Med Biol Eng Comput
DOI 10.1007/s11517-009-0572-7

ORIGINAL ARTICLE

Fast set-up asynchronous brain-switch based on detection of foot motor imagery in 1-channel EEG

Gernot R. Müller-Putz · Vera Kaiser · Teodoro Solis-Escalante · Gert Pfurtscheller

Received: 8 June 2009 / Accepted: 3 December 2009

Abstract Bringing a Brain–Computer Interface (BCI) out of the lab one of the main problems has to be solved: to shorten the training time. Finding a solution for this problem, the use of a BCI will be open not only for people who have no choice, e.g., persons in a locked-in state, or suffering from a degenerating nerve disease. By reducing the training time to a minimum, also healthy persons will make use of the system, e.g., for using this kind of control for games. For realizing such a control, the post-movement beta rebound occurring after brisk feet movement was used to set up a classifier. This classifier was then used in a cue-based motor imagery system. After classifier adaptation, a self-paced brain-switch based on brisk foot motor imagery (MI) was evaluated. Four out of six subjects showed that a post-movement beta rebound after feet MI and succeeded with a true positive rate between 69 and 89%, while the positive predictive value was between 75 and 93%.

Keywords Brain–Computer Interface · Electroencephalogram · Motor execution · Motor imagery · Brain-switch

1 Introduction

Bringing a Brain–Computer Interface (BCI) out of the lab represents a challenging task due to the number of problems that have not yet been solved. Two of these problems are to shorten the training time and to reduce the numbers of EEG channels. Solving these problems, the use of a BCI will be open not only for people who need the BCI for communication, e.g., persons in a locked-in state or suffering from a degenerative nerve disease. By reducing the training time, as well as the number of EEG channels to a minimum, also healthy people will make use of the system, for example, as an innovative controller for games.

In order to realize such a system, a brain pattern has to be found which occurs strong and stable without any subject training. Such a brain pattern is the post-movement beta rebound.

A number of electroencephalographic (EEG) studies reported on motor event-related desynchronization and synchronization (ERD/ERS) in the beta band, i.e., a decrease and increase of spectral amplitudes of central beta rhythms in the range from 13 to 35 Hz [1, 10, 16, 20]. Following an ERD that occurs shortly before and during the movement, bursts of beta oscillations (beta ERS, beta rebound) appear within a 1 s interval after movement offset [12]. Such a post-movement beta ERS has been shown after voluntary hand movements [8, 10, 14, 20], passive movements [2, 8], movement imagery [17], and also after movements induced by functional electrical stimulation [8]. Nevertheless, the functional meaning of the beta ERS is still an open question. There is strong evidence that cortical deactivation or inhibition of the motor cortex coincides with the beta ERS [12, 18]), but also the processing of somatosensory afferent stimuli [2] plays an important role. Interesting in this context is the finding of Schnitzler et al. [19]. He showed that the beta rebound (20 Hz) after median nerve stimulation could be blocked by attempted manipulatory finger movement in tourniquet-induced ischemia experiments. However, the overall goal of our study is not only to investigate the functional

G. R. Müller-Putz (✉) · V. Kaiser · T. Solis-Escalante · G. Pfurtscheller
Laboratory of Brain–Computer Interfaces, Institute for Knowledge Discovery, Graz University of Technology, Krenngasse 37, 8010 Graz, Austria
e-mail: gernot.mueller@tugraz.at

meaning of the beta rebound but also to use it for control purposes.

The hypothesis for the following study is that a classifier can be set up on the post-movement beta rebound found after the termination of a brisk (foot) movement, and that such a classifier can be used to detect imagined foot movements. This type of BCI is also known as brain-switch [7] because it offers only an on/off control. If this hypothesis is confirmed, the use of this classifier should be evaluated in a self-paced procedure.

2 Methodology

2.1 Participants, EEG recording, and experimental paradigm

Initially, seven healthy subjects (six male, one female) participated in this study. They were aged between 24 and 29 years. All of them had prior experience with BCI experiments.

Five Ag/AgCl electrodes were used to derive the EEG signal from Cz and four orthogonal positions 2.5 cm to Cz forming a Laplacian derivation. Reference was placed at the left mastoid and ground at the right mastoid. A bipolar amplifier (g.tec, Guger Technologies, Austria) was configured in a way that it served as monopolar amplifier. The filters were set to 0.5 and 100 Hz, the notch filter (50 Hz) was on and sampling rate was 250 Hz.

The experiment was organized in three different paradigms: (i) cue-based foot motor execution (ME), (ii) cue-based foot motor imagery (MI), and (iii) self-paced foot motor imagery.

2.1.1 Cue-based foot motor execution

An initial screening was performed with the following paradigm: subjects sat in a comfortable armchair 1.2 m in front of a computer screen. They were instructed to perform foot movements according to a cue presented on a screen. The paradigm was on a black screen a green cross appeared at second 0. A beep at second 2 caught the subject's attention and at second 3 a cue appeared for 1.25 s pointing either to the bottom of the screen indicating a foot movement or to the top border of the screen indicating no movement. In case of a movement indication, subjects were expected to perform a brisk dorsiflexion of both feet. This movement should last less than 1 s. After second 6 the cross disappeared and a black screen was shown for random time duration between 0.5 and 2.0 s. Three runs were performed containing 40 trials each, whereby 20 trials with motor execution and 20 trials with no movement were randomly recorded. Duration of this screening was about 15 min.

2.1.2 Cue-based foot motor imagery with feedback bar

The same paradigm as presented for the foot motor execution was used for the foot motor imagery task. However, two things were different. First, in this paradigm, all subjects were asked to imagine the same dorsiflexion they executed in the screening task and second, a feedback bar was presented to the subjects indicating the result of the online classification (for more details, see next section). Whenever a beta rebound was detected, the bar moved from the middle to the bottom of the screen. Therefore, the subjects could see the behavior of the online system. For this paradigm, six runs with 30 trials each were performed. Duration was about 20 min. All subjects showing no beta rebound in the MI task were excluded from further investigations.

2.1.3 Self-paced motor imagery

On a separate day, the self-paced paradigm was performed to verify the feasibility of this brain-switch. Here, one trial lasted 180 s and the subjects were free to perform brisk dorsiflexion imagery to activate a brain-switch. Whenever the beta rebound was detected, a high beep tone indicated the subject that the switch was triggered. A low beep tone thereafter indicated the subject that the system was ready for the next switch-action. For later analysis, subjects were asked to press a button with the right thumb some seconds prior the brisk foot motor imagination to indicate that the beta ERS following the button press was intended by the subject. Therefore, a true positive (TP) was counted, when the button was pressed and the high beep tone appeared. A false negative (FN) occurred, when the button was pressed, but no confirmation tone appeared, and whenever the switch-action was triggered without pressing the button in advance, it was counted as false positive (FP). In total, five runs were performed, and the task was to switch eight - times during each run.

2.2 Data analyses

2.2.1 ERD/ERS maps

In order to obtain a time–frequency map of the Laplacian channel, an ERD/ERS analysis [11] was performed for frequency bands between 1 and 40 Hz with respect to a specific reference interval (0.5–1.5 s). In order to that end, sinusoidal wavelets were used to assess changes in the frequency domain by calculating the spectrum within a sliding window, squaring, and subsequent averaging over the trials [6]. The statistical significance of the ERD/ERS values was determined by applying a t-percentile bootstrap algorithm [3] with a significance level of $\alpha = 0.05$. For all subjects, the significant frequency range of the beta rebound was selected and used for classifier calculation.

2.2.2 *Classification*

One logarithmic band power feature, obtained by band pass filtering, squaring, and averaging over 1 s in a sample by sample way, was used to calculate the weight vector for Fisher's linear discriminant analyzes to distinguish between the two classes, such as foot motor execution and no movement. A 10 times 10-fold cross validation was used to estimate the classification accuracy for each 0.5 s from second 0 to second 6. The classifier resulting in the highest accuracy was used for the cue-based online feedback paradigm. Data obtained from this experiments were used to recalibrate the classifier by calculating new ERD/ERS maps and redefining the frequency band of the beta rebound. This classifier was then used in the self-paced paradigm with an additional threshold in the foot class. The threshold was defined at the mean of the simulated LDA output for the foot class, and is needed to increase the probability that only real beta rebounds are detected and therefore FPs are minimized. However, in a first test run, this threshold was recalibrated to the final setting.

The values of TP, FP, and FN, as well as the true positive rate (TPR) and the positive predictive value (PPV) were used to measure the performance of the on-line self-paced paradigm. The definitions of TPR and PPV are given in (1) and (2), respectively. The TPR indicates the ratio between correctly detected (by the system) commands and all commands intended by the subject, through the button press. The PPV indicates the ratio between correctly detected commands and all commands detected (all activations of the switch, with or without a previous button press). Both values are in the range [0,1] and a TPR = 1 means that all the commands intended by the subject were successfully detected by the system, while a PPV = 1 indicates that all (positive) commands were intended by the subject.

$$\mathrm{TPR} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \qquad (1)$$

$$\mathrm{PPV} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad (2)$$

3 Results

Figure 1 shows the ERD/ERS maps of one representative subject during motor execution and motor imagery, as well as the LDA distance during the self-paced experiment. The patterns displayed on top of this figure correspond to the specific frequency band of the beta rebound used for classification.

In Table 1, the results of the initial cue-based foot motor execution and imagery and tasks are summarized. Besides

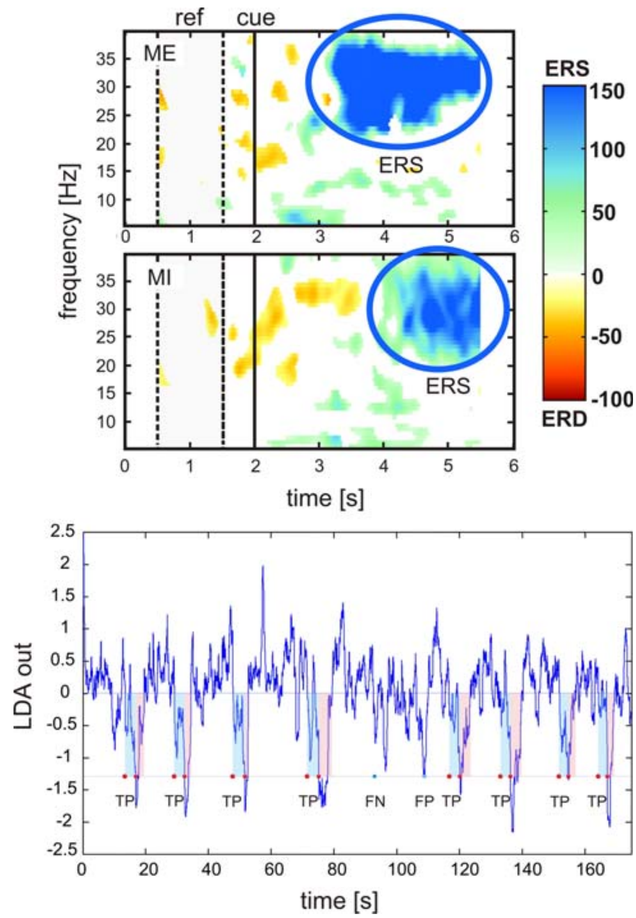

Fig. 1 ERD/ERS map of one subject (al10) during foot motor execution (ME). Below the ERD/ERS map for the motor imagery (MI) task is drawn. In the lowest row, the classifier output over time during self-paced control is presented. True positives (TPs), false negatives (FNs), as well as false positives (FPs) are marked, accordingly

the selected frequency bands also the offline classification accuracy is presented for ME as well as for those participants who showed a beta rebound after foot MI. The accuracy from the offline training (ME) of the classifier dropped from 91.7 to 68.8% during cue-based MI. Four subjects participated in the self-paced experiment, the results of this test are shown in Table 2. After calibration with the new MI data with feedback, the offline (MI) accuracy was 80.8% and, during self-paced MI the PPV was 0.84 (Table 2). Accordingly, the TPR was 0.79 and false positives were kept low (less than 2 per run).

4 Discussion

The main question to be answered in this study was, whether it is possible to set up a classifier on data of executed brisk foot movements and to use this classifier for the online single trial detection of imagined foot

Table 1 Summarized results of the cue-based screening (ME) and cue-based online MI experiment

ME			MI		
Subject	acc (%)	*f* (Hz)	OL (%)	acc (%)	*f* (Hz)
ap4	88	15–28	57	80	24–31
an7	98	12–24	65	81	10–22
ao10	89	15–30	59	75	26–31
al10	92	20–36	78	87	24–35
an8	92	20–30	–	–	–
ah3	92	22–30	–	–	–
Mean	91.8	17.3–29.7	68.8	80.8	21.0–29.8
Band width		12.3			8.3

Offline accuracy (acc) and the corresponding frequency band (*f*) is given for ME and MI. In addition, the online results (OL) are presented

Table 2 Summarized results of the self-paced brain-switch actuated with brisk foot MI

ID	TP	FP	FN	TPR	PPV
ap4	37/7.4	6 1.2	12/2.4	0.75	0.86
an7	40/8	8/1.6	18/3.6	0.69	0.83
ao10	38/7.6	13/2.6	7/1.4	0.84	0.75
al10	39/7.8	3/0.6	5/1.0	0.89	0.93
Mean	38.5/7.7	7.5/1.5	10.5/2.1	0.79	0.84

In each column the total number of five runs as well as the mean over five runs is presented for TP, FP, and FN. Further TPR and PPV are shown

movements. As, we could show with our results, this is possible. Subjects participating in this study showed a post-movement beta rebound in the mean range from 17.3 to 29.7 Hz. Classification accuracy (cross validated) was 91.8% on average. Using this classifier, gained from motor execution, cue-based online detection of foot movement imagination was performed with a mean average of 68.8%. Having the new data, the classifier was updated and led to an accuracy of 80.8%. For this update, the frequency bands were slightly changed according to the beta rebound after movement imagination (21.0–29.8 Hz), and the frequency band width of the beta rebound decreased. After the MI, the beta rebound has a smaller amplitude value, compared with ME, and the significant ERS values belong to a narrower band (see [9]). For the evaluation of the newly calculated classifier, the self-paced paradigm was carried out. Here, the performances, measured in TPR, vary from 0.69 to 0.89. Important here to discuss is the number of FPs. They range from 0.6 FP to 2.6 per run. Minimizing this number is one of the most important goals, because an FP means a wrong decision, whereas an FN results in a longer duration until the next correct switch could be released.

However, in self-paced paradigms, there is always the problem how to measure the performance. In off-line self-paced simulation studies the performance can be easily defined by calculating of TP, TN, FP, and FN rates (e.g., [4]), but it can only be evaluated with some special paradigms in on-line self-paced BCI experiments with feedback. One possibility is to introduce experimenter cued activity periods during self-paced intentional control and rest periods during no intentional control. In the former periods, the TP can be defined and in the latter the FP (e.g., [5]). A different strategy was used in our study. The user always pressed a button whenever he or she intended to switch using the foot MI. In this way, it is only possible to obtain estimates for TP, FP, and FN rates, but the TN remain unknown. Since the truly important events are the positive commands, completely obtained from our measurements, the lack of information due to the TN does not represent a problem.

The mean TPR of 0.79 from the online results (Table 2) is similar to the TPR about 0.60 (false positive rate = 0.10) obtained in the simulated self-paced BCI study with brisk foot motor imagery [13].

Another goal of this study was to shorten the training time and using only one Laplacian channel, but is one channel enough to realize a reliable foot MI detection in ongoing EEG? Recently, it was shown that the foot motor imagery ERD could be detected with a TPR of about 28%, while the TPR for the post-imagery ERS was 59% [13]. From this follows that only 1 EEG channel is enough, when the target signal is a frequency band specific, mentally induced amplitude increase (beta ERS). More EEG channels and a higher number of features are not always a guarantee to achieve a high classification accuracy. For example, only about 56% of executed finger movements could be detected with a highly complex self-paced BCI system using 18 bipolar EEG signals and 6 features for classification [4].

An interesting finding, beyond the scope of this study, is the brief occurrence of a beta rebound phenomena before the actual MI. It can be seen from Fig. 1 (lower part) that every time a TP was counted that was preceded by a small rebound probably related to the activation of the supplementary motor area (SMA) after the button press. Usually, the SMA is activated when a motor command is executed (see e.g., [15]). As reported in [9], the beta ERS after brisk foot motor imagery has the same frequency range than the beta ERS after foot movement.

It can be concluded that setting up a first classifier by motor execution and using it for motor imagery leads to a very fast setup of an online and self-paced BCI. A new user does not has to go through a training, which could be intensive, because the pattern (post-movement beta ERS) used for classification is already defined by the specific neural networks in the primary motor areas, and has to be measured during ME first. Having these parameters, the only work to be done is the adjustment of a threshold, and easily a self-paced BCI is created.

Acknowledgments The authors would like to thank Dr. Clemens Brunner for fruitful discussions. This study was supported by the Lorenz-Boehler Gesellschaft, Allgemeine Unfallversicherungsanstalt (AUVA), Wings for Life—Spinal Cord Research Foundation, EU funded PRESENCCIA (IST-2006-27731).

References

1. Alegre M, Labarga A, Gurtubay IG, Iriarte J, Malanda A, Artieda J (2002) Beta electroencephalograph changes during passive movements: sensory afferences contribute to beta event-related desynchronization in humans. Neurosci Lett 331:29–32
2. Cassim F, Monaca C, Szurhaj W, Bourriez JL, Defebvre L, Derambure P, Guieu JD (2001) Does post-movement beta synchronization reflect an idling motor cortex? Neuroreport 12:3859–3863
3. Davison AC (1997) Bootstrap methods and their application. Cambridge University Press, Cambridge
4. Fatourechi M, Ward RK, Birch GE (2008) A self-paced brain–computer interface system with a low false positive rate. J Neural Eng 5:9–23. doi:10.1088/1741-2560/5/1/002
5. Leeb R, Settgast V, Fellner DW, Pfurtscheller G (2007) Self-paced exploring of the Austrian National Library through thoughts. Int J Bioelectromagn 9:237–244
6. Makeig S, Debener S, Onton J, Delorme A (2004) Mining event-related brain dynamics. Trends Cogn Sci 8:204–210
7. Mason SG, Birch GE (2000) A brain-controlled switch for asynchronous control applications. IEEE Trans Biomed Eng 47: 1297–1307
8. Müller GR, Neuper C, Rupp R, Keinrath C, Gerner HJ, Pfurtscheller G (2003) Event-related beta EEG changes during wrist movements induced by functional electrical stimulation of forearm muscles in man. Neurosci Lett 340:143–147
9. Müller-Putz GR, Zimmermann D, Graimann B, Nestinger K, Korisek G, Pfurtscheller G (2007) Event-related beta EEG-changes during passive and attempted foot movements in paraplegic patients. Brain Res 1137:84–91. doi:10.1016/j.brainres.2006.12.052
10. Neuper C, Pfurtscheller G (2001) Evidence for distinct beta resonance frequencies in human EEG related to specific sensorimotor cortical areas. Clin Neurophysiol 112:2084–2097
11. Pfurtscheller G, Lopes da Silva FH (1999) Event-related EEG/MEG synchronization and desynchronization: basic principles. Clin Neurophysiol 110:1842–1857. doi:10.1016/S1388-2457(99)00141-8)
12. Pfurtscheller G, Neuper C (1997) Motor imagery activates primary sensorimotor area in humans. Neurosci Lett 239:65–68
13. Pfurtscheller G, Solis-Escalante T (2009) Could the beta rebound in the EEG be suitable to realize a "brain switch"? Clin Neurophysiol 120:24–29. doi:10.1016/j.clinph.2008.09.027
14. Pfurtscheller G, Zalaudek K, Neuper C (1998) Event-related beta synchronization after wrist, finger and thumb movement. Electroencephalogr Clin Neurophysiol 9:154–160. doi:10.1016/S0924-980X(97)00070-2
15. Pfurtscheller G, Guger C, Müller G, Krausz G, Neuper C (2000) Brain oscillations control hand orthosis in a tetraplegic. Neurosci Lett 292:211–214. doi:10.1016/S0304-3940(00)01471-3
16. Pfurtscheller G, Neuper C, Pichler-Zalaudek K, Edlinger G, da Silva FHL (2000) Do brain oscillations of different frequencies indicate interaction between cortical areas in humans? Neurosci Lett 286:66–68
17. Pfurtscheller G, Neuper C, Brunner C, da Silva FHL (2005) Beta rebound after different types of motor imagery in man. Neurosci Lett 378:156–159
18. Salmelin R, Hamalainen M, Kajola M, Hari R (1995) Functional segregation of movement related rhythmic activity in the human brain. NeuroImage 2:237–243. doi:10.1006/nimg.1995.1031
19. Schnitzler A, Salenius S, Salmelin R, Jousmki V, Hari R (1997) Involvement of primary motor cortex in motor imagery: a neuromagnetic study. NeuroImage 6:201–208
20. Stanck A, Feige B, Lücking CH, Kristeva-Feige R (2000) Oscillatory cortical activity and movement-related potentials in proximal and distal movements. Clin Neurophysiol 111(4):636–650