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First Study Towards Linear Control of an Upper-Limb Neuroprosthesis with an EEG-based Brain-Computer Interface

Javier Pascual[1], Francisco Velasco-Álvarez[2], Klaus-Robert Müller[1,3,4] and Carmen Vidaurre[1]

Abstract— **In this study we show how healthy subjects are able to use a non-invasive Motor Imagery (MI)-based Brain Computer Interface (BCI) to achieve linear control of an upper-limb neuromuscular electrical stimulation (NMES) controlled neuroprosthesis in a simple binary target selection task. Linear BCI control can be achieved if two motor imagery classes can be discriminated with a reliability over 80% in single trial. The results presented in this work show that there was no significant loss of performance using the neuroproshesis in comparison to MI where no stimulation was present. However, it is remarkable how different the experience of the users was in the same experiment. The stimulation either provoked a positive reinforcement feedback, or prevented the user from concentrating in the task.**

I. INTRODUCTION

Neural prostheses are assistive devices able to substitute a damaged motor function caused by a high level spinal cord injury or by genetic neuromuscular / neurodegenerative diseases. Upperlimb neuroprostheses, for example, allow severely motor impaired people to reacquire interacting capabilities with the environment, improving their quality of life. The functionality of the damaged limb is typically recovered using NMES. These devices can be operated with a manual switch, movements of a non-damaged muscle or by a residual muscle activity (electromyography), supporting with NMES the user intention (cf. [1], [2], [3]).

A novel proposal for users without voluntary muscle control is Brain-computer Interfaces. BCIs are systems that aim to provide control over a computer application or a neuroprosthesis by solely means of brain activity. Using a MI-based BCI to operate a NMES neuroprosthesis has been already successfully reported by [4] and [5]. However, these works did not report the linear control of the neuroprosthesis during NMES, but rather a sequential operation for the restoration of hand grasp function in a tetraplegic patient in [4] or the turning on/off of the stimulation by MI to trigger hand (and thumb) opening and closing in [5].

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[1]J. Pascual, K-R. Müller and C. Vidaurre are with the Machine Learning Group, Computer Science Faculty, Berlin Institute of Technology, Berlin, Germany

[2]F. Velasco-Álvarez is with the Department of Electrical Engineering, University of Malaga, Malaga, Spain

[3,4]K-R Müller is with the Bernstein Focus: Neurotechnology, Berlin, and the Department of Brain and Cognitive Engineering, Korea University.

Another option to recover the impaired functionality of a limb are robotic devices. A recent study ([6]) confirms the feasibility of a MI-BCI controlled robotic arm to assit in reaching and grasping tasks in chronic tetraplegics. However, the control is also based in a sequencial operation.

By linear control we understand the real-time computation of the neuroprosthesis position from the MI classifier output. The real-time nature of the task, makes the operation more challenging, and it is also more demanding for the user. We expect to accomplish effective linear BCI control when two imagery classes can be distinguished with a reliability over 80% in single trial. Above this threshold the output of the classifier can be used to determine in real time target positions on a given trajectory. Depending on the BCI control quality, the user can gain control of the exact stopping point of a movement along a trajectory. The number of targets effectively implemented strongly depends on the classification accuracy reached in the calibration phase by the individual subject.

We performed experiments with healthy users that operated an upper-limb neuroprosthesis in a simplified linear control version: a 1-dimension trajectory with two targets. The experiment was divided in two sessions: in the first one, a virtual arm was controlled by MI and in the second one a real NMES neuroprosthesis was used. The results of this first successful attempt to achieve linear control are reported, setting the baseline for further research.

II. METHODS

A. Data Processing and Classifier Training

The parameters needed to calculate a classifier to discriminate MI activity are frequency band of interest, time interval where the class discrimination is maximized and spatial filters. These parameters are subject-specific and an optimizing procedure is used in order to find them. Particularly, we use the methods described in [7], [8], [9].

After the signal is filtered in the optimal frequency and epoched in the computed time interval, it is spatially filtered using Common Spatial Patterns (CSP). CSP is a technique used to analyze high dimensional data based on recordings from two classes (in this study, EEG acquired from 60 scalp electrodes). It yields a data-driven supervised decomposition of the signal $x(t)$ parametrized by a matrix $\boldsymbol{W}$ that projects the signal from the original sensor space to a surrogate sensor space: $x_{CSP}(t) = x(t) \cdot \boldsymbol{W}$.

To calculate the matrix $\boldsymbol{W}$ we need the sample covariance matrices of the band-pass filtered EEG signals of two different motor imagery tasks $\mathbf{\Sigma}_+$ and $\mathbf{\Sigma}_-$.

$$\mathbf{\Sigma}_+ \cdot \boldsymbol{W} = (\mathbf{\Sigma}_+ + \mathbf{\Sigma}_-) \cdot \boldsymbol{W} \cdot \boldsymbol{D} \tag{1}$$

where $\boldsymbol{D}$ is a diagonal matrix.

Then, by simultaneously diagonalizing these matrices such that their eigenvalues sum 1, one can compute the filters for the CSP projections. The CSP filters maximize the variance of the spatially filtered signal under one task while minimizing it for the other task. Since the variance of a band-pass filtered signal is equal to band-power, CSP analysis is applied to band-pass filtered signals to obtain an effective discrimination of mental states that are characterized by event-related synchronization and desynchronization (ERD/ERS) effects ([9]).

The obtained features are used to train a Linear Discriminant Classifier (LDA) which has been shown to be a good classifier for motor imagery BCI data (See [8], [10]). For two equally distributed classes it is computed as follows:

$$o = \boldsymbol{w}^\top \cdot \boldsymbol{x} + b \tag{2}$$

$$\boldsymbol{w} = \mathbf{\Sigma}^{-1} \cdot (\boldsymbol{\mu}_+ - \boldsymbol{\mu}_-) \tag{3}$$

$$\mathbf{\Sigma} = \mathbf{\Sigma}_+ + \mathbf{\Sigma}_- \tag{4}$$

$$b = -0.5 \cdot (\boldsymbol{\mu}_+ + \boldsymbol{\mu}_-)^\top \cdot \boldsymbol{w} \tag{5}$$

where the output o is the distance of the feature vector $\boldsymbol{x}$ to the decision hyperplane perpendicular to $\boldsymbol{w}$. The location of the plane is defined by the bias b. If the o is negative, the class is $-$, otherwise, the class is $+$. $\mathbf{\Sigma}_+$ and $\mathbf{\Sigma}_-$ are the covariance matrices of the features of each class. Finally $\boldsymbol{\mu}_-$ and $\boldsymbol{\mu}_+$ are the mean values of the features of each class.

B. Electrical Stimulation

NMES was generated by a Hasomed Rehastim 2 with biphasic, rectangular constant current pulses at 50Hz. The amplitude of the stimulation for each electrode was selected for each user after a NMES calibration recording that took around 5 minutes and ranged from 5 to 20 mA. To elicit movement, 4 electrodes were placed on the deltoid muscle: one on the anterior division (medial rotation), one on the posterior (lateral rotation) and one on the medial division that contributed to both movements. The fourth electrode was placed on the base of the muscle to conduct the electrical current.

C. Experimental Procedure

Data were recorded in two sessions from 12 healthy BCI-novices. The brain activity was acquired from the scalp with multi-channel EEG amplifiers using 60 Ag/AgCl electrodes in an extended 10-20 system (with more density in the sensorymotor area) sampled at 1000 Hz with a band-pass filter from 0.05 to 200Hz For two users no feedback was performed in the first session since they were not able to achieve enough performance during the calibration phase (see BCI inefficiency, [11]). Accordingly, these two subjects did not participate in the second feedback session.

In both sessions, the users first performed MI of 3 limbs (left/right hand and feet) within a calibration session. Approximately every seven seconds one of three different visual

Fig. 1. Screenshot of the feedback in the first session. The trial was considered successful if the user could hold the arrow above a threshold (depicted as the red line) for a specific amount of time.

cues (arrows pointing left, right, or down) indicated to the participant which type of motor imagery task to perform. A 15s break followed after every 20 trials. One run consisted of 75 trials (25 trials/class) and a total of 3 MI runs were recorded, resulting in 225 trials.

In order to reduce the impact of the afferent brain activity elicited by NMES (cf. [12]), a limb not involved in the MI task was used for the neuroprosthesis. For this reason, after the calibration phase, only two combinations of classes (left hand vs. foot or foot vs. right hand) were considered. The pair with best predicted performance was selected to perform the feedback task.

1) Session 1: The feedback recording consisted of the control by means of MI of a virtual arm in a screen in front of the user (see Fig. 1). Different visual cues (left arrow or right arrow) indicated in which direction the virtual arm should be moved. A maximum time of 20 seconds was given to reach the target in each direction.

2) Session 2: During the feedback, an Hocoma ArmeoSpring device ([13]) was used for gravity compensation (see Fig. 2). It provided one degree of freedom at the shoulder, that allowed movement in a 1-D trajectory. Since this work studies the feasibility of linear control, and a simplified task (with only 2 targets) was performed, no exact position was calculated. Instead, the continuous output of the classifier (Eq. 2) during the active trial time was translated into the position of the cross in the screen and into the necessary stimulation amplitudes (linear combination of the position difference and the stimulation parameters) to achieve movement in the same direction and, aproximately, same speed as the cross. The stimulation amplitudes were defined by:

$$io(t) = \sum_{i=0}^{t-1} o(i) + o(t) \tag{6}$$

$$\boldsymbol{X}(t) = \begin{pmatrix} abs(max(0, \gamma_{ant} \cdot io(t)) \\ \gamma_{med} \cdot io(t) \\ abs(min(0, \gamma_{post} \cdot io(t)) \end{pmatrix} \tag{7}$$

Fig. 2. In the first session (top), the user was asked to move a virtual arm in a screen that simulated the selection of two targets (left/right). In the second session (bottom) the arm not involved in MI was controlled directly by the classifier output using the ArmeoSpring. The green line depicts the trajectory of the neuroprosthesis.

where the matrix $\boldsymbol{X}$ is the amplitude applied to each muscle (anterior, medial and posterior), t is the time in the active period in the trial, γ_x are scalars that weight the stimulation for each muscle, and $io(t)$ is the integrated output of the classifier.

After each trial, the user was asked to return the arm back to the initial position.

Both feedback sessions consisted of 4 runs of 50 trials each. The trial was considered successful if the user could hold the arrow above a subject-selected threshold (depicted as a red line) for a specific amount of time (also subject-dependent). These two parameters were empirically adjusted in a previous 5 minutes recording, where the volunteers tried out several values. If required, the parameters were corrected during the experiment. The trial was considered unsuccessful in two different situations: if the user did not move the arm in the correct direction (miss), or if the threshold was not reached or maintained long enough (reject).

By default, the bias of the classifier (Eq. 5) was updated using the "pmean" method ([14]), and the classifier obtained in the calibration session was manually re-biased

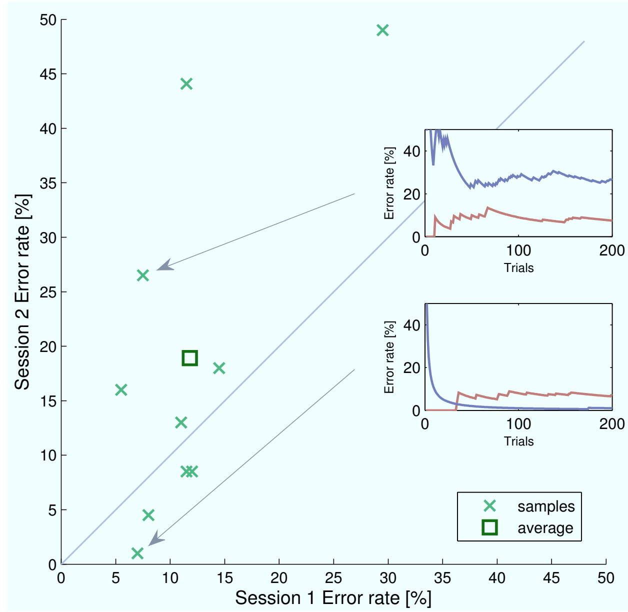

Fig. 3. This scatter plot depicts the error rates of the first (x-axis) and the second (y-axis) feedback sessions. All values above the diagonal show that session 1 is better than session 2. Additionally, the error rates in both sessions (red for session 1 and blue for session 2) of two subjects are shown. Subject F (bottom) increased the accuracy in the second session reaching a perfect control. Subject D (top), on the other hand, suffered from a performance drop.

if necessary.

III. RESULTS

Accuracy (% of successfully completed trials) was used as performance measure for the experiment. The results of the 10 (out of 12) users that could complete both feedback sessions are summarized in Table I. Although the mean accuracy of session 1 is higher than in the second, a Wilcoxon-test reveals that this difference is not significant (p=0.14).

Regarding the average values in Table I, it is worth noticing that although the number of rejects differs only slightly between sessions, the number of misses is twice as high in the second. The standard error is also much higher in this case, which suggests that the variability between users increases with the stimulation.

The results are presented in more detail in Fig. 3, which shows the scatter plot of the error rates in both sessions. It is noticeable that two users completely lost control of the system when the stimulation started, reaching only performance at chance level. The session 1 accuracy of subject H was around 70%, which showed not to be sufficient to achieve control in session 2 (a MI performance of 80% or more is desirable). This does not mean that all users who achieve less than 80% will lose control with an neuroprosthesis, but the undisturbed MI performance is a good indicator of success or failure.

Subject I, on the contrary, had a very good accuracy during session 1. However, during session 2 he reported that it was not possible for him to concentrate in the task when

TABLE I

ACCURACY RESULTS OF THE TWO FEEDBACKS SESSIONS FOR THE 10 USERS THAT COMPLETED BOTH SESSIONS.

	SESSION 1			SESSION 2		
Subject	Hit	Miss	Reject	Hit	Miss	Reject
A	89.00	5.00	6.00	87.00	7.50	5.50
B	92.00	5.50	2.50	95.50	3.50	1.00
C	85.50	10.50	4.00	82.00	6.00	12.00
D	92.50	1.50	6.00	73.50	16.50	10.00
E	94.50	5.00	0.50	84.00	6.50	9.50
F	93.00	5.50	1.50	99.00	0.50	0.50
G	88.50	5.50	6.00	91.50	4.00	4.50
H	70.50	7.50	22.00	51.00	10.00	39.00
I	88.50	5.50	6.00	55.91	10.22	33.87
J	88.00	5.00	7.00	91.50	3.00	5.5
MEAN ± SE	88.20% ± 2.15	6.15% ± 1.90	5.65% ± 0.71	81.10% ± 5.14	12.15% ± 4.24	6.75% ± 1.44

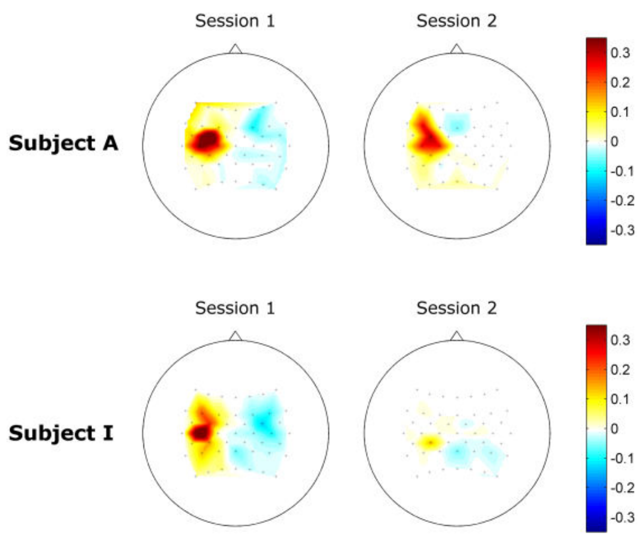

Fig. 4. Scalp maps of r^2-values of the selected MI classes of two users during the on-line phase in session 1 (left) and session 2 (right). Subject A exhibited a good performance in both sessions. Although the subject I had a good performance in the first session, he was not able to generate MI activity and, therefore, lost control of the system in the second.

the arm was being moved because the simultaneous NMES was very disturbing to accomplish the task. Therefore, he was not able to generate MI activity (see Fig. 4). Finally, subject D experienced a performance drop from around 90% to around 75%. This last value is not as good as expected, but the control is better than chance and still better than the psychological limit of 70% (cf. [15]). Additionally, for this user the arm could not be properly fixated due to his corpulence, and the intensities needed to induce movement were very high compared to the ones used with the other users. Therefore, a better performance could be expected with an appropriately sized orthosis.

The rest of the users (7 out of 10) exhibited very similar or even better performance using the neuroprosthesis as compared to controlling the virtual arm. They reported that the movement to the correct direction positively reinforced the feedback in contrast to session 1. This difference was, however, not significant (p=0.41).

IV. CONCLUSIONS

In this first study we have shown how healthy subjects are able to use a non-invasive MI-based BCI to achieve a simple linear control of an upper-limb NMES neuroprosthesis in a binary target selection task.

Despite of the stimulation, most of the subjects were able to perform the MI task in the second session with a high accuracy. Furthermore, there was no significant difference in comparison to undisturbed MI where the feedback was moving a virtual arm. Nevertheless, we need to take into account that these users had good or very good discriminability of two MI classes, and even then 2 out of 10 completely lost control of the system.

The fact that a high performance is necessary to successfully control a NMES neuroprosthesis is critical for clinical practice purposes, since it is known that in patients MI patterns are weaker and more unstable (cf. [16], [17]). For users for whom it is not possible to achieve control of the BCI, co-adaptation techniques or other paradigms like event-related potentials (ERP) or steady state visually evoked potentials (SSVEP) should be considered ([11], [18], [19]).

It is also remarkable how different the experience within users was during the second session. One user was not able to concentrate in the task due to the disturbance of the stimulation, whereas others described the benefits of the NMES as ”reinforcement” feedback.

Having demonstrated the feasibility of achieving linear control of a neuroprostheshis, as a next step, we will use machine learning techniques to robustify the classifier against the stimulation noise and study more realistic scenarios with more than two targets, in which the accuracy of the position is of much higher importance. Therefore, a proportional-derivative (PD) controller will be used (cf. [20]), in order to obtain an accurate control of the neuroprosthesis position.

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