*University of Macau*

Introduction: Steady-state visual evoked potential (SSVEP)-based brain-computer interface (BCI) has demonstrated the satisfactory system performance [1]. However, moving a SSVEP-based BCI system from the laboratory into real-life applications still poses several challenges. For example, placing multiple wet electrodes on the subject's parietal-occipital area, which is usually covered with hair, is very cumbersome and inconvenient. Recently, several researchers propose to measure the SSVEPs from the non-hair-bearing areas, such as frontal area, neck area, behind-the-ear area, and etc, but the resulting classification performance may be significantly degraded [2,3]. For this reason, we aim to propose an area-to-area transfer method that learns from SSVEPs at parietal-occipital area to enhance the classification performance of SSVEPs from non-hair-bearing areas as there is common knowledge between SSVEPs from these two areas. Material, Methods and Results: By utilizing the relation between the subject's SSVEPs from different areas, we apply the knowledge between the SSVEPs from source area and target area for the single-channel SSVEPs classification (see Fig. 1). The hypothesis is that there exists an invariant transformation between the SSVEPs from source area (e.g., parietal-occipital area) and target area (e.g., frontal area) since the frontal SSVEPs come from the occipital SSVEPs theoretically. In this preliminary study, such a transformation can be considered as a linear combination, which can be found by performing the canonical correlation analysis (CCA) [4] between the SSVEPs from two areas. To validate our idea, the CCA methods without learning, with learning from single-channel SSVEPs and with learning from multi-channel SSVEPs are compared using a benchmark SSVEP dataset [5]. Results show that there is significant performance difference between using the single-channel SSVEPs at FPz and Oz, which is consistent with [2,3], and importantly the CCA method with learning from multi-channel SSVEPs can boost the performance significantly in both cases. Discussion: Although the classification performance of the SSVEPs at FPz is not satisfactory, this is only a proof-of-concept study to verify that some knowledge of the SSVEPs from different areas can be transferred such that the classification performance of the single-channel SSVEPs can be enhanced. As a matter of fact, there are large inter-subject variations in their performance. For example, some subjects can achieve around 80% accuracy. The following study should focus on this issue. In addition, we can also apply the other advanced transfer learning technologies to improve the performance. Significance: Area-to-area transfer should be helpful to classify the SSVEPs from the non-hair-bearing area. Acknowledgement Supported in part by Macau Science and Technology Development Fund (036/2009/A, 142/2014/SB and 055/2015/A2) and Univ. of Macau Research Committee (MYRG: 139-FST11-WF, 079-FST12-VMI, 069-FST13-WF, 2014-00174-FST, 2016-00240-FST and 2017-00207-FST). Reference: [1] X. Chen, Y. Wang, M. Nakanishi, X. Gao, T.-P. Jung, and S. Gao, "High-Speed Spelling with a Noninvasive Brain-Computer Interface," Proc. Natl. Acad. Sci. U.S.A., vol. 112, no. 44, pp. E6058-E6067, 2015. [2] H.-T. Hsu, I.-H. Lee, H.-T. Tsai et al., "Evaluate the Feasibility of Using Frontal SSVEP to Implement an SSVEP-Based BCI in Young, Elderly and ALS Groups," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 24, no. 5, pp. 603 -615, 2016. [3] Y.-T. Wang, M. Nakanishi, Y. Wang, C.-S. Wei, C.-K. Cheng, and T.-P. Jung, "An Online Brain-Computer Interface Based on SSVEPs Measured From Non-Hair-Bearing Areas," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 25, no. 1, pp. 14 -21, 2017. [4] M. Nakanishi, Y. Wang, Y.-T. Wang, and T.-P. Jung, "A Comparison Study of Canonical Correlation Analysis Based Methods for Detecting Steady-State Visual Evoked Potentials," PloS One, vol. 10, no. 10, p. e0140703, Oct. 2015. [5] Y. Wang, X. Chen, X. Gao, and S. Gao, "A Benchmark Dataset for SSVEP-Based Brain-Computer Interfaces," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 25, no. 10, pp. 1746 -1752, 2016.

3-F-54 Artifact propagation in electrocorticography stimulation

Jeffrey Lim[1], Po Wang[1], Susan Shaw[1], Michelle Armacost[1], Hui Gong[1], Charles Liu[1], Payam Heydari[1], An Do[1], Zoran Nenadic[1]

[1]University of California, Irvine

Introduction:Current brain-computer interfaces (BCIs) primarily rely on visual feedback. However, visual feedback may not be sufficient for applications such as movement restoration, where somatosensory feedback plays a crucial role. For electrocorticography (ECoG)-based BCIs, somatosensory feedback can be elicited by cortical surface electro-stimulation [1]. However, simultaneous cortical stimulation and recording is challenging due to stimulation artifacts. Depending on the orientation of stimulating electrodes, their distance to the recording site, and the stimulation intensity, these artifacts may overwhelm the neural signals of interest and saturate the recording bioamplifiers, making it impossible to recover the underlying information [2]. To understand how these factors affect artifact propagation, we performed a preliminary characterization of ECoG signals during cortical stimulation.Materials/Methods/ResultsECoG electrodes were implanted in a 39-year old epilepsy patient as shown in Fig. 1. Pairs of adjacent electrodes were stimulated as a part of language cortical mapping. For each stimulating pair, a charge-balanced biphasic square pulse train of current at 50 Hz was delivered for five seconds at 2, 4, 6, 8 and 10 mA. ECoG signals were recorded at 512 Hz. The signals were then high-pass filtered (≥1.5 Hz, zero phase), and the 5-second stimulation epochs were segmented. Within each epoch, artifact-induced peaks were detected for each electrode, except the stimulating pair, where signals were clipped due to amplifier saturation. These peaks were phase-locked across electrodes and were 20 ms apart, thus matching the pulse train frequency. The response was characterized by calculating the median peak within the 5-second epochs. Fig. 1 shows a representative response of the right temporal grid (RTG), with the stimulation channel at RTG electrodes 14 and 15. It also shows a hypothetical amplifier saturation contour of an implantable, bi-directional, ECoG-based BCI prototype [2], assuming the supply voltage of 2.2 V and a gain of 66 dB. Finally, we quantify the worst-case scenario by calculating the largest distance between the saturation contour and the midpoint of each stimulating channel.Discussion:Our results indicate that artifact propagation follows a dipole potential distribution with the extent of the saturation region (the interior of the white contour) proportional to the stimulation amplitude. In general, the artifacts propagated farthest when a 10 mA current was applied with the saturation regions extending from 17 to 32 mm away from the midpoint of the dipole. Consistent with the electric dipole model, this maximum spread happened along the direction of the dipole moment. An exception occurred at stimulation channel RTG11-16, for which an additional saturation contour emerged away from the dipole contour (not shown), extending the saturation region to 41 mm. Also, the worst-case scenario was observed at 6 mA stimulation amplitude. This departure could be a sign of a nonlinear, switch-like behavior, wherein additional conduction pathways could become engaged in response to sufficiently high stimulation.Significance:While ECoG stimulation is routinely performed in the clinical setting, quantitative studies of the resulting signals are lacking. Our preliminary study demonstrates that stimulation artifacts largely obey dipole distributions, suggesting that the dipole model could be used to predict artifact propagation. Further studies are necessary to ascertain whether these results hold across other subjects and combinations of stimulation/recording grids. Once completed, these studies will reveal practical design constraints for future implantable bi-directional ECoG-based BCIs. These include parameters such as the distances between and relative orientations of the stimulating and recording electrodes, the choice of the stimulating electrodes, the optimal placement of the reference electrode, and the maximum stimulation amplitude. These findings would also have important implications for the design of custom, low-power bioamplifiers for implantable bi-directional ECoG-based BCIs.References:[1] Hiremath, S. V., et al. "Human perception of electrical stimulation on the surface of somatosensory cortex." PloS one 12.5 (2017): e0176020.[2] Rouse, A. G., et al. "A chronic generalized bi-directional brain-machine interface." Journal of Neural Engineering 8.3 (2011): 036018

3-F-55 Does previous experience with a steady-state visual evoked potential-based BCI for text-entry affect user performance?

James Norton[1], Nisha Patel[2], Timothy Bretl[2]

[1]Wadsworth Center, New York State Department of Health, [2]University of Illinois at Urbana-Champaign

Introduction: We investigated whether previous experience with a steady-state visual evoked potential (SSVEP)-based brain-computer interface (BCI) text-entry system affected user performance. Most studies investigating SSVEP-based BCIs study BCI naïve populations for a single session of BCI use. If SSVEP-based BCIs are to be used as an alternative augmentative communication device for those with severe motor disabilities, they will be used for many sessions over weeks or months. Thus, it is important to understand if user input performance with an SSVEP-based BCI changes over time. To help answer this, we conducted a pilot study where we asked three participants to use an SSVEP-based BCI (Fig. 1a; previously described in Akce [2015]) twice a week for four weeks. Material, Method, and Results: Electroencephalographic (EEG) activity was recorded from six occipital electrodes. Each of the eight sessions had three phases: a calibration phase; a training phase; and a spelling phase. During the calibration phase, participants were asked to attend to a sequence of targets. Each target flashed for four seconds at one of five frequencies (6, 6.67, 7.5, 8.57, or 10 Hz). The first participant attended to 40 targets, the second and third to 50 targets. Data from the calibration phase was used to set two parameters (window-length and threshold) for a classifier based on canonical correlation analysis that were then used in the training and spelling phases (Lin 2007). During the training phase, participants used an online SSVEP-based BCI to select target letters (10 targets for each frequency, 50 targets total). Finally, during the spelling phase, participants were asked to spell five texts. Two of these texts were repeated during every session and three were unique to the specific session. Analysis of the calibration data showed that SSVEPs (indicated by an increase in the canonical correlation coefficients) appeared sooner after the onset of the target stimulus in later sessions than in earlier sessions in two of the three participants (Fig. 1b). In the third participant, the time between stimulus onset and the appearance of an SSVEP varied from session to session. Because data from the calibration phase were used to set the window-length for the classifier, a change in window-length might indicate a change in the signal-to-noise ratios of the SSVEPs. The window-lengths did not change significantly across the eight sessions. Together, these two results indicate that the participants learned to respond to the targets faster. Data from the spelling phase show that the three participants increased their average character entry rates from 11.62 characters/min (CPM) to 16.07 CPM over the first seven sessions (Fig. 1c; spelling data from session 8 for Participant 2 were lost due to a technical error). Participant 3 even achieved a text-entry rate of 34.60 CPM spelling "brain-computer interface" in session 6. Most of the change in text-entry rate was for the repeated texts (169% increase from session 1 to session 7 [averaged across participants]). Increased text-entry rates could be the result of an increase in selection accuracy, a decrease in the time between target onset and target selection, or both. Further analysis of the data showed that the time between target onset and classification decreased by ~0.48 seconds in two of the participants (Participant 1 and Participant 3) and increased in Participant 2 by ~0.18 seconds. Selection accuracy on the other hand, increased in Participant 2 (~29%) and remained stable in Participant 1 and Participant 3. Different users might employ different strategies to improve performance. Discussion and Significance: The results suggest that previous experience with an SSVEP-based BCI system is an important factor to consider when reporting performance and thus warrants further investigation. They also suggest that the performance of SSVEP-based BCIs developed for those with severe motor disabilities may improve as the user learns to use the system. It remains unclear whether previous experience leads to measurable changes in the SSVEPs generated by users (i.e., SSVEPs generated by experienced users are larger). It is also unclear whether increases in SSVEP-based BCI performance for a specific application (e.g., text-entry) would generalize to other applications. Answering these questions and confirming the initial results represent potential directions of future work.

3-F-56 Investigating spatio-temporal aspects of feedback-related brain activity in motor imagery brain-computer interfaces

Mahta Mousavi[1], Virginia de Sa[2]

[1]University of California San Diego, [2]University of California, San Diego

Introduction: Non-stationarity of brain signals is a major barrier to real world usage of brain-computer interfaces (BCI). Feedback-related brain activity is one important contributor to this non-stationarity. In previous work (Mousavi et. al, BCI Journal, 2017), we have shown that feedback-related brain activity is classifiable in frequency bands higher than usually considered. We used a common spatial patterns (CSP)-based method to look for feedback-related signals in EEG. However, CSP methods (Blankertz et. al, IEEE Signal Processing Magazine, 2008) do not take into account the temporal aspects of the signal. In this work, through Euclidean and Riemannian approaches, we investigate temporal features along with spatial features of this brain-related feedback activity. Material, Methods and Results: We used data previously published in (Mousavi et. al, BCI Journal, 2017) comprising EEG data from 10 participants in a motor imagery experiment. In each trial, the participants imagined right/left hand movements to steer a cursor towards a target on the screen in front of them. The cursor movements however were pre-determined (and same for all participants) though the participants were led to believe they were in control. Previously, we looked at the classification of the brain activity after each cursor movement, to detect whether the participant was satisfied or not with the last cursor movement using a CSP based method. In the estimation of the covariance matrices for CSP, spatial covariances are estimated and temporal information is lost. However, one can consider using temporal covariances analogously as proposed in common temporal patterns (CTP) (Yu et. al, IEEE Trans. On Biomedical Eng., 2011). In this work, we investigated the CTP method and trained a logistic regression classifier on the signals passed through the top three filters from each class as opposed to the original log-variance across channels and show that the new classifier performs better in data filtered within lower frequency bands. We also applied the aforementioned modified CTP method to EEG signals passed through filter-bank CSP in various frequency bands where the optimal CTP was found for each frequency band separately. Our

results show that the overall performance is improved compared to a windowed-means time domain classifier on midline channels by ~5%. It was previously shown that looking at spatial covariances on the Riemannian manifold can be beneficial (Barachant et. al, IEEE Trans. On Biomedical Eng., 2012). We looked at time covariances on the Riemannian manifold and trained a logistic regression classifier on the distances to the Riemannian mean for each class where both the Riemannian means of the time and channel covariances for each class are considered. Our method can be considered a filter-bank version of a spatio-temporal Riemannian approach. The proposed approach performs as well as a filterbank CSP+LDA method; however, we believe it can be improved if the simple logistic regression on distances is replaced by a more sophisticated method such as tangent space LDA (Barachant et. al, IEEE Trans. On Biomedical Eng., 2012). Discussion: In this work, we investigated spatio-temporal features of feedback-related brain activity in a motor imagery task to classify after each cursor movement, whether the participant was satisfied with the last cursor movement or not. Our approach considers covariance matrices in both time and spatial domains and proposes a modification of the CTP method, a combined CSP and CTP method, and a Riemannian classifier that takes distances to the Riemannian mean of time and channel covariances for each class as features. Significance: Feedback-related brain activity is one important brain signal elicited during brain-computer interface use. We believe our work contributes to a better understanding of these other ongoing processes in the brain during BCI and will help reduce the loss of control experience for BCI users and improve real-world usability of EEG-based BCIs.
Acknowledgements: This work was supported by NSF IIS 1219200, SMA 1041755, IIS 1528214, FISP G2171, G3155 and IBM.

3-F-57 Between-class CCA for SSVEP based BCI

Ze Wang[1], Chi Man Wong[1], Ka Fai Lao[1], Feng Wan[1]|

[1]*University of Macau*

Introduction: In a variety of target detection approaches proposed for the SSVEP based BCI, the canonical correlation analysis (CCA) based methods are one of advanced versions [1], [2]. Based on the assumption that a SSVEP signal can be modeled by a linear combination of single frequency sinusoidal signal and its harmonics, the CCA is applied to find a spatial filter for each stimulus by maximizing the similarities between the EEG signals and the pre-defined reference signals (i.e. sine and cosine signals) of this stimulus [1]. Although the CCA can provide relative high performance for the SSVEP BCI, it generates the spatial filter for the EEG signals of one stimulus based on the corresponding single class information, which only extracts the within-class information and does not take full advantage of the multi-class information. [1], [3]. In this study, a between-class CCA (bcCCA) is proposed to improve the SSVEP based BCI performance by making the best of the multi-class information including both the within-class and between-class information. Material, Methods and Results: The proposed bcCCA is to find a spatial filter for each subject based on individual training data by not only minimizing the feature distances of the single class but also maximizing the feature distances between different classes. In this proposed method, first, two subspaces W1 and W2 of the spatial filters are computed. One subspace W1 contains the spatial filters that maximize the similarities between the EEG signals in the training data and corresponding reference signals both for the k-th class where k=1,2,...,K and K denotes the total number of classes, which extracts the within-class information. The other subspace W2 contains the spatial filters which maximize the similarities between the EEG signals in the k-th class of the training data and reference signals in other classes, which extracts the between-class information. Then, the final individual spatial filter is obtained by minimizing its distance with spatial filters in W1 and maximizing its distance with spatial filters in W2. To evaluate the proposed method, the publicly available SSVEP dataset recorded by Tsinghua University [4] is applied. Figure 1 illustrates the average classification accuracy of the standard CCA (sCCA), the individual template CCA (itCCA) proposed in [2] and our proposed method under different data lengths. Based on the one-way ANOVA and Figure 1, the average accuracy of the proposed method is significantly higher than other two methods in different data lengths ($p<0.05$). Discussion and Significance: To our best knowledge, this study is the first attempt to estimates the individual spatial filter using the CCA by considering not only minimizing the feature distances in same class but also maximizing the feature distances between different classes. In simulation studies, this proposed method provides the best performance, which means that it is a promising tool for the SSVEP based BCI. In the future, this proposed method also can be attempted to reduce the size of training data, transfer spatial filters from different subjects and be adopted to online systems. References [1] G. Bin, X. Gao, Z. Yan, B. Hong, and S. Gao, "An Online Multi-Channel SSVEP-Based Brain-Computer Interface Using a Canonical Correlation Analysis Method," J. Neural Eng., vol. 6, no. 4, p. 46002, Aug. 2009. [2] G. Bin, X. Gao, Y. Wang, Y. Li, B. Hong, and S. Gao, "A High-speed BCI Based on Code Modulation VEP," J. Neural Eng., vol. 8, no. 2, p. 25015, Apr. 2011. [3] B. Mack, R. Roscher, and B. Waske, "Can I Trust My One-Class Classification?," Remote Sens., vol. 6, no. 9, pp. 8779-8802, Sep. 2014. [4] Y. Wang, X. Chen, X. Gao, and S. Gao, "A Benchmark Dataset for SSVEP-Based Brain-Computer Interfaces," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 25, no. 10, pp. 1746-1752, Oct. 2017.

Thank you to our Sponsors

DIAMOND LEVEL

BRAIN PRODUCTS
Solutions for neurophysiological research

g.tec
GUGER TECHNOLOGIES

GOLD LEVEL

OpenBCI

SILVER LEVEL

WEARABLE Sensing

neuracle

BRONZE LEVEL

ant neuro
inspiring technology

intheon

MindAffect

mindmaze

neuromore

Puzzlebox

ripple