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Could the beta rebound in the EEG be suitable to realize a "brain switch"?

G. Pfurtscheller *, T. Solis-Escalante

Laboratory of Brain-Computer Interfaces, Institute for Knowledge Discovery, Graz University of Technology, Krenngasse 37, 8010 Graz, Styria, Austria

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ABSTRACT

Objective: Performing foot motor imagery is accompanied by a peri-imagery ERD and a post-imagery beta ERS (beta rebound). Our aim was to study whether the post-imagery beta rebound is a suitable feature for a simple "brain switch". Such a brain switch is a specifically designed brain–computer interface (BCI) with the aim to detect only one predefined brain state (e.g. EEG pattern) in ongoing brain activity.
Method: One EEG (Laplacian) recorded at the vertex during cue-based brisk foot motor imagery was analysed in 5 healthy subjects. The peri-imagery ERD and the post-imagery beta rebound (ERS) were analysed in detail between 6 and 40 Hz and classified with two support vector machines.
Results: The ERD was detected in ongoing EEG (simulation of asynchronous BCI) with a true positive rate (TPR) of 28.4% ± 13.5 and the beta rebound with a TPR of 59.2% ± 20.3. In single runs with 30 cues each, the TPR for beta rebound detection was 78.6% ± 12.8. The false positive rate was always kept below 10%.
Conclusion: The findings suggest that the beta rebound at Cz during foot motor imagery is a relatively stable and reproducible phenomenon detectable in single EEG trials.
Significance: Our results indicate that the beta rebound is a suitable feature to realize a "brain switch" with one single EEG (Laplacian) channel only.

1. Introduction

The most important brain–computer interface (BCI) application in the past was to install a non-muscular communication channel for patients with severe motor disabilities or restoration of motor function in patients with spinal cord injury (Wolpaw et al., 2002; Pfurtscheller et al., 2005a). At this time and in the near future, new BCI applications gain importance as for example to improve the BCI-based feedback therapy in patients with epilepsy, attentional disorders or stroke (e.g. Birbaumer et al., 2007; Strehl et al., 2006). Important here is to optimize the electrode locations and frequency bands of the recorded and analysed brain signals used for feedback. Another application is to use the BCI for healthy subjects. Here we can differentiate between the control of multimedia application or computer games (e.g. Nijholt and Tan, 2007; Scherer et al., 2008) and the use of the BCI for user authentication (Marcel and Millán J del, 2007). In the latter case, a user-specific thought-related brain pattern has to be compared with a variety of stored patterns. If there is a match, the user can login e.g. for high-importance applications or environments.

Due to these new/novel BCI applications, preferably in able-bodied subjects, new strategies should be explored to develop user-friendly, non-invasive EEG-based BCIs suitable for every-day life and home applications. One of these strategies is to utilise the beta rebound, a transient EEG phenomenon first reported after termination of finger movements (Pfurtscheller, 1981; Salmelin and Hari, 1994), for classification of a specific mental state. Another is to use only one EEG channel to realise a simple "brain switch". Such a brain switch differentiates between one predefined brain state (e.g. one motor imagery task) and all other active or passive brain states including resting and idling in ongoing bioelectrical brain activity.

2. Physiological background

The induced short-lasting beta oscillation after movement or in response to somatosensory stimulation is termed as beta rebound. This beta rebound shares the following interesting features:

(i) Strict somatotopic organization (Salmelin et al., 1995; Pfurtscheller and Lopes da Silva, 1999)
(ii) Somatotopically-specific frequency components, with slightly lower frequencies over lateralized sensorimotor areas as compared to the midcentral area (Neuper and Pfurtscheller, 2001)
(iii) Similar patterns after active and passive movement (Cassim et al., 2001; Alegre et al., 2002), electrical nerve stimulation (Neuper and Pfurtscheller, 2001) and motor imagery (Pfurtscheller et al., 2005b)

* Corresponding author. Tel.: +43 316 873 5300; fax: +43 316 873 5349.
E-mail address: Pfurtscheller@tugraz.at (G. Pfurtscheller).

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(iv) "Cross-talk" between hand representation area and mesial cortex (overlying the foot representation area and the supplementary motor area (SMA), Pfurtscheller et al., 2000a)
(v) Attenuation or suppression of the stimulus-induced beta rebound during enhanced motor cortex activation (Schnitzler et al., 1997; Pfurtscheller et al., 2002)
(vi) Attenuation of the stimulus-induced beta rebound while viewing another person's manipulation movements (Järveläinen et al., 2004)
(vii) Coincidence with a reduced excitability of motor cortex neurons as measured with transcranial magnetic stimulation (Chen et al., 1998).

From these observations two important conclusions can be drawn: First, the beta rebound does not necessarily depend on muscle activation or passive movement but is also present after motor imagery. Second, the beta rebound very likely reflects a somatotopically specific, short-lived brain state associated with deactivation (inhibition) and/or resetting of motor cortex networks.

Some explanation is needed for the term "cross-talk". Self-paced finger movements induce a beta rebound not only in the contralateral hand representation area but also with slightly higher frequencies and an earlier onset in midcentral areas overlying the supplementary motor area (SMA) (Pfurtscheller et al., 2003). This midcentrally induced beta rebound is especially dominant following voluntary foot movement (Neuper and Pfurtscheller, 2001) and foot motor imagery (Pfurtscheller et al., 2005). We speculate therefore that the termination of motor cortex activation, whether it follows the actual execution or just imagination of a body-part movement, may involve at least two neural networks, one in the primary motor area and another in the SMA. In the case of foot movement both the SMA and the cortical foot representation area are involved. Taking into consideration the close proximity of these cortical areas (Ikeda et al., 1992), associated with the fact that the response of the corresponding networks in both areas may be synchronized, it is likely that a large-amplitude beta rebound (beta ERS) occurs after foot motor imagery. Summarising it can be stated that the beta rebound after foot movement displays a high signal-to-noise ratio and is therefore especially suitable for detection and classification of foot motor imagery in single EEG trials.

The main objective of this study was to address the following questions:

(i) Is it possible to detect brisk foot motor imagery in ongoing 1-channel EEG (Laplacian) recordings?
(ii) Does the classification improve when not the ERD but the beta rebound (beta ERS) is classified?

3. Methods

3.1. Subjects, data acquisition and experimental setup

EEG recordings from 5 healthy subjects aged between 24 and 31 (mean 25.8 years; SD 2.9) years were collected during cue-based imagination of a brisk dorsiflexion of both feet (motor imagery; MI). Before the imagery runs each subject practised the task by active feet movement. Two of the subjects had some experiences with hand and foot motor imagery sessions with BCI feedback, while 3 had no experience with BCI feedback. During the recording every 8–10 s a cross was displayed for 6 s. Two seconds after the cross a short beep appeared together with a 1.25-s lasting cue in form of a downward pointing arrow on a monitor in front of the subject (see Fig. 1 top panel). Each subject performed three runs with 30 cues each with a short break in between. For the further

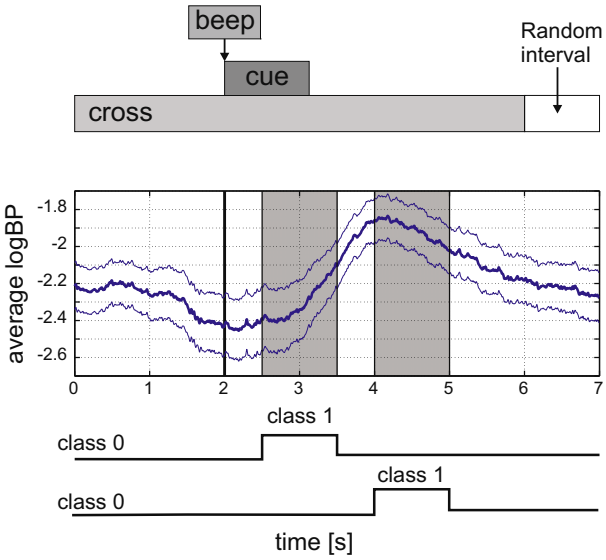

Fig. 1. Experimental paradigm; a cross was presented from t = 0–6 s and, a visual cue together with a short beep at t = 2 s (top). Time course of beta power changes (mean + SD) during cue-based motor imagery with peri-imagery ERD and post-imagery ERS; time windows (gray vertical bars) used to define classes 1 for ERD and ERS classification, respectively (C) (middle). Class 1 labels were assigned to the EEG segments during two different time windows for ERD detection between 2.5 and 3.5 s and ERS detection between 4 and 5 s; any other segment was labelled as class 0 (bottom).

cue-triggered processing, trials with 2 s before the cue and 5 s after were used.

Sixteen closely spaced (~2.5 cm) Ag/AgCl electrodes placed over the sensorimotor area including the electrode position Cz were used to record monopolar EEG signals with a biosignal amplifier system (Guger Technologies, Graz, Austria) and a sampling frequency of 250 Hz. From these 16 electrodes only 5 were used to calculate the Laplacian channel at Cz (Hjorth, 1975; the potential at 4 surrounding electrodes is subtracted from the potential at Cz) Filters were set at 0.5 and 30 Hz (40 dB/octave). All subjects gave written informed consent prior to participation. The study complied with the declaration of Helsinki.

3.2. Calculation of time–frequency maps

ERD/ERS is defined as the percentage of power decrease (ERD) or power increase (ERS) in relation to a reference interval (in this study 0.5–1.5 s; visual cue-onset at second 2; see Fig. 1 top panel) (Pfurtscheller and Lopes da Silva, 1999). Time–frequency maps for the 6–40 Hz frequencies were calculated to evaluate changes caused by motor imagery. 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 (Makeig et al., 2004). The statistical significance of the ERD/ERS values was determined by applying a t-percentile bootstrap algorithm (Davision and Hinkley, 1997) with a significance level of $\alpha = 0.05$.

3.3. Feature extraction and pattern recognition

Each trial was analyzed using time segments of 1 s in length with an overlap of 500 ms. The spectral description of each segment was computed by means of logarithmic band powers in the frequency range from 6 to 36 Hz. All patterns were labelled twice for the classification of either ERD or ERS against all other brain activity. The peri-imagery ERD pattern during MI was labelled as

class 1 from $t = 2.5$ s to $t = 3.5$ s, all other patterns were labelled as class 0. Similarly, the post-imagery beta ERS ($t = 4$ s to $t = 5$ s) was labelled as class 1 (details see Solis-Escalante et al., 2008). Fig. 1 shows the labelling procedure for each trial. These as class-1 labelled 1-s periods, are referred to as the intentional control period (ICP). As a consequence, the rest of the time is referred to as non-intentional control period (NICP). Because the peri-imagery (movement) ERD and post-imagery (movement) ERS share slightly different frequency components (Müller-Putz et al., 2007; Alegre et al., 2008) both, ERD and ERS are treated independently.

Two classifiers were trained for the individual detection of ERD and ERS within their respective ICP. Support vector machines (SVMs) with Gaussian kernels were used for this task by implementing the LIBSVM software (Chang and Lin, 2001) in combination with the Matlab interface from the BioSig software (Schlögl et al., 2007).

From the 3 runs available (each composed of 30 trials) one run was always used to train the SVM with a specific combination of parameters and a second run was used to select the hyperparameters of the SVMs (Müller et al., 2001; Chang and Lin, 2001); the performance of the SVM depends on the regularization parameter C and the width of the kernel (σ). Thereafter the performance of the SVM was tested on the third (unseen) run through simulation of an asynchronous system and computing the posterior probabilities of the ERD and ERS patterns. The output of the classifiers was additionally post-processed with three simple parameters: (i) threshold, (ii) dwell time (DT) and (iii) refractory period (RP). The DT and RP values were set at 62 samples (248 ms) and 500 samples (2 s), respectively. The optimal threshold was determined from the receiver-operator characteristic (ROC) curve. For evaluation the ICP was extended to 2 s, from $t = 2.5$ to 4.5 s for ERD and from $t = 3.5$ to 5.5 s for ERS. This was done since ERD and ERS display some intra- and intersubject variability and are not restricted to 1-s time windows (see examples in Fig. 2). The values of true positive ratio (TPR) and false positive ratio (FPR) were defined from event detection and not on a sample-by-sample basis. A *true positive event* (TPE) is regarded as any detection with at least DT ms over the threshold during an ICP and a *false positive event* (FPE) is any detection outside an ICP.

$$TPR = \frac{TPE}{N_{TPIC}}$$

$$FPR = \frac{FPE}{N_{FPIC}}$$

where N_{TPIC} is the maximum number of TPE (equal to the number of ICP since only one detection is allowed) and N_{TPIC} = (total EEG length pro run)/(DT + RP). The number of events are 30 and $N_{TPIC} = 110$.

4. Results

4.1. Intra- and intersubject variability of time–frequency maps

To give the reader an impression what the time–frequency maps from the 3 runs with brisk feet motor imagery looks like, the maps of all 5 subjects are displayed in Fig. 2. The most dominant feature in each map is the beta rebound, while the beta ERD is less pronounced and of larger variability. So for example the post-imagery beta ERS is dominant in subject s2, while the peri-imagery beta ERD is dominant in s4. Of interest is also a harmonic component of the beta ERS in subjects s4 and s5. It can be also recognized in Fig. 2 that the beta ERD generally always involves slightly higher frequency components than the beta ERS. On the

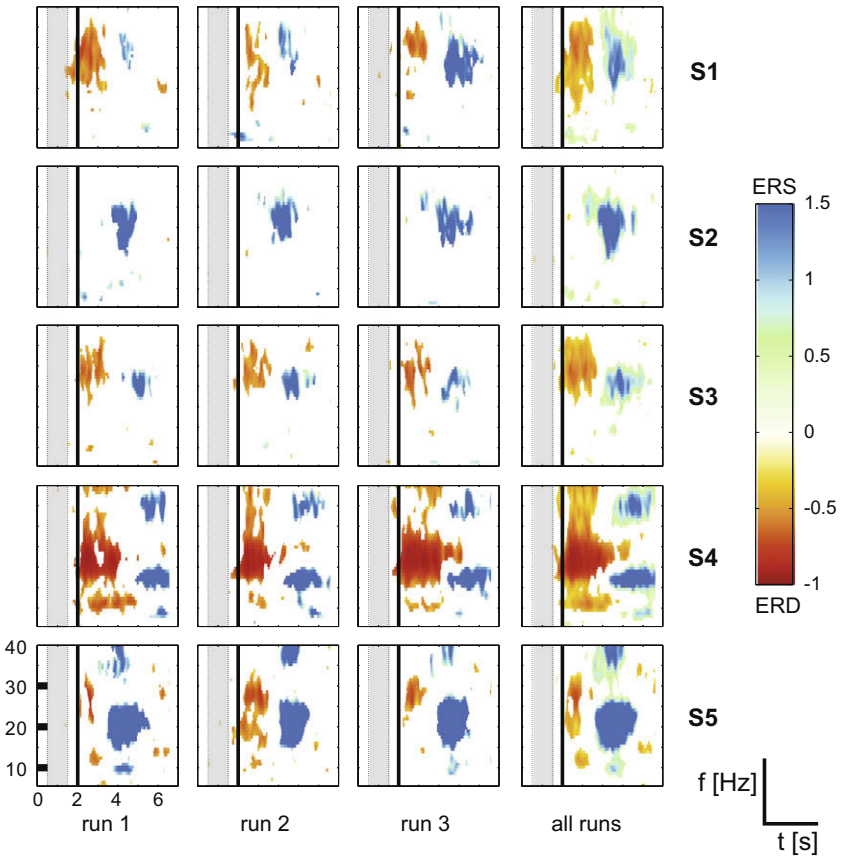

Fig. 2. Time–frequency maps of all subjects, calculated for the runs #1, #2 and #3 and all 3 runs together. Displayed are only significant ($p < 0.05$) band power changes in the ranges 0–7 s with 2 s prior to cue-onset in the range 6–40 Hz. The reference period for ERD/ERS calculation is marked by a gray vertical bar. The colour red indicates significant power decrease (ERD) and blue significant power increase (ERS).

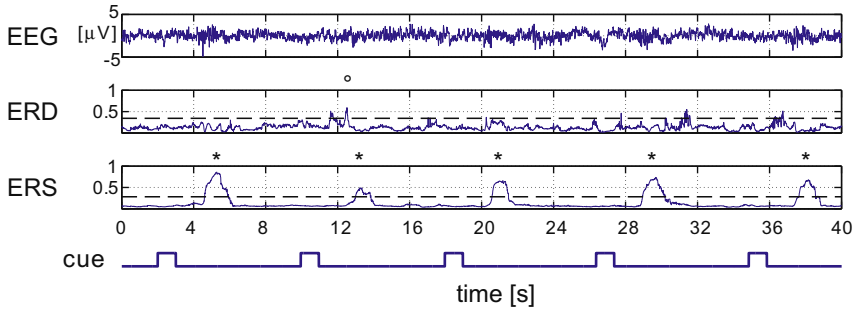

Fig. 3. Example of ongoing EEG (Laplacian) (top). Time courses of classifier probability for ERD and ERS detection. A control event is detected every time the class probability exceeds the threshold (dashed line) for a time equal to the dwell time; correct ERD detections are marked with a circle and correct ERS detections with an asterisk (middle). Timing of cue presentation (bottom).

right side of Fig. 2 the average time–frequency maps including data of all 3 runs are plotted.

5. Performance rates for simulation of an asynchronous BCI

A BCI can operate either in a cue-based mode with processing in predefined time windows (known as synchronous BCI) or uncued (self-paced) with continuous processing (asynchronous BCI) (Pfurtscheller et al., 2005a). Here we report the performance rates when the complete data from one run is used for detection of feet MI (simulation of an asynchronous BCI). An example of such ERD and ERS detections, respectively, in ongoing EEG (Laplacian) is displayed in Fig. 3. All ERS but only one ERD pattern are detected during 40 s of EEG data.

With all possible combinations (e.g. run #1 for training, run #2 for parameter selection and run #3 for testing, run #2 for training, #3 for parameter selection and run #1 for testing) each run served twice for testing and 6 performance measures were obtained for each subject. These numbers were averaged for each subject (mean ± SD) and displayed in Table 1 together with the best (max) and worst (min) TPR of the 6 values. The FPR was in all cases equal or below 10%. The average TPR for ERD detection was 28.4% ± 13.5 and the TPR for beta ERS detection in ongoing EEG (simulation of asynchronous BCI) 59.2% ± 20.3. The best (max in Table 1) TPR (78.6 % ± 12.8) give some indication which performance rate can be achieved in each subject under "good" conditions. A real control of the "goodness" of imagery is not possible but this true positive rate of nearly 80% suggests that the 5 subjects investigated displayed a good task performance.

6. Discussion

The question whether foot MI can be detected in one-channel EEG can be clearly answered with "yes". The time frequency maps in Fig. 2 demonstrate that all subjects displayed significant patterns of post-imagery band power increase (ERS) together with a band power decrease (ERD) during the imagery process with a relatively small variability between runs. The single trial analyses revealed in one run of subject s5, a classification performance of 100%. This means that each post-imagery beta ERS was correctly detected. On average at least in one run the TPR of beta ERS detection was 78.6%. Of importance is that in all subjects the same Laplacian EEG recording with 5 closely spaced electrodes at and around Cz was used and for the classification procedure all recorded EEG data (without artefact selection) were considered. From this it can be concluded that subject-specific EEG electrode optimization and artefact detection/rejection can improve the classification accuracy.

Table 1
Subject identification (ID) and true positive rates (TPR) for ERD and ERS detection. In addition to the mean ± SD over the 6 values from each subject also the best (max) and worst (min) TPR are displayed. In the last 2 rows the mean and SD over subjects are displayed.

ID	ERD TPR [%]			ERS TPR [%]		
	Mean ± SD	Max	Min	Mean ± SD	Max	Min
S1	12 ± 6	20	3	57 ± 14	73	43
S2	30 ± 11	40	17	51 ± 15	73	33
S3	23 ± 9	33	13	37 ± 19	67	20
S4	49 ± 13	70	30	59 ± 24	80	23
S5	28 ± 7	33	20	92 ± 10	100	80
Mean	28.4	39.2	16.6	59.2	78.6	39.8
SD	13.5	18.7	9.8	20.3	12.8	24.2

The classification results in Table 1 give clear evidence, that the beta rebound (beta ERS) is easier detectable in single trials than the beta ERD (59% compared to 28%). It was shown recently (Müller-Putz et al., 2007) that the beta ERD during foot movement execution and imagery comprises slightly higher frequency components as the post-movement beta ERS. They reported frequencies of ~29 Hz for the beta ERD and ~24 Hz for the beta ERS. A similar frequency difference is visible in the time–frequency maps displayed in Fig. 2. This means that not the same neural structures are involved in the initial beta desynchronization and the following beta rebound. This partial independence of the beta ERD and the beta rebound was also confirmed in a recently reported movement experiment (Alegre et al., 2008). When we assume, that in general more rapidly oscillating cell assemblies (higher frequency components; e.g. oscillations involved in generation of the centrally localised beta ERD) are comprised of fewer neurons as compared to slowly oscillating cell assemblies (e.g. oscillations responsible for the. beta ERS; Singer, 1993), then it can be speculated that larger and/or more widespread neural structures or networks contribute to the beta synchronisation (beta rebound) than to the beta desynchronization. The beta rebound is very likely related to resetting of the control system after the motor task involving at least the primary motor foot representation area and the SMA (Pfurtscheller et al., 2003a). Because of the great functional and anatomical complexity of the SMA and its somatotopic organization (Lim et al., 1994), it can be expected that not just one but a great variety of beta-generating networks exist and both linear and non-linear coupling with other motor areas can be expected.

Recently two studies were reported about self-paced (asynchronous) BCIs. One of it reported asynchronous detection of finger flexion movements with a low false positive rate (Fatourechi et al., 2008) and the other described a beta rhythm-based BCI suitable to classify repetitive wrist extensions (Bai et al., 2008). Both papers need some discussion. The BCI with a low false positive rate uses 3 features (movement-related potentials, mu ERD and beta

ERD) and 18 bipolar EEG signals to classify cue-based execution of finger flexions. The experiments revealed that 4 able-bodied subjects had an average true positive rate of 56% and a false positive rate of ~10%. In comparison to this study with a highly sophisticated multiple classifier system and 18 EEG signals, we reported a similar performance with only 1-channel (Laplacian) EEG recording and classification with only 2 simple features (ERD and ERS). One major difference is, however, that Fatourechi et al. (2008) classified real executed finger movements, while we classified imagined foot movements.

The second study (Bai et al., 2008) was focussed on classification of cue-based wrist extension either executed or imagined. They started with a calibration procedure using 29 EEG electrodes and 16 frequency components. Thereafter, one Laplacian channel and one beta frequency component were selected for classification. Motor execution was detected in 6 healthy subjects with an accuracy of ~90% and motor imagery with ~75%. The main feature classified was the beta ERS and the beta rebound, respectively. In contrast to our study, where a single brisk foot motor imagery was detected, repetitive wrist motor imagery over a 2.5-s window period has to be detected and compared to a 2.5-s window without motor imagery in Bai's experiment. There is no doubt that repetitive MI is easier to classify in the ongoing EEG than one brisk imagery event. Therefore, the slightly higher classification accuracy in Bai's study is not unexpected because of the extensive search for the best electrode location and frequency band after the calibration step.

Our reported approach is very simple because one standard EEG (Laplacian) channel at the vertex was used in every subject. But this also means there is still some potential to enhance the performance when the electrode positions used to calculate the Laplacian EEG derivation are optimised in each subject. From the results obtained it is also very clear, that not the ERD during the imagery task, but the ERS occurring after the end of the motor task is the dominant feature for realising an asynchronous brain switch. This beta ERS after motor imagery displays a relative great intrasubject stability, even when the recordings are made in intervals of some weeks (example from 8 sessions see Fig. 6 in Pfurtscheller et al., 1997). Of interest is also the long-term stability (over years) of the midcentrally induced beta oscillations during foot motor imagery in a tetraplegic patient (Pfurtscheller et al., 2000b, 2003b, 2008). Both observations underlines the importance of networks in the foot representation area and/or SMA to generate frequency-stable beta oscillation.

Because of the relative stability of the beta rebound at Cz and its great similarity during executed and imagined foot movements (Pfurtscheller et al., 2005b; Müller-Putz et al., 2007) we can speculate that similar networks became reactive during covert and overt movements. This means also that movement execution data may be suitable to train a classifier and to apply this classifier to motor imagery data even when only one EEG channel is available. A paper documenting the feasibility of this novel concept is already in preparation. This approach can be a new strategy in the future to realize a simple "brain switch" for healthy subjects with one EEG channel only. A limitation of the proposed method is the time delay of some seconds due to the beta rebound classification. Recently an information transfer rate of 11 bits/min was reported for classification of the beta rebound during overt brisk feet dorsiflexions (Solis-Escalante et al., 2008). It can be expected that a rate of ~15 bits/min is not unrealistic after some training sessions. For operating a spelling device this rate is relatively low, but sufficient for simple switching applications of course.

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