33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Brisk movement imagination for the non-invasive control of neuroprostheses: a first attempt

Gernot R. Müller-Putz, Patrick Ofner, Vera Kaiser, Guillaume Clauzel, Christa Neuper

Abstract— **The consequences of a spinal cord injury (SCI) are tremendous for the patients. The loss of motor functions, especially of grasping, leads to a dramatic decrease in quality of life. With the help of neuroprostheses, the grasp function can be substantially improved in cervical SCI patients. Nowadays, systems for grasp restoration can only be used by patients with preserved voluntary shoulder and elbow function. In patients with lesions above the 5th vertebra, not only the voluntary movements of the elbow are restricted, but also the overall number of preserved movements available for control purposes decreases. In this work, a new method for the non-invasive use of a Brain-Computer Interface (BCI) for the control of the hand and elbow function is presented.**

I. Introduction

The consequences of a spinal cord injury (SCI), which results in a loss of sensory, motor and autonomous functions, are tremendous for the patients. The loss of motor functions, especially of the grasping function, leads to a life-long dependency on helping persons and thereby to a dramatic decrease in quality of life. With the help of neuroprostheses, e.g. functional electrical stimulation (FES) systems, the grasp function can be substantially improved. All established FES systems for grasp restoration can only be used by patients with preserved voluntary shoulder and elbow function. The limited possibilities for functional restoration in case of extended paralysis as well as unexperienced controllers are the main barriers for a broad use of neuroprosthetic systems outside of research laboratories. Brain-Computer Interfaces (BCIs), systems which transform mentally induced changes of brain signals into control signals [1], might serve as an alternative human-machine interface. The ideal solution for voluntary control of a neuroprosthesis would be to directly record motor commands from the corresponding areas of the cortex, convert these into control signals and transfer those to the neuroprosthesis itself, thereby realizing a technical bypass around the interrupted nerve fiber tracts in the spinal cord.

Up to now, BCIs are able to detect thought-modulated changes in electrophysiological brain activity and transform those signal characteristics into control signals. One option for measurement of the brain signals is to place electrodes on the scalp (electroencephalogram, EEG). One prominent mental strategy to operate a BCI is imagination of limb movements (motor imagery, MI). MI induces measurable changes of oscillatory components in the ongoing EEG over sensorimotor areas known as event-related (de)synchronization (ERD, ERS, [2]). First attempts into the direction of EEG-based control systems for restoration of the hand function were performed by Pfurtscheller et al. [3] who described the control of a grasp orthosis by motor imagery. Heasman et al. [4] reported on a neuroprosthesis controlled with the alpha rhythm modulated by opening and closing the eyes. In [5], [6], [7] the Graz-BCI was used to control the hand movements in two tetraplegic patients controlling a non-invasive and invasive neuroprosthesis, respectively. Also a first attempt for the control of hand and elbow function was reported in [16], where the users were trained to imagine one limb movement over different time periods, which were then used for hand and elbow control. In myoelectric prosthesis (for a review, see [8]) the contraction of remaining extensor and flexor muscles of the forearm were used to control e.g. the grip (open/close) as well as the pronation and suppination of the forearm. This is a well accepted method and inspired us to this work: a single brisk movement and two consecutive brisk movement imaginations of the hand were used to serve as mental strategy to open/close the hand and flex/extend the elbow, respectively. In this work, a first study introducing this new kind of control is presented.

This work is supported by the European ICT Programme Project FP7-224631. This paper only reflects the authors' views and funding agencies are not liable for any use that may be made of the information contained herein.

Correspondence to Gernot R. Müller-Putz (gernot.mueller@tugraz.at)

All authors are with the Institute for Knowledge Discovery, BCI-Lab, Graz University of Technology, Krenngasse 37, 8010 Graz, Austria.

II. Methodology

A. Subjects

Ten healthy right handed subjects (6 females, aged 24.4 $\pm$ 2.8) participated in the experiment. All of them had prior experience with BCI measurements. The participants were comfortably seated in an armchair, with their forearm fully supported by the armrest, so they could focus on hand clenching.

B. Signal recording

EEG was recorded with thirty Ag/AgCl electrodes spread over sensorimotor areas arranged as shown in Figure 1, with approximately 2.5 cm interelectrode distance. Reference was placed on the left mastoid, whereas ground was placed on the right mastoid. EEG signals were recorded using two g.USBamp amplifiers (g.tec, Graz, Austria). The sample frequency was set to 512 Hz, with a notch filter at 50 Hz, a low-pass filter at 0.5 Hz, and a high-pass filter at 100 Hz.

Electromyographic (EMG) activity of the forearm was recorded with a custom built amplifier, to ensure that the forearm was not moved during motor imagination. Two EMG electrodes were placed on the flexor digitorum profundus, while the ground EMG electrode was placed on the inner wrist. The bipolar signal was filtered between 1 Hz and 1 kHz. The signal was full wave rectified and integrated with a time constant of 100 ms.

Matlab and Simulink (TheMathWorks Inc., Massachuses-tts, USA) were used to create and run the paradigm, while the TOBI Signal Server ([9], www.tobi-project.org/download) was used to acquire and distribute the signals (EEG and EMG) to the Simulink model and to a second computer dedicated to monitoring the EEG/EMG signals quality. Finally, an additional screen was used to display the paradigm to the participant.

C. Experimental paradigm

Subjects were instructed to execute and imagine brisk closing and opening sequences of the right hand (duration about 1 s) in a cue-based paradigm. Two classes were differentiated: single brisk closing and opening (class 1) versus double brisk closing and opening (class 2). In case of class 2, subjects were asked to execute/imagine movements successively and at a regular speed. No feedback was provided during the trials. The screening session consisted of 8 runs, 40 trials each, for a total of 320 trials. Runs were separated by a short break. The first run of the session was always a motor execution task, while the 7 remaining runs were motor imagery task. Each run consisted of 20 trials per class in random order.

At the beginning of each trial, a fixation-cross appeared on the computer screen. After 2 s, a cue appeared for 1.5 s in form of a roman digit (”I” or ”II”, corresponding to class 1 and 2, respectively) and prompted the subject to execute or imagine the related movement imagination sequence. At second 7, the trial stopped and the fixation-cross disappeared, leaving a blank screen. A short break, which duration was comprised between 1.5 and 2.5 s, followed after each trial.

D. ERD Analysis

Event-related desynchronization (ERD) and event-related synchronization (ERS) are defined as the percentage of band power decrease (ERD) or band power increase (ERS) in relation to a reference interval (in this study 0.5-1.5 s) [10]. To assess changes in the frequency domain for each class, ERD/ERS maps for frequency bands between 4 and 40 Hz were calculated, using overlapping frequency bands with 2 Hz bandwidth and 1 Hz step size [11]. The statistical significance of the ERD/ERS values was determined by applying a t-percentile bootstrap algorithm [12] with a significance level of α = 0.01.

E. Statistics

For assessing statistically significant differences in the physiological responses according to the different classes the mean ERD/ERS values were calculated for frequency bands between 4-40 Hz (4-6 Hz, 6-8 Hz, 8-10 Hz, 10-12 Hz, 12-16 Hz, 16-20 Hz, 20-24 Hz, 24-30 Hz, 30-40 Hz). The ERD/ERS values of the channels covering the motor cortex were merged to three regions of interest (ROI), with ROI ”left” consisting of C3 and the 8 surrounding channels, ROI ”central” consisting of Cz and the 8 surrounding channels and ROI ”right” consisting of C4 and the eight surrounding channels. In addition, the median ERD/ERS values for two periods of the trial corresponding to the timing of the class were calculated. For this purpose we looked at the EMG time course of the first run, where the participants actually performed the brisk movement and assessed the duration of muscular activation of the single and the double brisk movement. This resulted in two periods, t1, from second 2 to 4.5, and t2, from second 4.5 to 7.
For each frequency band a 2x2x3 ANOVA for repeated measures with ERD/ERS values as dependent variable and CLASS (single vs. double), TIME (t1 vs. t2) and ROI (left, central, right) as within-subject factors was computed. Whenever the sphericity assumption was violated Greenhouse-Geisser corrected values were used for further analysis. In case of statistically significant main factors or interactions a Newman-Keuls posttest was performed.

F. Single-trial analysis

1) Synchronous offline analysis: The recorded EEG data were filtered with common spatial patterns (CSP) [13] and classified with Fisher's linear discriminant analysis (LDA) afterwards. The classification procedure can be written as:

$$f\left(\mathbf{X};\{\mathbf{w}_j\}_{j=1}^{J},\{\beta_j\}_{j=0}^{J}\right)=\sum_{j=1}^{J}\beta_j\log\left(\mathrm{var}(\mathbf{w}_j^T\mathbf{X})\right)+\beta_0 \quad (1)$$

$$\mathbf{X}=[\mathbf{x}(t),\mathbf{x}(t+1),\ldots,\mathbf{x}(t+T-1)] \quad (2)$$

$\mathbf{x}(t)\in\mathbb{R}^C$ denotes the raw EEG signal at time t; C is the number of EEG channels. $\{\mathbf{w}_j\}_{j=1}^{J}\in\mathbb{R}^{C\times J}$ is the set of J spatial filters. The coefficients β_j were calculated with LDA.

In addition to existing classes (class 1, class 2), two additional classes were introduced: “CSP1” and “CSP2”. All samples between second 3 and 5 within a trial belonged to “CSP1” (regardless of single or double brisk movements) and all samples between second 0 and 2 within a trial belonged to “CSP2”. Using these “CSP classes”, the CSP method as described in [14] was used to calculate the spatial filters $\mathbf{w}_j$. The EEG signals $\mathbf{X}$ were filtered with a band pass (8 Hz – 30 Hz) and then $J = 2$ spatial filters were applied (all corresponding to “CSP1”). Afterwards we estimated the variance in equation (1) over a running time window of length $T = 1$ s and obtained CSP features. Noteworthy, the CSP method was used to enhance the signal–to–noise–ratio and not to differentiate two spatial patterns. Subsequently, we applied an LDA classifier on the CSP features using the original classes class 1/class 2. We evaluated the classification accuracy by performing a 10×10 cross validation on a trial-basis.

2) Asynchronous offline analysis: We developed an asynchronous brisk movement classifier and applied it offline. First, CSP features were extracted using the same CSP classes as the synchronous classifier. The used frequency band ranged from 8 to 30 Hz, the variance was calculated over 1 s. Then the CSP features were classified with an LDA classifier. However, the LDA was utilized to differentiate the control state vs. the non-control state (similar to the CSP). Finally, single and double brisk movements were classified using a temporal threshold. After a movement was detected, a refractory time of 2 s was introduced. Summarizing, CSP was used for enhancing the signal-to-noise ratio, the LDA was used to find a threshold for detecting the control-state, and a temporal threshold was used to differentiate one vs. double brisk movements.

As thresholds were subject specific, we applied a genetic algorithm to runs 2 to 5 to find them. After the training of CSP and LDA on runs 2 to 5, the asynchronous classifier was tested on runs 6 to 8. Here, true positives (TP), false positives (FP) and false negatives (FN) were counted as follows. First, a TP window was defined ranging from 4.5 s to 7 s within a trial. The first movement detection within this window was counted as TP if it corresponded to the correct one or as FN if not or if no movement was detected at all. All further detections within this window, as well as all detections outside were counted as FP.

III. Results

A. Statistics

The ANOVA revealed a significant threefold interaction CLASS X TIME X ROI in the lower theta (4-6 Hz; $F_{(2,18)} = 4.31$; $p < .05$) and the gamma band (30-40 Hz; $F_{(2,18)} = 4.51$; $p < .05$). In the lower theta band, ROI left at t2, there is an ERS for single brisk movements ($M = 5.12$; $SD = 8.75$), whereas for double brisk movements, there is still ERD ($M = -3.47$; $SD = 15.85$). In the gamma band something similar could be observed, with ERS or significantly weaker ERD for single brisk movements and stronger ERD for double brisk movements, not only for ROI left (single: $M = 1.62$; $SD = 11.24$; double: $M = -9.26$; $SD = 10.11$), but also for ROI central (single: $M = 0.11$; $SD = 24.15$; double: $M = -5.01$; $SD = 6.35$) and ROI right (single: $M = -2.63$; $SD = 9.64$; double: $M = -6.93$; $SD = 4.35$). In the frequency band 24-30 Hz the ANOVA showed a significant main effect CLASS ($F_{(1,9)} = 8.96$; $p < .05$) with significantly lower ERD for single brisk movements ($M = -3.42$; $SD = 5.04$) as compared to double brisk movements ($M = -9.40$; $SD = 9.61$). In addition to these significant effects a trend towards statistical significance could be found for the interaction CLASS X TIME in the upper theta (6-8 Hz; $F_{(1,9)} = 4.51$; $p = .08$) and the upper alpha band (10-12 Hz; $F_{(1,9)} = 3.67$; $p = .09$), pointing towards a possible difference for t2 with ERS or weaker ERD for single brisk movement as compared to stronger ERD for double brisk movements in this time period. In Figure 1 exemplarily the ERD maps of one subject are presented. In this case the difference in the occurence of the short lasting ERD in the upper figure compared to the long lasting ERD in the lower figure can be seen.

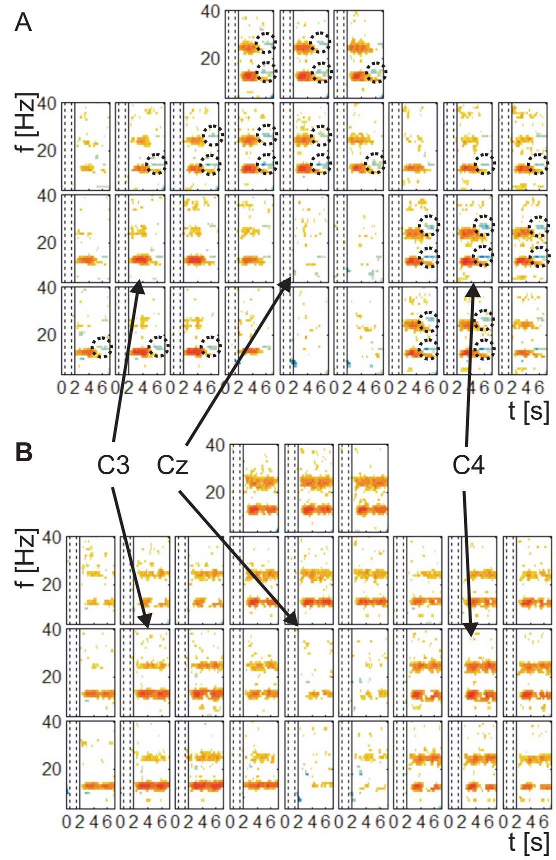

Fig. 1. Time-frequency map for single (A) and double (B) brisk movement for 30 channels. Orange coloured dots represent ERD, blue dots represent ERS (indicated with dotted circles). The dashed lines enclose the reference interval. The line at second 2 indicates the appearance of the cue.

B. Single-trial analysis

Results obtained from *synchronous* classification are presented in Figure 2 and Table I. Figure 2 shows classification accuracies for each subject as well as the grand average. Table I shows 90 % quantiles and maximum values of classification accuracies over the interval from cue to end of trial. Here the mean is 66.7±12.0 % (90 % quantile) and 69.7±12.7 % (maximum), respectively. Removing the results from those subjects who showed no significant results (below 60 %) these values increase to 72.3±9.8,% (90 % quantile) and 75.6±10.2 % (maximum), respectively.

TABLE I

Synchronous offline analysis. 90 % quantiles and maximum values of classification accuracies of 10 subjects.

subj	s1	s2	s3	s4	s5	s6	s7	s8	s9	s10
90 %	78	87	69	73	79	54	60	61	53	55
max %	81	92	73	76	81	56	62	64	55	57

The *asynchronous* classifier yields a mean true-positive-rate (TPR) of 45.2±16.2 % over all subjects. Noteworthily,

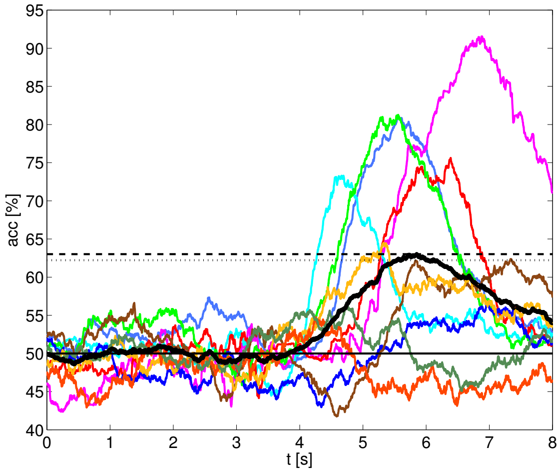

Fig. 2. Synchronous offline classification accuracies for all subjects; the thicker black line shows the average classification accuracies of all subjects; the dashed line shows the maximum and the 90 % quantile, respectively, of the averaged classification accuracies.

one subject showed a good performance with a TPR of 70.8 %. EMG analysis showed that there was no movements during brisk movement imagery.

IV. Discussion

In the past, we have shown the successful implementations of EEG-based brain-switches for neuroprosthetic control in SCI patients. However, one prerequisite for doing so is that the patients are able to generate characteristic brain patterns by motor imagery which can be detected in the EEG [15], [6]. Also an attempt of applying a pulse coded brain switch to control hand and elbow function was presented recently [16]. However, all these methods have in common that an arbitrary type of MI was used, namely the one which was the most reactive in the individual case.

In this work, we were focusing on a more natural, or better to say, a more accepted type of control in the field of rehabilitation. Specifically, we focused on brisk movement imaginations of the hand. For the first time, we introduced a control for hand and elbow function by applying brisk and double brisk movement imagination, respectively. The idea for this type of control was derived from prosthetic control, where it is a common approach to use residual muscle activation, either extensor or flexor muscles, to control the opening, closing, pronation and suppination of the hand.

First results presented here, show that it is possible to detect the two different patterns induced by either brisk or double brisk MI although they origin in the same sensorimotor area. Classical synchronous analysis has shown promising results, though, for an asynchronous approach, there are still open questions to be solved. Therefore, more detailed analyses are necessary in the future as well as an online study has to be carried out. As long as it is not easily possible to decode the trajectories directly from the EEG this new approach might be a good compromise for a basic neuroprosthetic control.

References

[1] J. R. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, “Brain-computer interfaces for communication and control,” *Clinical Neurophysiology*, vol. 113, pp. 767–791, 2002.

[2] G. Pfurtscheller and F. H. Lopes da Silva, “Event-related EEG/MEG synchronization and desynchronization: basic principles,” *Clinical Neurophysiology*, vol. 110, pp. 1842–1857, 1999.

[3] G. Pfurtscheller, C. Guger, G. Müller, G. Krausz, and C. Neuper, “Brain oscillations control hand orthosis in a tetraplegic,” *Neuroscience Letters*, vol. 292, pp. 211–214, 2000.

[4] J. M. Heasman, T. R. D. Scott, L. Kirkup, R. Y. Flynn, V. A. Vare, and C. R. Gschwind, “Control of a hand grasp neuroprosthesis using an electroencephalogram-triggered switch: demonstration of improvements in performance using wavepacket analysis,” *Medical and Biological Engineering and Computing*, vol. 40, pp. 588–593, 2002.

[5] G. Pfurtscheller, G. R. Müller, J. Pfurtscheller, H. J. Gerner, and R. Rupp, ““Thought”-control of functional electrical stimulation to restore handgrasp in a patient with tetraplegia,” *Neuroscience Letters*, vol. 351, pp. 33–36, 2003.

[6] G. R. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp, “Eeg-based neuroprosthesis control: a step towards clinical practice.” *Neurosci Lett*, vol. 382, no. 1-2, pp. 169–174, 2005. [Online]. Available: http://dx.doi.org/10.1016/j.neulet.2005.03.021

[7] G. R. Müller-Putz, R. Scherer, G. Pfurtscheller, and R. Rupp, “Brain-computer interfaces for control of neuroprostheses: from synchronous to asynchronous mode of operation,” *Biomedizinische Technik*, vol. 51, pp. 57–63, 2006.

[8] M. Zecca, S. Micera, M. C. Carrozza, and P. Dario, “Control of multifunctional prosthetic hands by processing the electromyographic signal.” *Crit Rev Biomed Eng*, vol. 30, no. 4-6, pp. 459–485, 2002.

[9] C. Breitwieser, A. Kreilinger, C. Neuper, and G. Müller-Putz, “The TOBI Hybrid BCI – The data acquisition module,” TOBI Workshop 2010 Graz, 2010. [Online]. Available: http://www.tobi-project.org/sites/default/files/public/Publications/Breitwieser – The TOBI Hybrid BCI – The Data Acquisition Module.pdf

[10] G. Pfurtscheller and A. Aranibar, “Evaluation of event-related desynchronization (ERD) preceding and following voluntary self-paced movements,” *Electroencephalography and Clinical Neurophysiology*, vol. 46, pp. 138–146, 1979.

[11] B. Graimann, J. E. Huggins, S. P. Levine, and G. Pfurtscheller, “Visualization of significant ERD/ERS patterns in multichannel EEG and ECoG datas,” *Clinical Neurophysiology*, vol. 113, pp. 43–47, 2002.

[12] A. C. Davison and D. V. Hinkley, *Bootstrap methods and their application*. Cambridge University Press, 1997.

[13] H. Ramoser, J. Müller-Gerking, and G. Pfurtscheller, “Optimal spatial filtering of single trial EEG during imagined hand movement,” *IEEE Transactions on Rehabilitation Engineering*, vol. 8, pp. 441–446, 2000.

[14] B. Blankertz, R. Tomioka, S. Lemm, M. Kawanabe, and K.-R. Müller, “Optimizing spatial filters for robust EEG single-trial analysis,” *IEEE Signal Processing Magazine*, vol. 25, pp. 41–56, 2008.

[15] G. Pfurtscheller, C. Neuper, G. R. Müller, B. Obermaier, G. Krausz, A. Schlögl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, M. Wörtz, G. Supp, and C. Schran, “Graz-BCI: state of the art and clinical applications,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 11, pp. 177–180, 2003.

[16] G. R. Müller-Putz, R. Scherer, G. Pfurtscheller, and C. Neuper, “Temporal coding of brain patterns for direct limb control in humans.” *Front Neurosci*, vol. 4, 2010. [Online]. Available: http://dx.doi.org/10.3389/fnins.2010.00034