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Detection of movement intention from single-trial movement-related cortical potentials

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Abstract

Detection of movement intention from neural signals combined with assistive technologies may be used for effective neurofeedback in rehabilitation. In order to promote plasticity, a causal relation between intended actions (detected for example from the EEG) and the corresponding feedback should be established. This requires reliable detection of motor intentions. In this study, we propose a method to detect movements from EEG with limited latency. In a self-paced asynchronous BCI paradigm, the initial negative phase of the movement-related cortical potentials (MRCPs), extracted from multi-channel scalp EEG was used to detect motor execution/imagination in healthy subjects and stroke patients. For MRCP detection, it was demonstrated that a new optimized spatial filtering technique led to better accuracy than a large Laplacian spatial filter and common spatial pattern. With the optimized spatial filter, the true positive rate (TPR) for detection of movement execution in healthy subjects ($n = 15$) was $82.5 \pm 7.8\%$, with latency of -66.6 ± 121 ms. Although TPR decreased with motor imagination in healthy subject ($n = 10$, $64.5 \pm 5.33\%$) and with attempted movements in stroke patients ($n = 5$, $55.01 \pm 12.01\%$), the results are promising for the application of this approach to provide patient-driven real-time neurofeedback.

1. Introduction

The Bereitschafts potential (BP) or readiness potential (RP) was first introduced in 1964 (for review see [1]) and is now considered as part of the movement-related cortical potential (MRCP). These potentials can be observed in electroencephalogram signals (EEG), and are associated with movement planning and execution. The MRCP consists of a BP, followed by a motor potential (MP) [2] and a movement-monitoring potential (MMP) [3]. The BP consists of a slow decrease in EEG amplitude starting approximately 1500 ms prior to the onset of the movement, and is considered as a cortical representation of motor preparation [1]. It is also believed that BP may reflect an intention to act, which remains unconscious for part of its time course [4] or an index of resource mobilization [5]. Therefore, it has been suggested

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Table 1. Stroke patients' details.

Patient	Diagnosis	Affected site	Gender	Age	Days since event	FIM[a]	Medication
1 (OL)	Infarction	Left	Male	55	48	119	SSRI
2 (RO)	Hemorrhage	Right	Male	43	41	113	
3 (UL)	Infarction	Right	Male	39	21	95	
4 (TR)	Hemorrhage	Right	Male	15	99	121	Baclofen
5 (TO)	Hemorrhage	Left	Female	69	62	68	SSRI

[a] Functional Independence Measure, range (18–126).

that the motor areas are active even if the movement is not executed but only imagined. Because they are directly related to volitional movement, MRCPs can be used to detect a movement or intention to move.

Detecting intentions for neurofeedback corresponds to a brain–computer interface (BCI)-driven assistive technology. This approach can be used for example in stroke rehabilitation for inducing activity-dependent brain plasticity. However, any applications using neurofeedback require that a causality of action (at least the intention of action) and the corresponding feedback must be established, i.e. the patient needs to initiate (or intend to initiate) a motor task, and receive a corresponding feedback within a short delay, which can be perceived by the user as the result of the execution or imagination of the motor task [6]. This requirement of causality has two implications. First, the action (or the intention of action) and the resulting feedback must have physiological relevance. For example, a left dorsiflexion imagination should be accompanied by a haptic stimulation to the left tibialis anterior (TA) muscle. Second, the delay from the (intention of) action and the resulting feedback should be short. There is no consensus in the literature on the maximum allowable delay. However, it is likely that this delay should not exceed 300 ms [7]. Because of the processing delay and the extra time needed for the actual delivery of the feedback, the detection of action should be as early as possible, so that such a causal association can be established. Therefore, a feedback triggered by MRCP detection has the potential to be used for inducing plasticity.

One major challenge in detecting EEG waveforms from single trials is the poor signal to noise ratio (SNR) of the EEG. EEG signals represent indeed the superposition of potentials generated by a large population of cortical neurons [8]. For this reason, the amplitude of the spontaneous EEG activity is relatively large (in the range of 100 μV) with respect to the activity directly related to motor planning and execution, such as the initial negative phase of MRCP (range 8–10 μV). Spatial filtering can be used to enhance the SNR of EEG signals [9, 10]; however, commonly used spatial filters, such as the common average referencing and large Laplacian filter, may not be optimal for detection of slow cortical potentials, such as MRCP [11]. These considerations make the task of detecting MRCPs from the background EEG activity very challenging.

The hypothesis of the current study is that human voluntary movements, or the intention to move, can be identified with short latency (not exceeding the indicated limit of 300 ms [7]) by detecting MRCPs from background EEG activity. Based on current approaches, the detection of MRCP from single trials is still an open issue. We thus propose a method for filling this gap, based on the initial negative phase of the MRCPs. The method is extensively tested for motor execution (ME) and motor imagery (MI) in healthy subjects, and for attempted tasks in a limited sample of stroke patients.

2. Methods

Three experiments, which will be discussed in detail in the following sections, were conducted. In the first experiment, healthy subjects executed self-paced movements of ankle dorsiflexion. This experiment served the purpose of analyzing the latency between the detection of the movement execution and the produced EMG activity. The performance of different spatial filters was also investigated. In the second experiment, healthy subjects performed self-paced motor imagination of the same type as executed in the first session. This experiment served to investigate the true positive rate (TPR) and the false positives (FP) in the detection of imagined movements. Finally, a third experiment was performed on stroke patients with cognitive or motor impairments who attempted the execution of the same task as the healthy subjects. This last experiment was intended as a preliminary validation of the feasibility of the proposed method to early detect movement attempts in stroke patients.

The experimental data were analyzed with different spatial filters and a matched filter supervised approach for determining the detection accuracy and latency of MRCP.

2.1. Subjects

This study mainly focuses on the detection of movement intention in healthy volunteers and not in stroke patients. This is a necessary step for the validation of the method, as done in several recent BCI studies (e.g., [11–13]). Nonetheless, in addition to an extensive validation on healthy volunteers, we also present preliminary results on a small sample of stroke patients. The analysis on stroke patients provides an indication of the potential feasibility of the approach for neurorehabilitation but should be considered preliminary. Therefore, nineteen healthy subjects (24.5 ± 4.7 yrs) and five stroke patients (table 1) participated in the experiments. None of the healthy subjects had known sensory-motor deficiencies or any history of psychological disorders. All subjects gave their informed consent before participation and the procedures were approved by the local ethics committee of Nordjylland, Denmark (N-20100067).

2.2. Experimental setup

The subjects were seated comfortably on a chair, with the right leg secured in a custom-made fixture. A pair of surface EMG electrodes was mounted on the TA muscle of the right side (dominant in all cases). Surface EMG signals were recorded in bipolar derivation, amplified with gain 1 k (healthy subjects: EMG-16 amplifier, OT Bioelettronica; stroke patients: BrainAmp EXG, Brain Products), sampled at 1000 Hz (healthy subjects) and 2500 Hz (stroke patients), and analog to digital converted with 32 bits. Different amplification systems were used for healthy subjects and stroke patients since stroke patients were measured in a clinical setting. The reference electrode was placed at the ankle. Monopolar EEG signals were recorded (EEG amplifiers, Nuamps Express, Neuroscan and BrainAmp DC, Brain Products, respectively) from Ag/AgCl scalp electrodes (EC80, Easy cap) (healthy) and from an active electrode cap (actiCAP, Brain Products, Germany) (stroke patients). The electrodes were located at the International 10–20 system locations FP1, F3, F4, FCz, Pz, P3, P4, C3, C4 and Cz. The right ear lobe was used as a reference and the ground electrode was placed at nasion. In all cases, EMG and EEG signals were synchronized by a common external trigger.

2.3. Self-paced ME of healthy subjects

Fifteen healthy subjects (25.7 $\pm$ 5.9 yrs) were instructed to perform ballistic ankle dorsiflexions, at random intervals. No external stimuli or cues were presented to the subjects for task executions. However, the subjects had feedback on their ankle dorsiflexion torque on a computer screen as a moving vertical bar. They were asked to reach a torque level corresponding to 20–30% of the maximum voluntary contraction torque, as determined during a familiarization session. This procedure resulted in a fully self-paced set of executed movements. In each experimental session, five runs of 5 min duration each were recorded with resting periods of 2–3 min in between. The first two runs were used as a training set and the remaining as testing data sets. In addition, the same protocol was repeated on two different days for two subjects one and two weeks after the first session.

2.4. Self-paced MI of healthy subjects

Ten healthy subjects (24.6 $\pm$ 2.3 yrs) participated in this experiment. Six of them also participated in the ME session. The same paradigm was presented to them as that described for foot ME. However, in this experiment, the subjects were asked to imagine the kinematics of ballistic ankle dorsiflexion without executing it. In this paradigm, four runs of 5 min duration were performed. During the first and second runs, the subjects performed the real movements so that they were able to develop their strategies of MI of ballistic ankle dorsiflextion. During the last two runs, they performed self-paced imaginary dorsiflexion. To identify the occurrences of MI in this fully self-paced paradigm, the subjects were asked to press a button using their left thumb, approximately 2 s after the MI. Subjects were also asked to perform the real dorsiflexion to maintain their strategies for MI during the breaks between the last two sessions. The runs of the self-paced ME (run 1 and 2) were used as training data sets. The last two runs of self-paced MI were used as testing data sets.

2.5. Self-paced attempted ME of stroke patients

In order to preliminarily validate the clinical feasibility of the proposed method, a further experimental session was conducted on five hospitalized stroke patients. The conditions of these stroke patients are summarized in table 1. Lesions were located by CT or MRI-scans. The degree of disability was evaluated by Functional Independence Measure (FIM®). The FIM is widely used in rehabilitation settings to assess the general level of functioning of a stroke patient. The score consists of 18 items grouped into seven sub-scales: self-care, sphincter control, mobility, locomotion, communication, psychological and cognitive functions (minimum score is 18, maximum is 126 points). All stroke patients were instructed to randomly attempt ballistic dorsiflexions of the right ankle, at a pace that the subject felt comfortable. No external stimuli or cues were presented to the subjects. A total of five runs of approximately 5 min duration were recorded with resting periods of 3–5 min in between. The first two runs were used as a training data set and the rest as testing sets.

2.6. Signal analysis

The signal analysis will be discussed in detail in the subsequent sections. In summary, the analysis was divided into two steps: MRCP template extraction and MI/ME detection. First, three spatial filters were applied to obtain a surrogate channel from the EEG channels recorded. The first spatial filter was a large Laplacian spatial filter (LLSF), which has been shown to be better than other similar fixed coefficient spatial filters [9]. The second spatial filter was a novel optimized spatial filter (OSF) designed to maximize the SNR of the surrogate channel. The third was the common spatial pattern (CSP) filter which maximizes the variance of two-class signals in BCI paradigms [14]. Subsequently, the MRCP template was extracted from the surrogate channel using training data. The coefficients obtained in the last step were used on the testing EEG data. The initial negative phase of the extracted MRCP template was used to detect movement intentions by a matched filter algorithm.

2.6.1. Pre-processing. The EEG signals were band pass-filtered from 0.05 to 10 Hz, and then down-sampled to 20 Hz. LLSF, OSF and CSP [14] were compared. The SNR of the MRCPs in the spatially filtered channel (later referred to as surrogate channel) should be higher than those in the raw EEG channels. The channel coefficients obtained by the three spatial filters from the training set were applied to the testing data set to get a surrogate channel for each of them. The general scheme of detection is shown in figure 1.

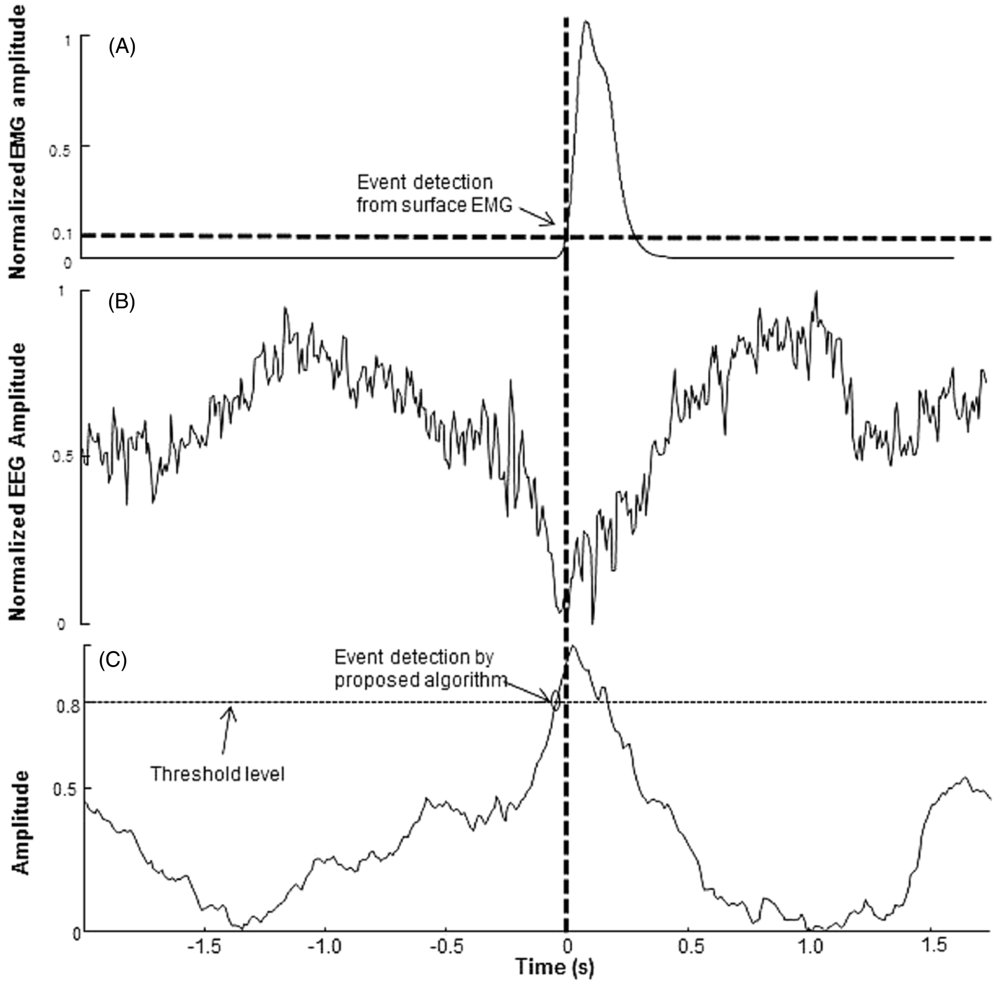

Figure 1. General scheme of detection during movement execution task. A representative sample from subject 3: detection of an initial negative phase of MRCPs in a surrogate channel obtained through the set threshold (cross-validation on the training set). (A) Rectified and averaged EMG trace for event detection, the horizontal dashed line is the EMG detection threshold and the vertical line is the reference point for detection latency. (B) Single trace of MRCP in the surrogate channel, obtained by the optimized spatial filter during self-paced ME task. (C) Output of the matched filter. The horizontal dashed line is the detection threshold of the proposed algorithm. All vertical axes are in arbitrary units.

2.6.2. Definition of reference events. For the experiments with ME, the reference movement onset (event) was estimated as the time instant when the rectified EMG signal amplitude crossed a threshold equal to one tenth of its maximum during the ME process. In MI experiments, the event was identified by the trigger pressing (approximately 2 s after the imagination). For stroke patients, the residual EMG signal was used in the same way as in healthy subjects to mark an event.

2.6.3. Spatial filtering. Spatial filtering has been used for source localization in EEG. For a multi-channel recording obtained at different spatial locations, such as EEG, a virtual channel can be obtained by a linear combination of all the channels. The set of coefficients of the channels defines a spatial filter. Different coefficients provide different characteristics of the filter. In this study, we investigated three different spatial filters: LLSF, which is a commonly used source localization filter with fixed coefficients; optimal spatial filter (OSF), which provides an optimized coefficient set maximize signal-to-noise ratio in the virtual channel; CSP, which maximizes the variance ratio of two-class signal matrices.

Large Laplacian spatial filter. The channel coefficients in this case were based on the EEG Laplacian montage:

$$x_i = \begin{cases} 1, & i = 1 \\ -\dfrac{1}{(N_{\text{ch}} - 1)}, & i \neq 1, \end{cases} \tag{1}$$

where N_{ch} is the number of channels. In this study, the first channel corresponded to Cz. The sum of the N_{ch} coefficients is zero so that the spatial dc components are rejected.

Optimized spatial filter. The filter coefficients were optimized on the training set with the following procedure. First, 'signal' epochs of 3 s were selected (2 s before and 1 s after each event). These epochs contained the initial negative phase of an MRCP, as shown in figure 2. Then, 'noise' epochs of 3 s duration were selected between the events, where there were no observable artifacts, such as EOG or movement artifacts.

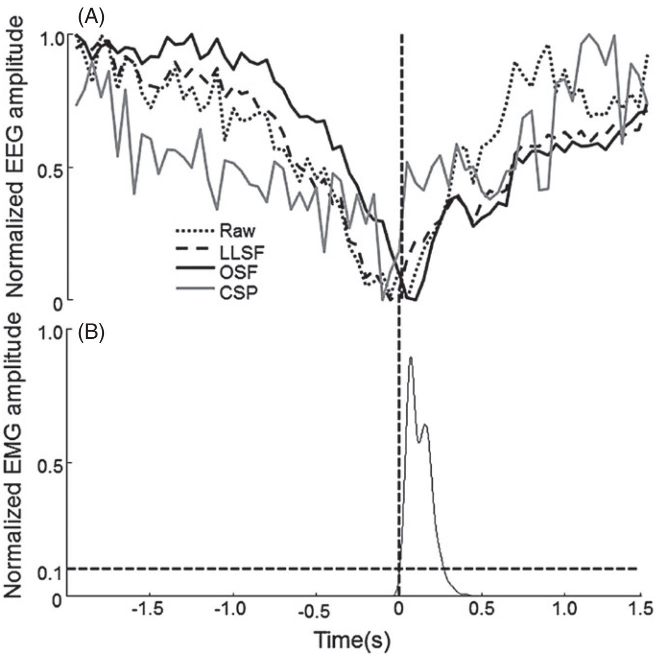

Figure 2. Normalized MRCP and EMG trace (training session). (A) Normalized MRCP of subject 4 from the training session ($n = 20$ epochs used) using raw signals from Cz (dotted) and three spatial filters: LLSF (dashed), OSP (thick) and CSP (thin). The initial negative phase of the MRCP (part before the vertical dashed line) was used as template for the matched filter. (B) Normalized trace of the rectified and averaged EMG for event detection. The event is detected from the EMG as reference at the intersection of the dashed vertical line and the horizontal line (threshold at 10% of signal power).

The aim of the OSF was to find the combination of channels that maximizes the MRCP energy while minimizing the noise energy. Therefore, we used SNR as the criteria to maximize. Let us consider a set of data containing N samples of noise and N samples of EEG signal with N_{ch} channels ($N_{\text{ch}} = 9$ in our case). Let $S_{i,k}(t)$ and $N_{i,k}(t)$ be the ith signal epoch and noise epoch of the kth channel. Given a set of channel coefficients $\boldsymbol{x} = (x_1, \ldots, x_c)$, we define $S_i(t) = \sum_{k=1}^{N_{\text{ch}}} x_k S_{i,k}(t)$ as the ith signal epoch of the virtual channel and $N_i(t) = \sum_{k=1}^{N_{\text{ch}}} x_k N_{i,k}(t)$ as the jth signal epoch of the virtual channel. The variance operator of the above equations runs over time. The SNR is

$$\text{SNR} = 10 * \log_{10}\left(\frac{P_S}{P_N}\right), \quad (2)$$

where P_s and P_N are the powers of the signal and noise, respectively.

The purpose of the optimization is to find a set of $\boldsymbol{x}$ that maximizes the SNR, with the constraint that the sum of the coefficients is zero. A quasi-Newton method was used for the optimization. The Broyden–Fletcher–Goldfarb–Shanno method for the Hessian update was applied [15].

From an initial guess and an approximate Hessian matrix H_o, the following steps were repeated until x converges to the solution:

- At step k, the direction is computed:

$$\Delta x = -H_{k-1}^{-1} \nabla f(x^{k-1}). \quad (3)$$

- Line search (finding a local minimum) was performed to find an acceptable step size α_k in the direction found in the first step, then update:

$$x_k = x_{k-1} + \alpha_{k-1} * \Delta x. \quad (4)$$

- Compute the updated Hessian matrix H_K:

$$H_k = H_{k-1} + \frac{yy^T}{y^T s} - \frac{H_{k-1} s s^T H_{k-1}}{s^T H_{k-1} s}, \quad (5)$$

where

$$s = x^{(k)} - x^{(k-1)},$$

$$y = \nabla f(x^k) - \nabla f(x^{k-1})$$

The initial vector of coefficients was based on the EEG large Laplacian montage.

Common spatial pattern. The CSP method was first proposed for classification of multi-channel EEG during imagined hand movements [16]. The main idea was to use a linear transform to project the multi-channel EEG data into a low-dimensional spatial subspace with a projection matrix, of which each row consists of weights for channels. This transformation maximizes the variance of two-class signal matrices. In our case, signal and noise epochs were considered as two classes obtained as described for the OSF. The CSP method was based on the simultaneous diagonalization of the covariance matrices of both classes. The first and last rows of the projection matrix represent the most important spatial patterns that exhibit the largest variance of one task and the smallest variance of the other. In this study, only the first row of the projection matrix was used as CSP filter coefficients.

2.7. *Template extraction and detection of MI/ME*

The template of the initial negative phase of MRCPs (from the start of the depression phase to its peak negativity, as illustrated in figure 2) was extracted from the surrogate channel in the training set. For detection of movement, a receiver operating characteristic (ROC) curve was obtained through cross-validation on the training data. The detector decision was based on the likelihood ratio (Neyman Pearson lemma) method, computed (2 s sliding window with 200 ms shift) between the surrogate channel of the testing data and the template in training and testing data. In order to make reliable detections with minimal FPs, the threshold was selected on the midpoint of the turning phase of the ROC for all the subjects; thus, a balance between TPR and FPs can be obtained.

A movement was identified in the testing data set when two out of three consecutive windows crossed the threshold corresponding to a desired false alarm probability. The following performance parameters were calculated on the testing sets: TPR (%), FPs in 5 min, and latencies (detection time with respect to onset of the events).

A one-way ANOVA was applied on the TPR, FPs and latencies with the spatial filters (OSF, LLSF and CSP) as factors and the subjects as a random variable. Tukey's post hoc test was then applied to reveal the significance levels amongst different spatial filters. To test if there was any statistically significant difference for healthy subjects performing ME and MI tasks, the Wilcoxon matched pair test was performed to compare TPRs and FPs of the six subjects who participated in both MI and ME experiments. The Mann–Whitney test was performed to investigate if there were statistically significant differences between healthy subjects' ME tasks and stroke patients, as well as between healthy subjects' MI tasks and stroke patients.

3. Results

The healthy subjects performed on average a minimum of 15 movements per run for all types of data sets. The duration of one session containing five runs of 5 min with EEG electrode preparation was on average 1 h for both healthy and stroke subjects. Epochs with EOG activity exceeding 125 μV were discarded.

In general, the results, which will be detailed in the following, demonstrated that it is possible to detect voluntary movement attempts (or imagination) using the early phase of MRCPs (BP). For example, with the best processing parameters, the detection of ME in healthy subjects had an accuracy of 82.5 ± 7.8% and latency of −66.6 ± 121 ms. The accuracy decreased to 64.5 ± 5.33% for imaginary movements of healthy subjects and to 55.01 ± 12.01% for attempted movements of stroke patients.

3.1. Self-paced ME of healthy subjects

All results shown in this and the following sections are based on the testing data sets. Comparisons of group results for the three spatial filters in healthy subjects are given in figure 3. The average (across all healthy subjects) TPR obtained with OSF was 82.5 ± 7.81% which was significantly ($P < 0.05$) better than that of LLSF (68.7 ± 14.9%) and CSP (55.4 ± 14.01%). The FPs in 5 min for OSF (6.90 ± 7.4) were also less than those with LLSF (11.5 ± 13.40) and CSP (57.3 ± 17.8). Figure 4 shows the latencies for detection time of the initial negative phase of the MRCP with reference to the movement when using the OSF. The mean detection time ranged from −100 to +100 ms with reference to the onset of the movement. The average latency was −66.6 ± 121 ms with OSF, −79.7 ± 92.8 ms with LLSF and 153 ± 148 with CSP. Table 2 shows results across different ME sessions for two subjects based on current and previous available sessions on different days.

One-way ANOVA showed that spatial filters have a statistically significant effect on all three performance measures, TPR, FP and latencies (all $p < 0.05$). The post hoc Tukey test showed that the OSF always outperformed the other two filters.

3.2. Self-paced MI of healthy subjects

The results for this experiment are reported only for the OSF since this filter outperformed the other two spatial filters in all tests, as was reported for ME. In MI data, the amplitude of the peak negativity was lower than that of executed movements, in agreement with previous results [17]. Therefore, the performance deteriorated with respect to ME. The average TPR (%) was 64.5 ± 5.33% and the FPs in 5 min was 15.8 ± 9.42 when detecting MI using self-paced ME runs data as a training set.

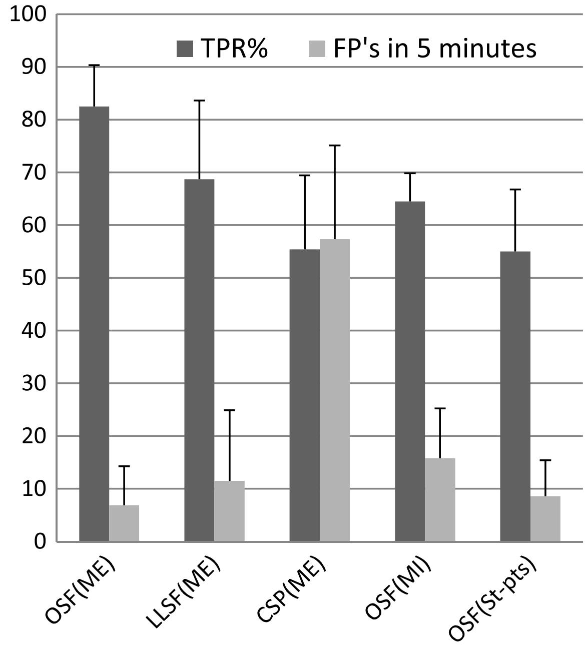

Figure 3. Performance/results. Summary of the results from ME ($N = 15$), MI ($N = 10$) and five stroke patients (St-pts) testing data set with the TPR% (mean ± SD) and FP (mean ± SD) in 5 min.

3.3. Self-paced ME of stroke patients

The proposed filter setups were applied and compared for stroke patients. The results were similar to the case of MI of healthy subjects, i.e. the OSF performed better than LLSF and CSP. Results based on only the OSF are reported in figure 3 for the stroke patients. Figure 5 shows a representative MRCP trace from a motor impaired stroke patient. The average detection latency for stroke subjects was −56.8 ± 139 ms.

3.4. Comparisons between groups

For the repeated measure over ME and MI tasks of the six healthy subjects, the Wilcoxon matched pair test showed no significant difference in the TPR measure ($z = 2.2$, $p = 0.08$), and also in the FP measure ($z = 2.2$, $p = 0.08$). The test statistics are exactly the same because all six paired measures had the same trend. This result is expected, as it was shown that ME tasks usually produce more pronounced MRCPs [17].

When comparing stroke patients with the healthy subjects' ME tasks, the Mann–Whitney test showed significant difference in TPR ($z = 3.01$, $p = 0.0026$), while no significant difference in the other two measures: FP ($z = 0.74$, $p = 0.46$) and latency ($z = 1.35$, $p = 0.18$). When comparing stroke patients with the healthy subjects' MI tasks, the Mann–Whitney test showed no significant differences in either TPR

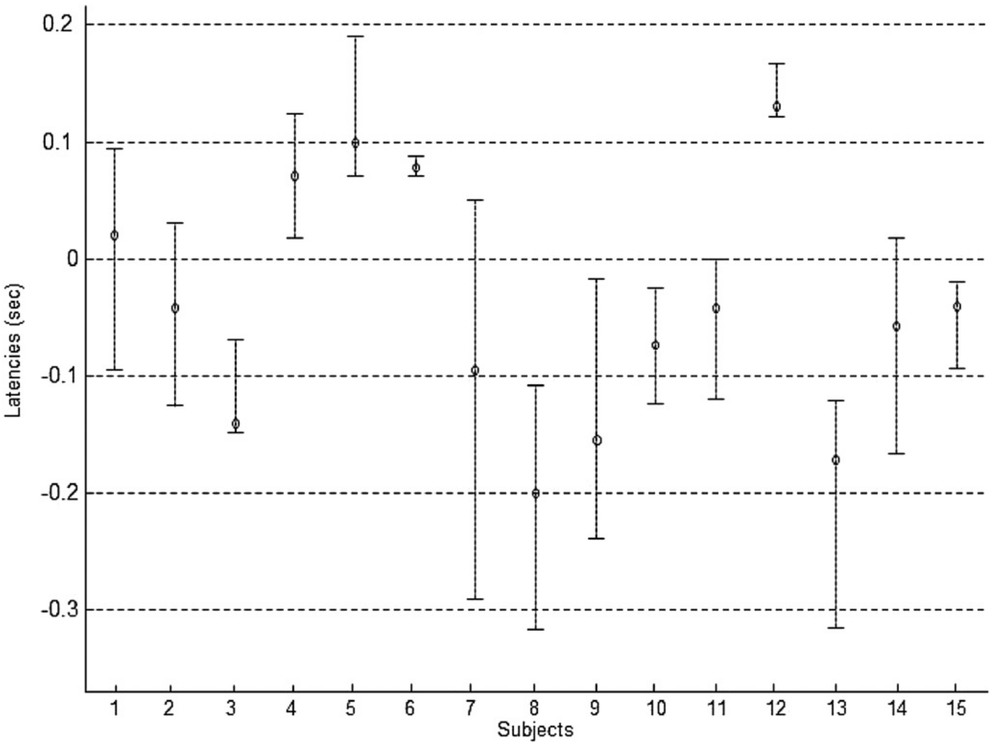

Figure 4. Latencies in testing sets of healthy subjects' ME experiment. Mean (± SD) latencies of all subjects for the testing data set of ME with reference to the onset of the task when using OSF.

Table 2. Motor execution results in different sessions.

	First day			Second day			Third day		
Subjects	TPR%	FPs /5 min	Latencies (ms)	TPR%	FPs /5 min	Latencies (ms)	TPR%	FPs 5 min^{-1}	Latencies (ms)
1	70.25 ± 2.5	10.5 ± 2.1	−97.9 ± 35.6	76.7 ± 4.7	8.5 ± 0.7	−91.7 ± 130	87.1 ± 0.6	4.5 ± 0.7	91.7 ± 88.6
						First day as training			
				79.5 ± 9.19	8.5 ± 4.94	24 ± 120	68.5 ± 26.2	8.50 ± 4.94	5.3 ± 113
							Second day as training		
							72.5 ± 1.39	20.5 ± 0.70	−71.81 ± 11−.6
2	92.1 ± 1.7	8.0 ± 0.0	−243.2 ± 101	74.4 ± 27.4	6.5 ± 3.5	−257.6 ± 107	80 ± 0.0	7.5 ± 0.7	−61.5 ± 63.3
						First day as training			
				80.6 ± 0.89	7 ± 5.65	−149 ± 60.8	89.2 ± 5.89	25.5 ± 3.53	−256 ± 161
							Second day as training		
							79 ± 8.45	25 ± 2.82	−69.9 ± 15.6

($z = 1.71, p = 0.086$) or FP ($z = 1.65, p = 0.098$). The results of comparing stroke patients with healthy subjects are also very encouraging, since it indicated, in general, that the algorithm's performance on stroke patients was not significantly different from that of the healthy subjects' ME.

4. Discussion

Executed and imagined movements were detected from single-trial EEG with short latency. The detection accuracy was evaluated in both healthy subjects and stroke patients. For some subjects, a prediction was possible. For example, for subject 3 the latency was −119 ± 43.8 ms. With the proposed OSF technique, the detection performance was relative high (TPR: 82.5 ± 7.8%; FPs: 6.9 ± 7.41.8 in 5 min), with ME tasks performed by healthy subjects. The performance worsened for MI, as expected. The results from stroke patients were promising (TPR: 55.2 ± 6.30%; FPs: 16.9 ± 3.03 in 5 min) and indicated that the proposed method can detect movement execution (or intention of execution) both for healthy subjects and stroke patients, thus providing a new potential approach for inducing neural plasticity in stroke patients.

4.1. *Self-paced BCIs*

This study focused on movement detection and thus the performance obtained should be compared with those shown for self-paced BCI paradigms. A recent study [13] presented a brain switch (self-paced BCI) using post-movement beta rebound, which is found ∼500 ms after the termination of a

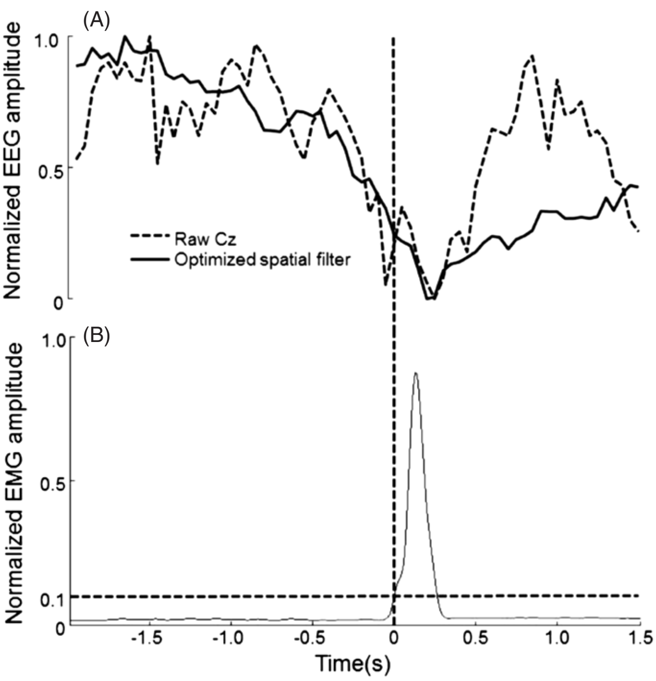

Figure 5. Normalized MRCP of a motor impaired stroke patient (patient 2) from the training session ($n = 15$ epochs used). The initial negative phase of the MRCP (part before the vertical dashed line) was used as template for the matched filter. (B) Normalized trace of rectified and averaged EMG as a reference for event detection (intersection of dashed vertical and horizontal lines). Note the improved signal quality after the OSF.

brisk (foot) movement. The performance of that approach in self-paced MI experiments was better than that of the proposed method (TPR: 79.2%), but with a substantially greater latency (∼0.5 s). Another study [12] described a self-paced BCI paradigm for wrist extension ME, based on an unsupervised Gaussian mixture model (GMM); however, the results were reported with a different performance index and thus cannot be compared with the current study. Beside the performance, that study did not investigate the latency of detection which was one of the main parameters of interest in this study. Mason and Birch [18] presented a very similar algorithm for self-paced BCI, called low-frequency asynchronous switch design. Their work and followups, such as [19, 20], focused on the EEG bandwidth 1–4 Hz [19], and were intended for communication purposes, without analysis on the detection latency. Moreover, we showed, for the first time, preliminary tests on stroke patients which indicate the possibility of identifying the intention to move within a very short time.

4.2. Signal processing

One of the results of this study was the importance of spatial filtering to improve the SNR in single-trial EEG analysis. The spatial resolution of EEG signals is poor due to volume conduction through the scalp, skull and other tissue layers [21]. The surface Laplacian filter reduces the far-field potentials and the dc component. These characteristics were also used for the design of the proposed OSF, which maximized the SNR with a supervised approach. Since the OSF is optimized on a signal basis, it outperformed the LLSF, which has fixed channel coefficients. OSF also outperformed CSP, the results of which are in line with the current literature showing overfitting of CSP algorithm on small training sets [22]. The generalization performance of the CSP algorithm could improve if more trials can be used as training sets. However, in the context of stroke rehabilitation, it would be difficult to obtain a large training set because the data collection session has to be short enough so that the stroke patient can complete the protocol. In our experience, the session on stroke patients should not be longer than 90 min to be practical.

The proposed algorithm is computationally efficient. The extracted brain signal was spatially and spectrally consistent with the characteristic waveforms reported in several previous studies [17, 10]. To further improve the detection performance, more advanced (and computationally intense) approaches have been explored in pilot tests. These included Kalman filter (KF) as a denoising approach [23], and the Gaussian mixture model (GMM) [24] for detection purposes. However, in preliminary analyses (results not shown) neither KF nor GMM produced superior results than the simpler matched filter, which is less computationally intensive.

4.3. Detection latency

One of the main advantages of the proposed algorithm is the ability of providing ME/MI detection with short latency. The latency of detection for the ME tasks was within the range of 200 ms from the movement onset. The results of the latency parameter in stoke patients further substantiated the findings from the healthy subjects. The short latencies obtained would allow the control of external devices volitionally for neurorehabilitation. For these applications, a causal relation should be established between the movement intention and an action. For this association to be effective, the FPs should be reduced to the minimum. In this study, the trade-off between TPR and FPs allowed us to make detections every 200 ms with a limited number of FPs.

4.4. Trade-off between TPR and FPs

As discussed above, a limited number of FPs were considered essential in this study. This ensures that once detection is made, it is very likely that the subject had the intention to move.

For early detection purpose, the EEG signal portion prior to the onset of the task (figures 2 and 5) was used as a template. Higher TPR could be achieved with one of the following strategies: (1) using the complete initial negative phase of the MRCP as a template (based on peak negativity rather than event onset, especially in stroke patients) or even using the complete MRCP as a template, or (2) increasing the number of FPs. The first strategy would lead to longer detection latencies which is undesirable. The second strategy consists in simply choosing another threshold in the ROC.

4.5. Measures on stroke patients

BCI systems have been applied in stroke patients previously [25, 26]. However, these two studies were not based on EEG, but on MEG and ECoG, respectively. Recently, Daly *et al* presented a case study with one stroke patient, in which an EEG-based BCI system was shown to have positive effects in rehabilitation [27]. In this study, we demonstrated, with five stroke patients, that not only is it possible to detect movement attempts of a stroke patient, but also that the proposed protocol was simple enough to be completed easily by stroke patients with the help of therapists, even in the case of mild cognitive impairments. This characteristic is important since many stroke patients with motor impairments usually have accompanying cognitive impairments, and a cue-based synchronized paradigm might be too demanding for them.

Generally, in stroke patients the morphology of MRCPs was different from that in healthy subjects. For example, there was a shift in peak negativity of the MRCPs in stroke patients (figure 5). The major factors influencing the performance of the system when applied to stroke patients were spasticity and concentration issues. This made it difficult for stroke patients to produce the repetitions as consistently as healthy subjects. In addition, the stroke patients sometimes could not complete the task of dorsiflexion, aborting midway through the task.

4.6. Implications

The reliable detection of human movement intentions from MRCPs using the OSF technique has the potential of providing subconscious control of external devices (such as FES or robotic systems) for neuromodulation (therapeutic approach). Such subconscious BCI control can be very important for the development of a patient-driven rehabilitation paradigm, which targets at inducing cortical plastic changes in stroke patients. With respect to other approaches, the proposed results are the first that prove the possibility of detection of movement intention with very short latency, which would allow the establishment of a causal relation between motor intention and artificially induced afferent volley with the control of external devices.

4.7. Limitations

In this study, the signals were processed offline, in a pseudo-online fashion. Due to instrumentation limitations, no real online detection was done. Due to the simplicity of the detection algorithm (all linear operations), it is anticipated that online detection is feasible, but this needs to be verified through online studies.

In the MI studies of healthy subjects, the occurrence of a movement imagination was identified through a button press by the subject, approximately 2 s after the imagination. It is possible that such motor task could interfere with the movement imaginations. However, for self-paced motor imaginary protocols, this or similar methods are the only option to obtain a relatively accurate 'event marker'.

For the stroke patient part of the study, the sample size was much smaller than healthy controls, and was not aged matched, due to the limitation of the patient access. Some stroke patients had cognitive impairment as well, which prevented them from easily executing the experiment protocol without constant intervention of the therapist. This intervention might also produce unaccountable variability in the EEG recordings. Despite the preliminary nature of the investigation in the stroke patient group, this analysis was included in this study, together with the extensive analysis in healthy subjects, to prove the feasibility of the approach in stroke patients. A full validation of the proposed method in stroke patients will require a larger patient sample.

5. Conclusion

The study presents and demonstrates the potential of a paradigm for detection of movement intention with a latency limited to less than 200 ms. These results are particularly relevant for the development of assistive technologies that provide physiological meaningful neurofeedback.

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