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A novel approach to decode hand motor tasks from intraneural recordings in an amputee

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***Abstract*— In the field of neuroprosthesis, intraneural interfaces represent an interesting solution to restore lost functions in amputees. In particular, recent results have shown that transverse intrafascicular multichannel electrodes (TIMEs) can re-establish natural and sophisticated sensory feedback. However, the possibility to decode motor intentions in humans has not been explored yet. In this study, we developed a framework able to decode several hand movements intention from neural signals recorded from intrafascicular electrodes in an upper limb amputee. Four intraneural multichannel electrodes (TIMEs) were implanted in the median and ulnar nerve of the amputee, and the electroneurographic (ENG) activity was recorded during hand motor tasks imagined by the subject. We built a stable decoder, reliable in all the experimental sessions and able to decode four classes of movements plus rest with about 80% accuracy. This approach could improve the efficacy of sensitive hand prosthesis resulting in a more natural and dexterous device relying on a single device for both sides of the closed-loop.**

Keywords-neuroprosthesis, neural decoding, neural interface

I. Introduction

Restoring lost functions in patients after hand amputation is one of the main challenges of neuroengineering applications [1]. Studies showed that dexterous hand prostheses can be successfully controlled by processing electromyographic (EMG) signals recorded from the residual muscles of the amputee [2]. Alternatively, in the case of high level amputations, Targeted Muscle Reinnervation (TMR) [3] showed to provide a suitable surgery technique to enable prosthesis control. However, to restore the full bidirectional information (i.e., decode motor control and provide sensory feedback), it is necessary to increase the level of selectivity using intraneural or intrafascicular interfaces. Indeed, neural interfaces have shown to be able to restore sensory feedback [4] but they can also record electroneurograms (ENG) related to hand motor commands from the residual nerves of amputees [5], [6]. Recently, Transversal Intrafascicular Multichannel Electrode (TIME) [7] have been demonstrated to provide a rich and useful sensory feedback to trans-radial amputees [4], [8]. In the present work, we investigated the possibility to record neural signals from TIMEs and decode hand movement intentions in an amputee subject. We proposed a procedure to automatically select channels and a new framework to decode several motor intentions from ENGs based on the compound neural signals.

II. Methods

A. Experimetal protocol

The subject was a 48-years right-handed female with a transradial amputation. Four Transversal Intrafascicular Multichannel Electrodes (TIMEs), with 14 active sites each, were implanted two in the median (M1 and M2) and two in the ulnar (U1 and U2) nerve of the subject as in Fig. 1 (see subject 1 in [8] for details and ethical approval). The subject was asked to perform finger flexion movements with the amputee arm but also with the healthy hand (right one) in order to check the subject's attention. Three different grasping movements were defined, i.e. Tridigital Pinch (Tr), Thumb opposition (Th), Ulnar finger movement (Ul), and each grip was repeated 10 times. The patient had to move her phantom hand for each trial as shown on the screen; each trial lasted 2 seconds and was followed by 3 seconds of motionless rest. Overall, the task consists of 1 seconds for the movement (Phase 1 - flexion) and 1 seconds for coming back to rest position (Phase 2 – open task). Here we reported recordings in 5 sessions, from day 16 to day 23 after implantation.

B. Neural recordings and ENG analysis

Four electrodes (56 active sites) were recorded simultaneously (using Grapevine neural Interface System, Ripple, LLC), and digitally sampled at 30 kHz. Collected electroneurographic (ENG) data were analysed in MATLAB as follows. Raw ENG data were pre-processed with a band-pass filter between 300 and 3000 Hz (4th order Butterworth filter) and down-sampled at 10 kHz. The root mean square (RMS) was extracted for each channel and a band pass 2nd order Butterworth filter at [2 100] Hz was applied. Finally, signals were binned into 25 millisecond windows obtaining a binned-RMS-ENG sampled at 40 Hz (Fig. 1). This procedure

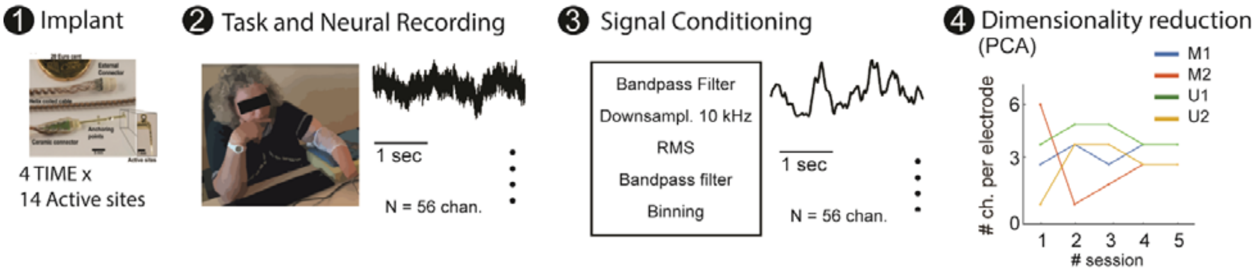

Figure1. Workflow of the experimental design and neural recording analysis: 1) The subject was implanted with four TIMEs in the median (M1, M2) and in the ulnar (U1, U2) nerve of the amputee arm. 2) The subject imagined to perform the movement indicated on a screen with the phantom hand while neural signals were recorded and stored. 3) Recordings from each channel were bandpassed filtered and downsampled at 10 kHz. Then, each signal was binned at 40 Hz after computing the Root-Mean-Square 4) PCA allowed to select a set of 14 channels for each sessions and reduce

allowed to improve drastically the signal-to-noise ratio (data not shown).

C. Channel selection and neural decoding algorithm

After computing the Principal component analysis (PCA), we selected the first two channels more correlated with each of the first 10 principal components. The final list resulted in 14 instead of 20 channels as some of them matched the condition more than once. As shown in Fig.1, at least one active site for all the four implanted electrodes was selected for each experimental session. The first 200 milliseconds after the external starting trigger were labelled and associated to a specific movement. These values from the selected channels were used as input for training and testing the decoding algorithm. We applied a Support Vector Machine with a quadratic kernel (qSVM) classifier to decode movements (one-vs-one strategy, five-fold random cross-validation procedure). The overall classification accuracy was defined as the mean value of the percentage of correct predictions per class, which corresponds to the mean value of the diagonal in the confusion matrix.

III. Results

We tested our decoding procedure across sessions to show the ability to classify different tasks, i.e. tri-digital pinch, thumb opposition and ulnar finger movement, which require the activation of both the median and the ulnar nerves. We consider other two additional classes: the opening hand task and rest. Confusion matrix in Fig. 2A shows results related to the first sessions: percentage of false positive is low even if some tasks are classified as rest. We repeated the same procedure across sessions and we obtained high performances and a stable accuracy (see blue markers in Fig. 2B) always higher than 83%. Additionally,

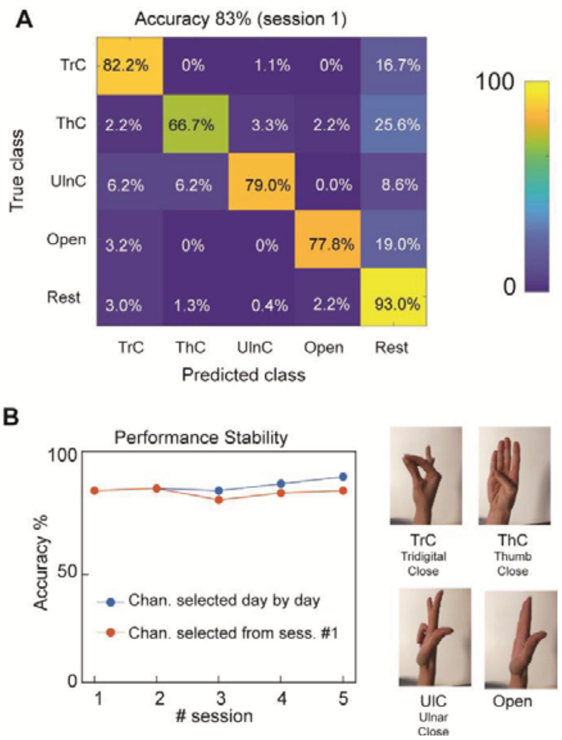

Figure 2. Accuracy and performance stability for 5-class SVM classifier (Tridigital Pinch TrC, Thumb opposition ThC, Ulnar finger movement UlC, Open task and rest). (A) Confusion matrix from day 16 (first session, accuracy 85%). (B) Comparison of the accuracy for each of the five sessions considering channels selection PCA-based and the same channels selected during the first session (red markers).

to evaluate the stability of channel selections, we computed classification performances for every session using channels selected during the first day (red markers in Fig. 2B). In this case, accuracy was more than 79% meaning that performances are still high even without the customized channel selection strategy. This could be an advantage in a real-life situation: in fact, it would be possible to select channels only during the first session, and to use them during the following days.

IV. Discussion

Several studies explored the possibility to decode motor intention from neural activity using intrafascicular/ intraneural electrode as tf-LIFE [5] or Utah array [6]. In this work we demonstrated the feasibility of decoding hand tasks intentions using TIMEs implanted in an amputee, which have been shown to be very promising in restoring sensory feedback [8]. As we are working with multichannel interfaces, one of the main challenge is the appropriate selection of active sites as inputs for the classifier. Herein we developed a new channel selection approach which differs from previous studies like in [9], based on the signal-to-noise ratio or in [6] where the correlation between the firing rate and the movement cue was the discrimination parameter. Moreover, we proposed the root mean square as the signal feature for a SVM decoder which could offer advantages for online application. In fact, the RMS represents a compound multiunit activity signal which considers the whole neural activation without computing spike sorting or using advanced techniques requiring a high computational cost. The robustness and the stability of this multi-class decoding based on ENG recorded with TIMEs envisioned the possibility of using the present approach as part of a bidirectional prosthesis in order to restore both motor control and sensory feedback in amputees.

References

[1] D. Borton, S. Micera, J. d. R. Millan, e G. Courtine, «Personalized Neuroprosthetics», *Science Translational Medicine*, vol. 5, n. 210, pagg. 210rv2-210rv2, nov. 2013.

[2] A. L. Ciancio *et al.*, «Control of Prosthetic Hands via the Peripheral Nervous System», *Frontiers in Neuroscience*, vol. 10, apr. 2016.

[3] T. A. Kuiken *et al.*, «Targeted reinnervation for enhanced prosthetic arm function in a woman with a proximal amputation: a case study», *The Lancet*, vol. 369, n. 9559, pagg. 371–380, feb. 2007.

[4] S. Raspopovic *et al.*, «Restoring Natural Sensory Feedback in Real-Time Bidirectional Hand Prostheses», *Science Translational Medicine*, vol. 6, n. 222, pagg. 222ra19-222ra19, feb. 2014.

[5] S. Micera *et al.*, «Decoding Information From Neural Signals Recorded Using Intraneural Electrodes: Toward the Development of a Neurocontrolled Hand Prosthesis», *Proceedings of the IEEE*, vol. 98, n. 3, pagg. 407–417, mar. 2010.

[6] S. Wendelken *et al.*, «Restoration of motor control and proprioceptive and cutaneous sensation in humans with prior upper-limb amputation via multiple Utah Slanted Electrode Arrays (USEAs) implanted in residual peripheral arm nerves», *Journal of NeuroEngineering and Rehabilitation*, vol. 14, n. 1, dic. 2017.

[7] T. Boretius *et al.*, «A transverse intrafascicular multichannel electrode (TIME) to interface with the peripheral nerve», *Biosensors and Bioelectronics*, vol. 26, n. 1, pagg. 62–69, set. 2010.

[8] G. Valle *et al.*, «Biomimetic Intraneural Sensory Feedback Enhances Sensation Naturalness, Tactile Sensitivity, and Manual Dexterity in a Bidirectional Prosthesis», *Neuron*, vol. 100, n. 1, pagg. 37-45.e7, ott. 2018.

[9] P. M. Rossini *et al.*, «Double nerve intraneural interface implant on a human amputee for robotic hand control», *Clinical Neurophysiology*, vol. 121, n. 5, pagg. 777–783, mag. 2010.