Detection of the Onset of Voluntary Movements Based on the Combination of ERD and BP Cortical Patterns

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Abstract. The electroencephalographic activity allows the characterization of movement-related cortical processes. This information may lead to novel rehabilitation technologies with the patients' cortical activity taking an active role during the intervention. For such applications, the reliability of the estimations based on the electroencephalographic activity is critical both in terms of specificity and temporal accuracy. In this study, a detector of the onset of voluntary upper-limb reaching movements based on cortical rhythms and slow cortical potentials is proposed. To that end, upper-limb movements and cortical activity were recorded while participants performed self-paced movements. A logistic regression combined the output of two classifiers: a) a naïve Bayes trained to detect the event-related desynchronization at the movement onset, and b) a matched filter detecting the bereitschaftspotential. On average, 74.5±10.8 % of the movements were detected and 1.32 ± 0.87 false detections were generated per minute. The detections were performed with an average latency of -89.9 ± 349.2 ms with respect to the actual movements. Therefore, the combination of two different sources of information (event-related desynchronization and bereitschaftspotential) is proposed as a way to boost the performance of this kind of systems.

1 Introduction

The development of Brain-Computer Interfaces (BCIs) based on the electroencephalographic (EEG) activity for the functional rehabilitation of patients with motor disabilities has gained special interest over the last years [1, 2]. The main purpose of BCIs in such scenarios is to provide a way to promote the neural rehabilitation of the patient. EEG systems allow the online characterization of the cortical activity over the motor cortex while the measured subject is performing motor tasks. This way, it becomes possible to detect online when a person is attempting or imaging a movement [3, 4, 5], and to predict certain properties of the movement to be performed [6, 7, 8].

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This information may in turn be used to close the loop with neuroprosthetic or neurorobotic devices, thus providing a natural interface between the patient's intentions and the actuation of external devices [9]. In this regard, recent studies have proven the importance of the proprioceptive feedback timing to achieve associative neural facilitation [10, 11].

In a series of previous studies, it has been proposed the use of the Bereitschaftspotential (BP) to detect the movement intention [4, 12, 13, 8, 14]. The BP is defined as a slow decay of the EEG voltage over the central regions of the cortex right before a voluntary movement is performed [15]. Given the nature of the BP as an identifiable pattern that is decaying until the movement starts, it becomes suitable to achieve temporal precision in the detection of the onset of the movement. In fact, previous studies showing results of online systems based on this pattern indicate that average latencies of 315 $\pm$ 165 ms can be obtained [14].

The BP, nonetheless, presents some limitations. First, this pattern shows a reduced amplitude (in the order of few μV), which makes it vulnerable to external sources of noise. In addition, the BP is not always detectable, since some subjects do not present a significant pattern during self-paced movements.

A second cortical pattern associated to the execution of voluntary movements is the event-related desynchronization (ERD). This pattern consists of a decay of the power in some specific cortical rhythms that takes place mainly over the sensorimotor cortex in areas contralateral to the limb (in case upper-limb movements are considered) [16]. Although a variable anticipation may be observed in the ERD of a specific channel and frequency in a subject during consecutive movements, the spatio-tempo-frequential distribution of the ERD observed when averaging a number of EEG segments preceding voluntary movements shows a clear pattern attached to the movement event.

In this present study, a detector of the onsets of movements is proposed based on the combined detection of the ERD and the BP patterns preceding volitional movements. The design of the system as well as its validation with data collected from healthy subjects performing self-paced reaching movements is presented here.

2 Methods

2.1 Participants

Six healthy subjects (all males, right-handed and between 27 and 35 years old) were measured for the present experiments. None of them had any prior experience with BCI paradigms.

2.2 Experimental Protocol

Each participant was measured during one single session. The study was performed in a sound and light-attenuated room. Participants sat in a comfortable chair with their arms supported on a table. During the measurement phase, participants were instructed to remain relaxed with their eyes open and their gaze fixated on a point on the wall. They were asked to perform self-initiated reaching movements with the dominant arm. The average distance between consecutive movements was around 8-15 s. During the resting state between movements, participants were asked to remain as relaxed and quite as possible, whereas they were asked to start a movement as soon as they felt the urge to do it.

The intervals containing at least 5 s of resting activity followed by a self-initiated reaching movement were considered valid trials and were used in the subsequent steps of the data analysis. On average, 53 ± 8 trials were collected.

2.3 Data Acquisition

The movements of the arm were measured with solid-state gyroscopes. Three gyroscopes (Technaid S.L., Madrid, Spain) placed on the hand dorsum, the distal third of the forearm, and the middle of the arm measured the limb kinematics. The data were sampled at 100 Hz.

EEG signals were recorded from 31 positions (AFz, F3, F1, Fz, F2, F4, FC3, FC1, FCz, FC2, FC4, C5, C3, C1, Cz, C2, C4, C6, CP3, CP1, CPz, CP2, CP4, P3, P1, Pz, P2, P4, PO3, PO4 and Oz, all according to the international 10-20 system) using active Ag/AgCl electrodes (Acticap, Brain Products GmbH, Germany). The reference was set to the voltage of the earlobe contralateral to the arm moved. AFz was used as ground. The signal was amplified (gUSBamp, g.Tecgmbh, Austria) and sampled at 256 Hz.

2.4 Detection of the Onset of the Movements

To detect the onsets of the movements, the data from the gyroscopic sensor that activated the first during reaching movements in each subject was used. The data were low-pass filtered (Butterworth, order 2, < 10 Hz). The peak amplitude was estimated for each subject performing the reaching movement. The threshold amplitude for the detection of the onsets of the movements was set to 5 % of this reference amplitude.

2.5 Description of the Classifier Architecture and Validation

The core of the detector was a combination of the information associated to the ERD and BP patterns observed in the participants. The validation of the system was carried out following a leave-one-out methodology, i.e. once the trials had been identified, each of them was classified with a detector trained with the rest of the trials of the session.

2.5.1 ERD-Based Detection of the Movement Onset

A naïve Bayes classifier was used to detect the ERD pattern observed at the onset of the movements. First the signals were bandpass filtered (Butterworth, 3th order, 6 Hz $<$ f1, 35 $>$ f2) and a small laplacian filter was applied [17]. The channels from the frontal, fronto-central, central, centro-parietal and parietal positions were kept. The power values were estimated for the frequency interval 7-30 Hz in steps of 1 Hz. Welch's method (Hamming windows of 1 s, 50 % overlapping) was used to estimate the power values of windows of 1.5 s. Estimations were performed at a rate of 8 Hz.

The power estimations obtained in all the training trials from -3 s to -0.5 s (with respect to the movement onsets) were labeled as resting state examples, whereas the estimations generated at t = 0 s where labeled as movement examples. The Bhattacharyya distance was used for space dimensionality reduction. The 10 best features according to this distance were selected to build the classifier.

The classifier was applied to the test data. Estimations about movement intention were generated every 125 ms.

2.5.2 BP-Based Detection of the Movement Onset

A similar procedure to the one proposed in [8] was used to detect the BP. A finite impulse response (with linear phase) bandpass filter (0.05 Hz $<$ f1, 1 Hz $>$ f2, 15th order) was used. This solution was adopted since linear preservation is crucial to extract the entire BP pattern.

Then spatial filtering and channel selection were performed. Three virtual channels were computed from the original 31 channels in the experimental set-up. These channels were extracted applying the same spatial filter as in [8] to positions C1, Cz and C2, i.e. the average potential of channels F3, Fz, F4, C3, C4, P3, Pz and P4 was subtracted to these three channels. The average BP was computed for the three virtual channels using the training data and the channel with highest absolute peak at the movement onset was selected for the movement onset detection.

Using the training data set, a matched filter was obtained using the previously selected channel. To that end, the average BP was obtained from the time interval between -1.5 s and 0 s (with 0 s being the movement onsets estimated by the gyroscopes). The matched filter was applied to the virtual channel in the validation data set.

2.5.3 Combination of the Two Estimations

The combination of the outputs from ERD and BP detectors (real-valued signals from the application of the Bayesian classifier and the matched filter, respectively) was carried out by a logistic regression classifier. To build the classifier, the examples of the resting and movement conditions were extracted from the training data set. The estimations of the two classifiers (ERD and BP) from -3 s to -0.5 s with respect to the movement onset (in steps of 125 ms) were used to model the resting state. The movement state was modeled from the output estimations of the ERD and the BP classifiers at the movement onset.

2.5.4 Threshold Selection

A threshold was applied to the output of the detector to decide at each moment whether movement intention was detected. The threshold was optimally obtained from the training data set, following the criterion of maximizing the percentage of good trials (GT), which were trials with a true positive (TP) and no false positives (FP). The definition of these metrics is further elaborated in 2.6

2.6 Metrics of the Detector Performance and Threshold Selection

Three metrics were used to evaluate the ability of the system to reliably detect movement intentions. The TP rate was defined as the percentage of trials with a movement detection in the time interval from -0.75 s to +0.75 s with respect to the movement onset. The precision of the detector was characterized as the number of FP per minute (rate of detections during the resting intervals). Therefore, one or more false activations could be encountered in a single trial. The percentage of GT was obtained by counting the amount of trials in which no FP were generated and a TP was achieved. Finally, the latencies of the detections of the onsets of movements were also computed to analyze the time accuracy of the system.

3 Results

The average BP observed in all subjects is shown in Fig. 1. The average (across subjects) BP peak was found at -19.8 $\pm$ 57.6 ms with respect to the onset of the movements. An homogeneous BP pattern could be found in all measured subjects. In addition, Fig. 2 presents the spatial distribution of the

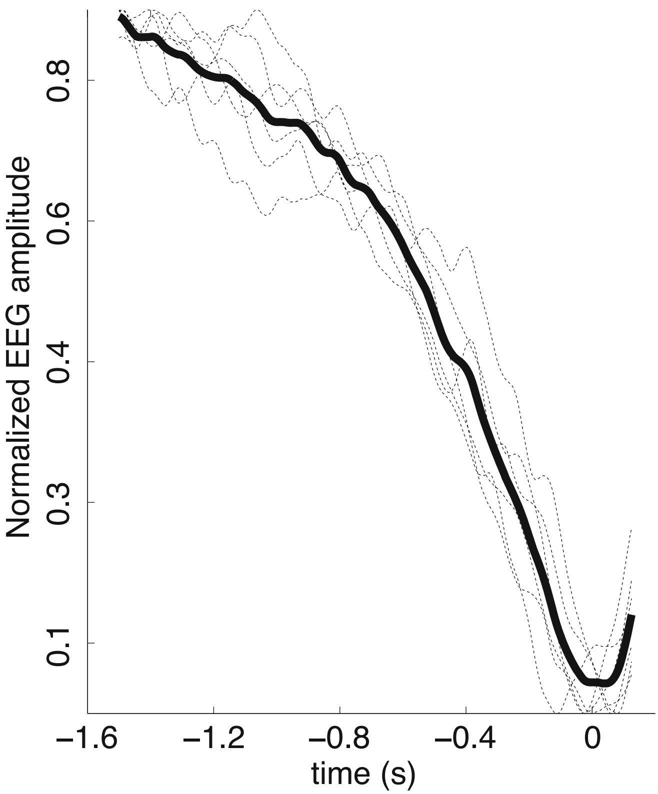

Fig. 1 Average BP of all subjects (discontinuous lines, and average BP across subjects (solid line)

ERD and BP patterns for all subjects measured. Unlike with the BP, the ERD presented visible variations in terms of spatial distribution, although, in general, a contralateral predominance was observed.

The results obtained in the detection of the onsets of movements using the proposed methodology are summarized in Table 1. On average, in 63.3±13.8 % of the trials the movement was detected and no previous false activations were generated in the same trial. In addition, 74.5±10.8 % of the movements were detected with a rate of 1.32±0.87 false activations per minute during the resting intervals.

The average latency of the TP was -89.9 ± 349.2 ms. The histogram of the latencies of all detections is shown in Fig. 3. The figure shows a tendency of the detections to anticipate the actual onsets of the movements.

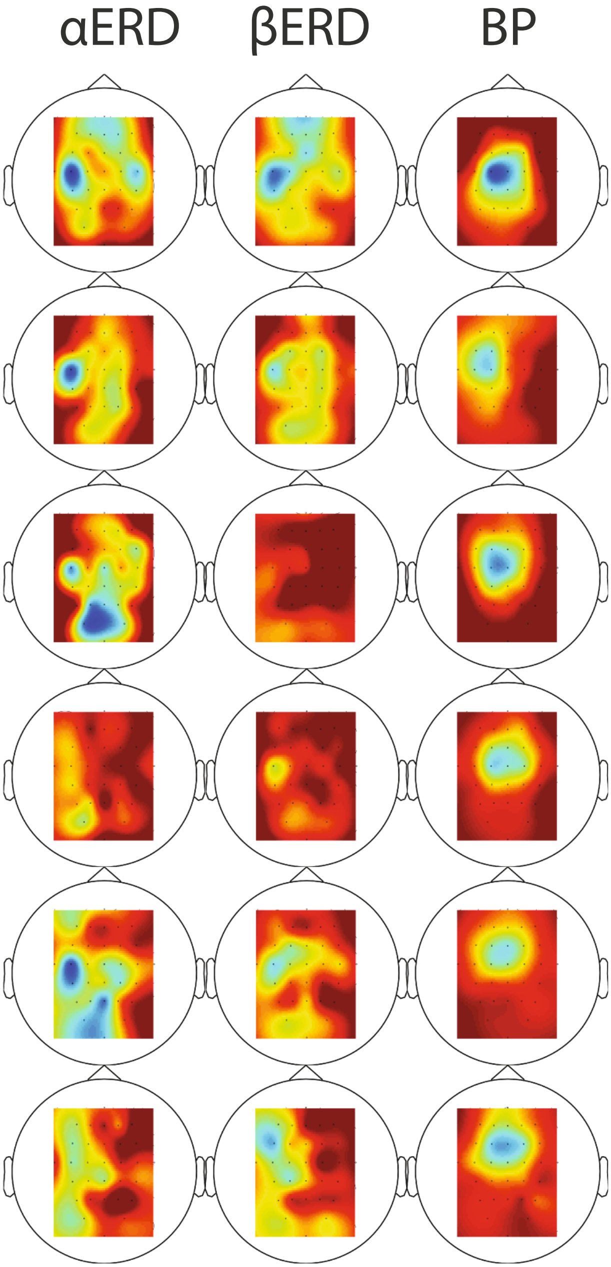

Fig. 2 First and second columns show the patial distribution of the α-ERD (between 8-12 Hz) and β-ERD (between 13-30 Hz) obtained by comparing a window of 1.5 s ending at the movement onset with an equivalent window 4 s before the onset. The third column shows the spatial distribution of the BP peak amplitude.

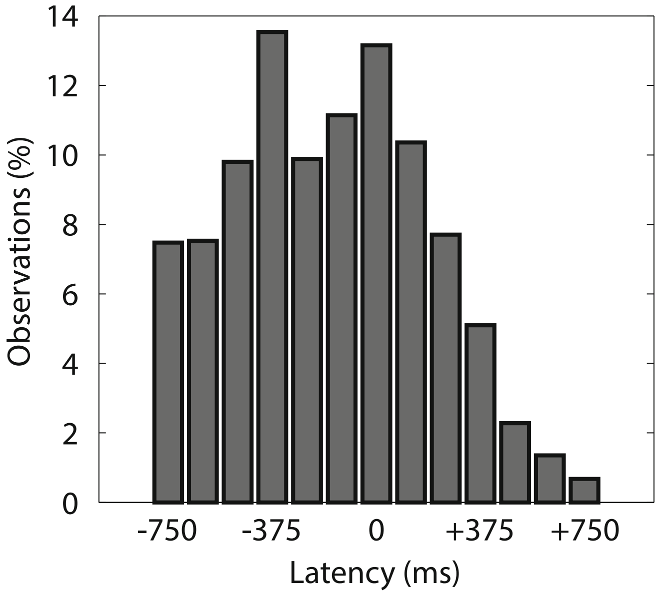

Fig. 3 Latencies of the TP with respect to the actual onsets of the movements

Table 1 Results obtained with all subjects and average results

Code	GT (%)	TP (%)	FP/min	Latency (ms)
C1	81.3	82.8	0.47	-48±351
C2	63.8	81.0	1.34	-24±278
C3	39.0	56.1	2.63	-180±476
C4	64.6	70.8	0.38	-198±322
C5	69.8	84.9	1.13	-3±388
C6	61.5	71.2	1.96	-164±290
Average	63.3±13.8	74.5±10.8	1.32±0.87	-89±349

4 Discussion and Conclusions

A methodology to detect the onset of voluntary movements with time precision based on the EEG activity has been proposed. The novelty of the study lies in the combination of the two most well-known movement related cortical patterns: the ERD and the BP. These patterns are known to reflect different underlying aspects of the motor planning process [18, 15]. Therefore, it is expected that a successful fusion of them may result in an improved estimation of the onset of voluntary movement events, specially in those cases in which either the ERD or the BP is not reliably detected in a given subject [19]. The results obtained with the here proposed detector point to an improvement in the temporal accuracy of the estimations, as compared with other similar online-feasible techniques [14]. Nevertheless, the use of a significantly higher number of electrode positions to detect ERD information in this study makes it less suitable for clinical applications. Therefore, it should be further studied the detection improvement associated with different number of EEG channels and how significantly the ERD-based classifier improves the detection of movement intentions.

The use of gyroscopes to detect movement events has proven to be adequate for functional tasks (as the reaching movements used for the present experiments) since the average BP patterns show similar latencies than the ones observed in studies using the electromyographic activity to detect movement events.

In future studies it should be studied how reliably can this kind of EEG-based systems work with patients suffering from brain damages (as stroke patients), and how would a patient react to an external stimulus (electrical or mechanical) driven by a system as the detector proposed here.

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