ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

The error-related potential and BCIs

Sandra Rousseau[1], Christian Jutten[2] and Marco Congedo [2]

Gipsa-lab - DIS
11 rue des Mathématiques BP 46 38402 Saint Martin d'Héres Cedex - France

Abstract. The error-related potential is an event-related potential triggered by errors. Recently it has been the subject of many attentions notably for its possible use in BCI systems. Since it is linked to error occurrence, it could be used in the design of control loop to build more robust systems. In this paper we studied the characteristics of the error potential and present how it could be used for BCI systems improvement.

1 Introduction

The error-related potential (ErrP) is an event-related potential (ERP) which is generated when a subject commits or observes the commitment of an error. It was first reported in 1991 [1]. Lately several authors have become interested in its integration in a control loop for BCI systems. The integration of the ErrP in BCIs involves two main operations: its single trial detection and the use of this information to modify the system on-line. As any ERP the ErrP can easily be seen by summing up several trials (its signal to noise ratio is very low). The detection of the ErrP is a crucial point for its integration in BCIs, thus learning its characteristics to design optimal filtering method is a key point for its integration in BCIs. The paper is divided into three parts. First we present the ErrP and what makes it interesting for BCIs. Then we present an experiment we designed to study the characteristics of the ErrP and the results we obtained. Eventually we make propositions on how this ErrP could be integrated in BCIs.

2 The error-related potential

There exists different types of ErrPs characterized by the way the error is reported and depending on the agent committing the error. The most known ErrP is the response ErrP (ErrPr) [1]. It appears when subjects perform an incorrect action instantly detected (mostly studied in reaction time tasks). The second major type is the feedback ErrP (ErrPf) [2]. It appears when the subject gains access to the outcome of an action through an external feedback (mostly studied in gambling tasks). More recently, in [3] the authors reported an ErrP when a subject interacts with an interface that does not respond in the expected way. It is called the interaction ErrP (ErrPi) (mostly studied in BCI-like context). All these potentials share some common characteristics. They are mainly characterized by a negative deflection with a fronto-central localization (electrodes FCz and Cz) (see figure 1) which latency depends on the type of ErrP observed.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

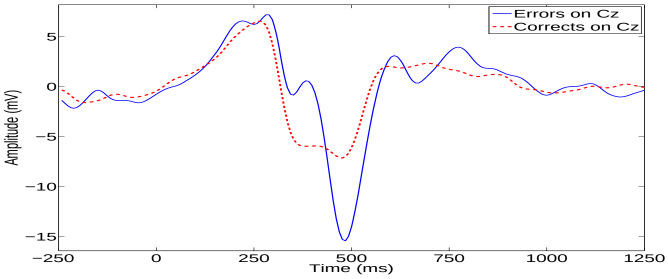


Fig. 1: *Temporal evolution of the ErrPf at electrode Cz*
Grand averaged error-potential. Data were averaged over 10 subjects. 72 trials were used for each subject with a mean error rate of 18%. Data were bandpass filtered between 1-12Hz.Blue line corresponds to the error condition, red dashed line to the correct condition.

3 The ErrP and the BCIs

ErrPs are much studied today in the framework of BCI. Indeed they provide an opportunity to check if the machine has selected the command sought by the user. Such an information could be used in a control loop for current BCI protocols. Some authors, as in [4] and [5], already studied the on line detection of this potential and its possible integration on BCI devices. In the case of a BCI experiment the ErrPi would be the potential to study. In a BCI context the user aims at controlling a device by means of cerebral orders. EEG signals are classified and turned into commands. A misclassification results into an incorrect action of the device. Thus the subject observes an error of the interface (generating the ErrPi). In some cases, the error could come directly from the subject which would use the wrong cerebral order or change his mind. Then the corresponding error would be the ErrPf. Thus two different types of ErrPs could co-exist and their disentanglement might be difficult. However when looking at the temporal shape of both potentials it seems that they share the same characteristics (some authors even make no distinction between both). Thus one can hope that both could be detected by the same classifier.

4 Presentation of an error-potential experiment

We studied the ErrPf in the case of a memory game, with no monetary gain or loss. The experiment involved two sessions, each consisted of six blocks of six trials, for a total of 72 trials. Stimuli were presented on a computer screen in front of the subjects. Nine square boxes were arranged in circle. Each trial consisted in a random sequence of two to nine digits appearing sequentially in random positions. Subjects had to memorize positions of all digits. At the end of the sequence the target digit was displayed and subjects had to click on the box where it had appeared. If the answer was correct, the box background turned into green, otherwise it turned into red. Subjects were then asked if the result matched their expectation, giving four classes of outcomes (expected corrects,

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

unexpected corrects, expected errors, unexpected errors). A random rest period was allowed before starting the next trial. The number of digits to memorize was fixed within blocks (between two and nine) and adaptively increased or decreased of one digit at each block, according to subject performance. The temporal order of each trial is illustrated in Figure 2. 22 healthy volunteer subjects participated. Due to the presence of artifacts, four subjects were excluded from analysis. The age of participants ranged from 20 to 30 with a mean (standard deviation) of 24(2.5). The mean error rate (standard deviation) was equal to 18(4.6)% of the trials.

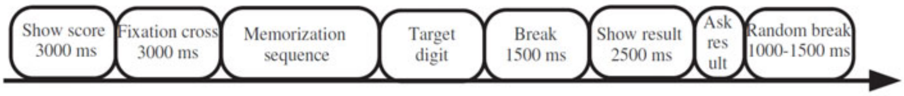


Fig. 2: *Temporal order*

5 Characterization of the ErrP

Analysis was conducted to determine the differenciation between errors and corrects (expectancy was not taken into account in this analysis). Two types of analysis were conducted: a temporal and a time frequency analysis. Temporal analysis was applied to the EEG signal filtered between 2-20Hz. Time-Frequency analysis was conducted using fieldtrip software ([6]). Frequency analysis was performed using ERD/ERS (event-related desynchronization / event-related synchronization) measures ([7]), in order to mitigate subject and inter-trials variability. This measure is defined as follows:

$$ERD/ERS(s,f,t) = \frac{TFR(s,f,t) - TFRb(s,f,tj)}{TFRb(s,f,tj)}$$

where TFR(s,f,t) is a time-frequency representation averaged over trials of our signal at sensor s, frequency bin f and time t and TFRb is the TFR of the baseline (baseline was chosen to be [-1s : 0s] pre-stimulus) averaged over time. Here TFRs were calculated using a hanning sliding window over the 2-32Hz band using a 1Hz step, on times [-0,5s 1,2s] using a time step of 0,05s. Frequency dependent time window were used so as to reduce the spectral leakage. TFRs were calculated for each subject and each trial and then averaged.

Statistical differences between error and correct trials were assessed using a within subjects non-parametric cluster based randomization test. 1000 permutations were performed. A cluster based multiple comparison correction was applied: at each permutation only the t_values which p_values are higher than a given threshold (set here to 0.05) are kept. Clusters are then formed by means of time, spatial and frequency adjacency. For each cluster the statistic is defined as the sum of the t_value contained in this cluster. The maximum cluster statistics is kept as the test statistic for this permutation. The global significance threshold was set to $p\_value \leq 0.05$. This method allows not to take into account outliers and to assess for global effect.

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

Statistical tests on the temporal signal allowed the identification of three components: a significant positivity for errors at time [300ms 400ms] at electrode Cz ($p \leq 0.01$), a significant negativity for errors at time [450ms 520ms] at clustered electrodes Fz,FCz,Cz ($p \leq 0.01$) and a significant positivity for errors at time [600ms 700ms] at clustered electrodes Fz,FCz ($p = 0.025$) (see figure 3). For the frequential domain, TFRs showed a post-stimulus synchronization in the theta band in both conditions. Statistical tests showed a significantly higher synchronization for errors in the band 5-8Hz for the time [350ms 600ms] over the electrode Fz and FCz ($p = 0.015$)(see figure 4).

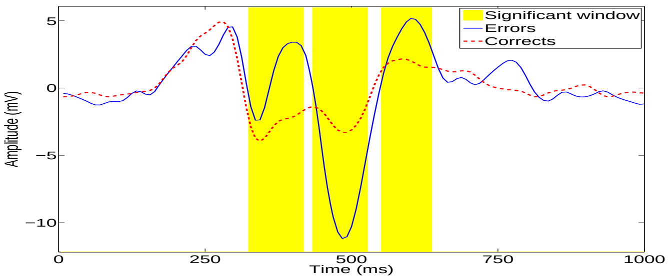
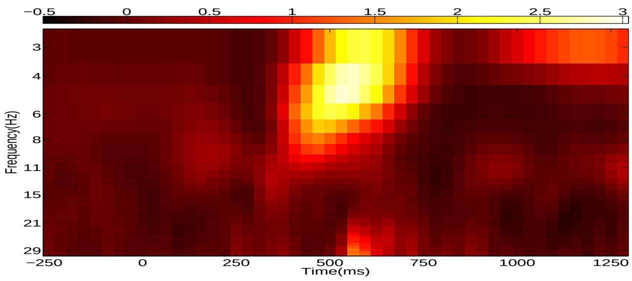
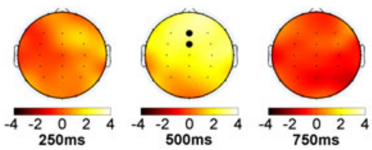


Fig. 3: *Temporal evolution of the ErrPf averaged over electrodes Fz,FCz,Cz and the significant time windows.*

Grand averaged on 18 subjects with 72 trials (mean error rate of 18%). Data were bandpass filtered between 2-20Hz. Blue line corresponds to the ERP on error condition, red dashed line to correct condition, yellow bars to the statistically significant time windows.



(a)



(b)

Fig. 4: *Theta power increase*

(a)ERD/ERS for errors minus ERD/ERS for corrects averaged over electrodes Fz and FCz. (b) Topographic maps of t-values averaged over theta band. Thick points correspond to statistically significant electrodes

ESANN 2012 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning. Bruges (Belgium), 25-27 April 2012, i6doc.com publ., ISBN 978-2-87419-049-0. Available from http://www.i6doc.com/en/livre/?GCOI=28001100967420.

6 Perspectives of integration

The integration of the ErrP in BCIs starts by its single trial detection. Several authors have already studied this point leading to varying results going from 64% (60% for errors and 64% for corrects) [8] of good detection up to 88% [9]. The characterization of the ErrP allows us to better know its components. This is of great use for the design of specific spatial and frequential filters which could greatly improve the detection rate. Indeed most authors only used the temporal evolution of the ErrP, our results show that some frequential components might also exist and could be used to improve results.

Once an ErrP is detected the question that arises is how it can be used to improve a BCI. Different approaches have already been proposed. To assess the performance of a BCI the commonly used measure is the information transfer rate (in bits per trial (BpT)) which takes into account both the accuracy and the speed of the system. The first method to be proposed was the cancellation of the erroneous action. In [4] the author obtained an average gain on the BpT of 72% for a 2-class paradigm and 28% for a 3-class paradigm. In [10] the author observed that this improvement depended on the initial performance of the BCI. Another possible integration has been proposed in the case of a P300 speller in [11]. The author proposed to select the second best letter when an error was detected, the total number of mistypes was reduced for every subject. Another possible integration could be to improve the classifier. For example in the case of a SVM (support vector machine) classifier [12] the regularization parameter which determines the trade off between the regularized term and the empirical error could be adapted in the case of an error detection. For future works we plan to select different methods and to test them first in a theoretical framework for different BCI initial BpT and different ErrP classification rates, in order to determine what strategy is the best and in which conditions. In a second time we will test the selected strategies on a real BCI experiment in order to see if the theoretical results match the real one and how the subject responds to this error correction.

7 Conclusions

In this paper we have discussed the integration of the ErrP in BCI. First we have shown temporal and frequential results on the characterization of the ErrP in the aim of improving its single trial detection detection which is the first step toward its integration in BCI systems. Then we have discussed how this late could be integrated in a BCI system by presenting already existing results and proposing future works to test several methods and compare them. Future works will focus on studying the impact of error (and correct) expectation on the different characteristics of the ErrP and its possible impact on BCI integration.

References

[1] M. Falkenstein, J Hohnsbein, J Hoormann, and L Blanke. Effects of crossmodal divided attention on late ERP components.II. Error processing in choice reaction tasks. *Electroencephalogr. Clin. Neurophysiol.*, 78:447–455, 1991.

[2] W.H.R. Miltner, C.H. Braun, and M.G.H. Coles. Event-related brain potentials following incorrect feedback in a time-estimation task: Evidence for a generic neural system for error detection. *Journal of Cognitive Neuroscience*, 9(6):788–798, 1997.

[3] P.W. Ferrez and J.R. Millán. Error-related EEG potentials in brain-computer interfaces. *Towards Brain-Computer Interfacing, MIT Press, Cambridge,Massachusetts*, 2007.

[4] P.W. Ferrez and J.R. Millán. You are wrong!—automatic detection of interaction errors from brain waves. In *Proceedings of the 19th International Joint Conference on Artificial Intelligence, 2005*, 2005.

[5] J.M. Bollon, R. Chavarriaga, J. Millán, and P. Bessiere. EEG error-related potentials detection with a Bayesian filter. 2009.

[6] R. Oostenveld, P. Fries, E. Maris, and J.M. Schoffelen. Fieldtrip: open source software for advanced analysis of meg, eeg, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, 2011:1, 2011.

[7] G. Pfurtscheller and FH Lopes da Silva. Event-related eeg/meg synchronization and desynchronization: basic principles. *Clinical Neurophysiology*, 110(11):1842–1857, 1999.

[8] B. Dal Seno, M. Matteucci, and L. Mainardi. Online detection of p300 and error potentials in a bci speller. *Computational intelligence and neuroscience*, 2010:1–1, 2010.

[9] N. Jrad, M. Congedo, et al. Spatio-temporal feature extraction and classification of event-related potentials. *7e Plateforme AFIA: Association Française pour l'Intelligence Artificielle, Chambéry, 16 au 20 mai 2011*, page 233, 2011.

[10] G. Visconti, B. Dal Seno, M. Matteucci, and L. Mainardi. Automatic recognition of error potentials in a P300-based brain-computer interface. pages 238–243, 2008.

[11] A. Combaz, N. Chumerin, N.V. Manyakov, A. Robben, J.A.K. Suykens, and M.M. Van Hulle. Error-related potential recorded by eeg in the context of a p300 mind speller brain-computer interface. In *Machine Learning for Signal Processing (MLSP), 2010 IEEE International Workshop on*, pages 65–70. IEEE, 2010.

[12] N. Jrad, M. Congedo, R. Phlypo, S. Rousseau, R. Flamary, F. Yger, and A. Rakotomamonjy. sw-svm: sensor weighting support vector machines for eeg-based brain–computer interfaces. *Journal of Neural Engineering*, 8:056004, 2011.