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Published in:
Journal of Neural Engineering

DOI (link to publication from Publisher):
10.1088/1741-2560/10/5/056015

Publication date:
2013

Document Version
Accepted author manuscript, peer reviewed version

Detection and classification of movement-related cortical potentials associated with task force and speed

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Abstract

Objective. In this study, the objective was to detect movement intentions and extract different levels of force and speed of the intended movement from scalp electroencephalography (EEG). We then estimated the performance of the closed loop system. *Approach.* Cued movements were detected from continuous EEG recordings using a template of the initial phase of the movement-related cortical potential in 12 healthy subjects. The temporal features, extracted from the movement intention, were classified with an optimized support vector machine. The system performance was evaluated when combining detection with classification. *Main results.* The system detected 81 % of the movements and correctly classified 75±9 % and 80±10 % of these at the point of detection when varying the force and speed, respectively. When the detector was combined with the classifier, the system detected and correctly classified 64±13 % and 67±13 % of these movements. The system detected and incorrectly classified 21±7 % and 16±9 % of the movements. The movements were detected 317±73 ms before the movement onset. *Significance.* The results indicate that it is possible to detect movement intentions with limited latencies, and extract and classify different levels of force and speed, which may be combined with assistive technologies for patient-driven neurorehabilitation.

1. Introduction

The movement-related cortical potential (MRCP) is a low-frequency potential generated in association with the planning and execution of a cued or self-paced voluntary movement [1-3]. Typically, a negative deflection is observed in the electroencephalogram (EEG) up to two seconds before a movement is executed, with the peak of maximal negativity occurring shortly after the onset of the movement [4, 5]. The onset of the negative deflection associated with a cued movement precedes that of a self-paced movement [6]. In general, the negative deflection is followed by a rebound after the peak of maximum negativity [5]. The negative deflection may be divided into two potentials: readiness potential and motor potential. There is an increase in negativity from the former to the latter in proximity to the onset of the movement [2, 4]. The readiness and motor potential have been associated with planning and execution of a movement, respectively [7]. The rebound after the peak of maximum negativity is also known as a movement-monitoring or reafferent potential [2, 4] and has been associated with the precision of the movement [8]. A similar negative deflection with smaller amplitude is observed when the movement is imagined [5]. The initial negative phase of the MRCP is modulated by various factors (reviewed in [4, 9]). Among these factors are the movement-related parameters: speed and force [5]. Since the initial negative phase of the MRCP is observed before the onset of the real or imaginary movement, it has been proposed as a control signal in a brain-computer interface (BCI). A BCI is a system designed to extract its user’s intention from a brain signal and translate it into device commands (reviewed in [10, 11]). The early detection of an intended action in relation to the task onset is crucial in systems where the brain signal is used to drive an external device for neuromodulation purposes [12, 13].

We have shown that it is possible to detect a user’s intention from MRCPs [14] and to use this to drive an electrical stimulator [13]. The electrical stimulator was used to provide afferent feedback from the periphery that was timed to arrive during the motor execution phase of the MRCP when imagining a dorsiflexion of the ankle [15]. The afferent feedback must coincide with the motor execution phase of the MRCP, thus the timing of the two events is crucial [15]. Increased excitability of the corticospinal projections to the target muscle was observed when the afferent feedback coincided with the motor execution phase [15]. This could have implications for rehabilitation of patients with motor impairments.

In rehabilitation the retention of learned motor skills is optimized through variable training schedules [16] which can be introduced if the movement intention is decoded. By introducing task variability in the training, patients may optimize the generalization of the practiced movements. This can help them to transfer the practiced movements to activities of daily living. To replicate movements and close the motor control loop, movement-related parameters (such as force and speed) should be decoded from the brain signals and in this way match the afferent input according to the user's intention.

A technique for discriminating between different levels of force and speed has been proposed by using the marginal distribution of optimized wavelets [17]. This technique has previously been applied to extract different levels of force and speed when using information from the complete MRCP [18]. The aim of the present study was to detect MRCPs with limited latency and to differentiate between different levels of force and speed using general time domain features (such as amplitude and slope) with the constraint that they must be extracted from the initial negative phase of the MRCP (movement intention). The constraint is due to triggering of an external device according to the temporal association found by Mrachacz-Kersting *et al* (2012). These classification accuracies were compared to classification accuracies obtained using general time domain features extracted from the complete MRCP. Furthermore, the performance was estimated from combined detection of the movement intentions with classification of various levels of force and speed.

2. Methods

2.1. Subjects

Twelve healthy volunteers without any prior BCI experience (four females and eight males: 27±6 years old) participated in the study. All the subjects gave their informed consent before participation and the procedures were approved by the local ethical committee (N-20100067).

2.2. Experimental protocol

Each subject was seated in a chair, in an electrically shielded room, with his right foot fixed to a pedal with an attached force transducer. Each subject was instructed to perform four types of isometric dorsiflexions of the right (dominant side in all subjects) ankle. Each session started with recording of the maximum voluntary contraction (MVC) force followed by 4x50 repetitions of cued movements. The subjects performed four tasks: I) 0.5 s to reach 20 % MVC, II) 0.5 s to reach 60 % MVC, III) 3 s to reach 20 % MVC and IV) 3 s to reach 60 % MVC. The subjects were constrained to spend either 0.5 or 3 seconds to reach the correct percentage of MVC (see figure 1). Cued movements were performed to assist the subjects in performing the movements at the correct velocities and to reach the correct force levels. Before each task the subjects spent ~5 minutes familiarizing with the specific task; the order of the tasks was randomized in blocks for each subject. Subjects were cued by a custom made program (Knud Larsen, SMI, Aalborg University); force was used as input to the system where subjects followed a specific force trace (see figure 1) and were provided with visual feedback of their performance. All trials were included in the analyses. The subjects were seated two meters from the screen and instructed to focus their gaze on the center of the screen to minimize artifacts from eye movements.

2.3. Signal acquisition

2.3.1. EEG

Ten channels of monopolar EEG were recorded (EEG amplifiers, Nuamps Express, Neuroscan) continuously from self-adhesive scalp electrodes (20 mm Blue Sensor Ag/AgCl (sensor area: 13.2 mm^2), AMBU A/S, Denmark) with a sampling rate of 500 Hz. The signals were analog to digital converted with 32 bits accuracy.

The electrodes were located at FP1, F3, F4, Fz, C3, C4, Cz, P3, P4 and Pz according to the International 10-20 system. The right earlobe was used as a reference, and the ground electrode was positioned at the nasion. The impedance of the electrodes was below 5 kΩ during the experiment. A trigger was sent from the interface software at the beginning of each trial (time=0 s in figure 1) to the EEG amplifier to synchronize the continuous EEG into epochs.

2.3.2.Force and MVC

The force was recorded from a force transducer mounted on the pedal and used as input to the main program. The recordings were performed by ‘Mr. Kick software’ (Knud Larsen, SMI, Aalborg University). The signal was sampled at 2000 Hz. At the beginning of the experiment, the MVC was determined. Three MVCs were performed with one minute rest between each contraction; the highest value was used as the reference MVC. The onset of a movement, determined from the force trace (see the lower graph in figure 1), was used for synchronizing all epochs and for calculating detection latencies. The movement onset was identified when all values of the force signal in a 200 ms window, which was shifted by one sample, exceeded the baseline. The baseline was defined as the mean value of the force signal computed in the last 1-s interval of the ‘Rest’ phase and in the initial 2-s interval of the ‘Preparation’ phase (see figure 1).

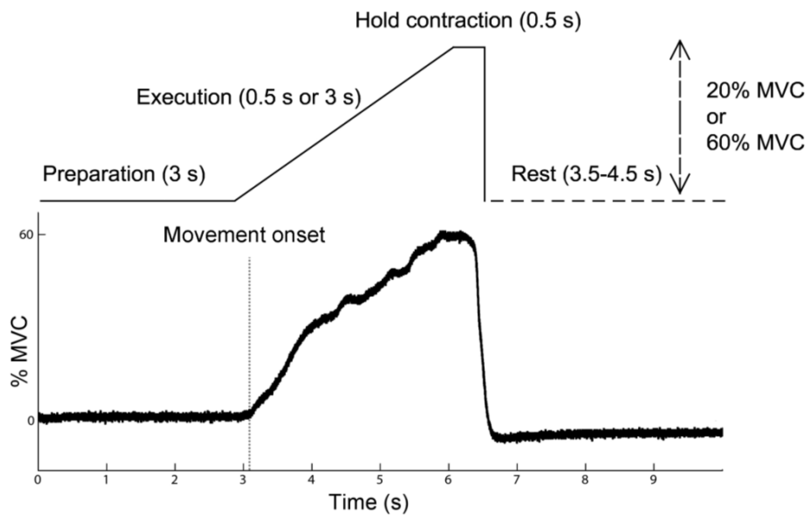

Figure 1) Upper: Force trace that the subjects had to follow. The subjects prepared for three seconds (preparation phase) before executing the specific movement which they maintained for 0.5 seconds. The break between two trials was randomized between 3.5-4.5 seconds. Lower: Force trace produced by a representative subject.

2.4. Detection of movements

The EEG signals were bandpass filtered from 0.05 to 10 Hz with a 2nd order digital Butterworth filter in the forward and reverse direction. To compensate for the poor spatial resolution of scalp EEG [19], a Large Laplacian spatial filter was applied. The formula for this is: Cz-(F3+F4+Fz+C3+C4+P3+P4+Pz)/8. The spatially filtered signal will be referred to as surrogate channel in the following.

The method for extracting the template and detecting movements in the continuous EEG is similar to the one proposed by Niazi *et al* (2011).

Although movements were recorded in a cue-based paradigm, and information of the timing was available, they were detected from the continuous EEG to estimate the detection performance of a simulated self-paced BCI.

Initially, the entire data set was divided randomly into four parts, three for training and one for testing. From the surrogate channel of the training data a template was extracted when averaging all trials from the peak negativity to 2 s prior to this point (see figure 2). For determining the detection threshold, a receiver operating characteristic (ROC) curve was obtained through cross-validation on the training set. To obtain a tradeoff between the true positive rate (TPR) and number of false positive detections (FPs) for all subjects, the detection threshold was based on the TPR and FPs corresponding to the midpoint of the upward convex part of the ROC curve. Detector decisions were based on the likelihood ratio method (Neyman Pearson lemma) computed between the surrogate channel of the testing set and the template (2 s sliding window with 200 ms shift). Detection occurred when two out of three consecutive windows crossed the detection threshold and were below the electrooculography (EOG) threshold (125 µV in FP1).

Besides the TPR (%) and FPs/min, the detection latencies of movements (detection time with respect to the movement onset) were used as measures for the detection performance.

2.5. Classification of movements

2.5.1. Feature extraction

Before computing the features for classification, epochs were extracted from the surrogate channel using the trigger sent to the EEG amplifier and synchronized to the force onset (movement onset). Epochs with EOG activity higher than 125 µV were rejected from further analysis due to the fact that the EOG threshold would be exceeded when using the detection algorithm.

Six temporal features were extracted from the initial negative phase of the MRCP until the point of detection to predict which of the four tasks the subjects intended to do. This was also done using data until 100 ms before the movement onset which is approximately the point of detection in Niazi *et al* (2011). As reference for these classification accuracies, features were also extracted from the complete MRCP, in which case the reafferent potential was included for discrimination. Features were extracted from single-trial EEG epochs for each subject. The features extracted from the initial negative phase of the MRCP (point of detection and 100 ms before the movement onset) were: I) point of maximum negativity, II) mean amplitude, III and IV) slope and intersection of a linear regression in the interval from -2 s to the point of detection or -0.1 s, V and VI) slope and intersection of a linear regression in the interval from -0.5 s to the point of detection or -0.1 s.

The features extracted from the complete MRCP, in addition to those mentioned above, were: I) point of maximum negativity, II) mean amplitude in the interval from -0.5 to 0.5 s, III) mean amplitude in the interval from movement onset to 0.75 s, IV and V) slope and intersection of a linear regression in the interval from the movement onset to 1 s.

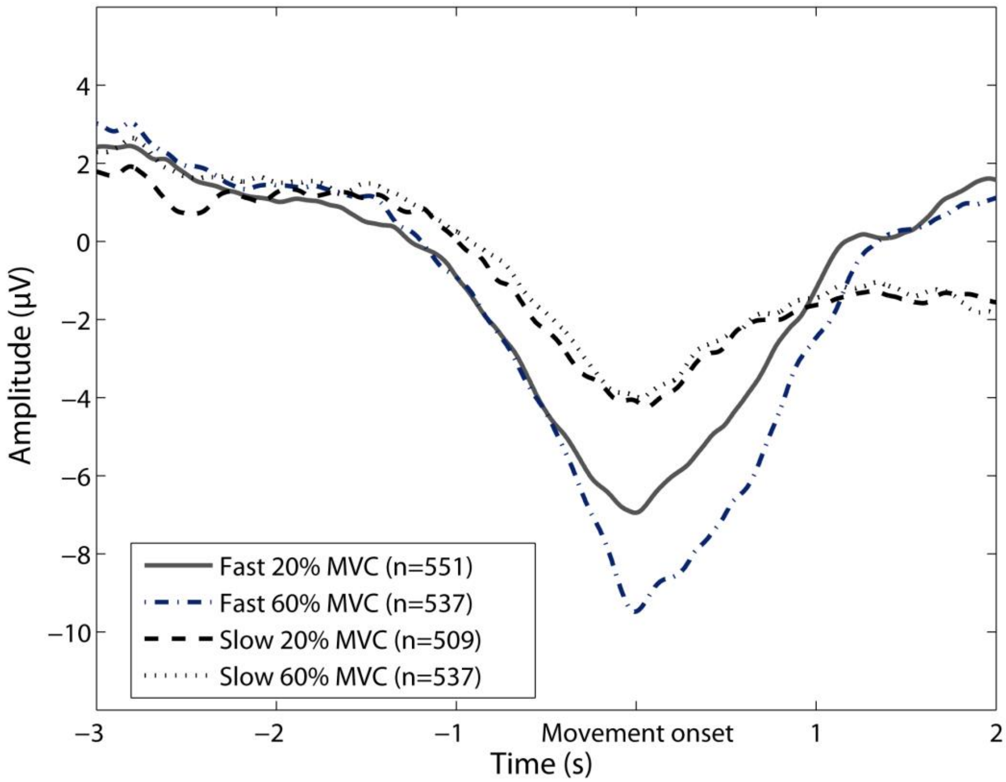

Figure 2) Average of the four tasks across the twelve subjects. 'Fast' means 0.5 s to reach the desired level of MVC, 'Slow' means 3 s to reach the same. 'n' is the number of trials included in the average. The standard deviation of the peak of maximum negativity in the four tasks was: 7 µV (Fast 20% MVC), 8 µV (Fast 60% MVC), 6 µV (Slow 20% MVC) and 7 µV (Slow 60% MVC).

2.5.2.Classifier

The classification was divided into two main categories: 2-class and 4-class problem. The two categories were further divided into classification based on features with respect to the three different timings: initial negative phase until point of detection (T1), initial negative phase until 100 ms before the movement onset (T2) and the complete MRCP (T3).

The features were classified using a support vector machine (SVM), which is a robust classification method that has demonstrated good generalization properties in BCI applications (see [20] for a review of classification methods in BCI research). An optimized Gaussian kernel and regularization parameter was used in the SVM. The two optimization processes allowed maximization of the classification accuracy when applied to the training set. The optimized parameters were applied to the test set for evaluation of method performance (classification accuracy).

2.5.3. Two classes

The classification accuracy of each task pair was calculated (e.g. Fast 20% MVC versus Fast 60% MVC) with a 3-fold cross-validation. The sets of signal features were randomly divided into three subsets of equal size; two were used as training set while the remaining set was the testing set.

2.5.4. Four classes

The classification accuracy for each task was found using a multi-class SVM which is an extension of the binary classification. Two approaches can be used to extend the binary classification of two classes to classification of four classes: ‘one-versus-one’ and ‘one-versus-rest’ schemes. In this study the one-versus-one scheme was used, where one classifier was constructed for each task pair (Fast 20% MVC vs. Fast 60% MVC, Fast 20% MVC vs. Slow 20% MVC etc.). A test sample was classified by each of the classifiers and labelled according to the class with most votes. To obtain the classification accuracies, the correctly classified samples were summed up for each class and divided by the total number of movements in each of the specific classes.

2.6. System performance

In this study, system performance is defined as the TPR for detection multiplied with the classification accuracy for the task pair or task for a 2-class and 4-class system, respectively.

To obtain an estimate for the system performance for all possible 2-class systems the following formula was used:

$$\text{Performance} = \frac{\text{CA}(1,2) * [\text{TPR}(1) + \text{TPR}(2)]}{2}$$

CA(1,2) is the classification accuracy of the task pair. TPR(1) and TPR(2) is the TPR of detection for task one and task two, respectively. The assumption for using this formula to estimate the system performance is that the classification accuracy and TPR are independent. The system performance was evaluated using two measures: correct detection and correct classification, and correct detection and incorrect classification. The last measure was found using the formula above when substituting CA(1,2) with its complement.

To estimate the performance of a system using four classes the same two measures were used. The first measure, correct detection and correct classification, was found when multiplying the classification accuracies for the tasks with the corresponding TPRs. The second measure, correct detection and incorrect classification, was found using the same formula with the classification accuracy substituted with its complement.

2.7. Statistics

A one-way repeated measures analysis of variance (ANOVA) test with 'task' as factor was applied on the TPR for the four tasks. Similarly, a one-way repeated measures ANOVA with 'timing' as factor was performed to compare classification accuracies when using features extracted with respect to the three different timings. The Bonferroni's post hoc test was used to reveal the significance of the factor 'timing'. For the two tests, statistical significance was assumed if $P<0.05$.

3. Results

The results are summarized in tables 1, 2 and 3 representing the detection performance, classification accuracies and system performance for the 12 subjects. Epochs with EOG activity exceeding 125 μV were rejected from further analysis; the averaged number (across subjects) of rejected trials was 6±7 per task.

3.1. Detection

The averaged results (across subjects) of the detection of cue-based movements are presented in table 1. The TPRs were in the range 76-86 % with fast movements having higher TPRs compared to slow movements. The one-way repeated measures ANOVA revealed a significant difference between the TPRs of the four tasks (P=0.005). The post hoc test revealed a significant difference between the fast movements compared to 'Slow 20% MVC'. The number of FPs in the four sessions was 56±11 and the total length of the sessions was 39 min which leads to approximately 1.5 FPs/min. The movements were detected 317±73 ms before the movement onset.

Task	**TPR (%)**
Fast 20% MVC	83±10
Fast 60% MVC	86±10
Slow 20% MVC	76±10
Slow 60% MVC	79±12
	Mean±SD

Table 1) Detection of four types of movements. The TPR is presented as an average across subjects. SD = Standard Deviation. The movements were detected 317±73 ms before the movement onset with less than 1.5 FPs/min.

3.2. Classification

The averaged single-trial classification accuracies for each task pair and for each task in a 4-class classification problem are presented in table 2. Classification accuracies are reported when using features extracted from the initial negative phase of the MRCP until the point of detection ('T1'), 100 ms before the movement onset ('T2') and classification accuracies based on features from the complete MRCP ('T3'). The highest classification accuracies for task pairs were obtained when the speed was different; this was also valid for classification at 'T3' where the classification accuracies in general were significantly higher. The highest classification accuracies for movements in the 4-class problem were obtained for fast movements. The best performance was obtained using 'Fast 20% MVC' trials that were correctly classified 69±13 % of the time. When more of the signal was included in the feature extraction, i.e. going from ‘T1’ to ‘T3’, the classification accuracies improved, except for the comparison of force in the slow movements.

Task pair / task	**CA (%) – T1** ***Point of detection***	**CA (%) – T2** ***100 ms before movement onset***	**CA (%) – T3** ***Complete MRCP***	**Paired t-test (P-value)**	**Difference between timings** ***Post hoc test***
Fast 20 vs. Fast 60	75±9	76±9	79±9	0.08	
Fast 20 vs. Slow 20	78±5	80±5	85±5	0.003 *	T1 & T3, T2 & T3
Fast 20 vs. Slow 60	77±8	79±8	85±9	0.007 *	T1 & T3, T2 & T3
Fast 60 vs. Slow 20	80±8	82±6	89±5	0.002 *	T1 & T3, T2 & T3
Fast 60 vs. Slow 60	80±10	82±10	89±8	0.001 *	T1 & T3, T2 & T3
Slow 20 vs. Slow 60	76±6	75±5	74±7	0.2	
Fast 20	62±11	69±13	73±13	0.006 *	T1 & T3
Fast 60	55±18	63±16	69±13	0.006 *	T1 & T3
Slow 20	54±10	60±12	64±9	0.008 *	T1 & T3
Slow 60	37±13	45±18	53±12	0.001 *	T1 & T3
	Mean±SD	**Mean±SD**	**Mean±SD**		

Table 2) Classification accuracies averaged across subjects using 2-class SVM and 4-class SVM. ‘Fast 20% MVC ’is abbreviated ‘Fast 20’,‘CA’ is the classification accuracy and ‘T1’ is ‘Timing 1’. T1 is ‘Point of detection’ which refers to features extracted from the initial negative phase of the MRCP until the point where the movement has been registered. T2 is ‘100 ms before movement onset’ which refers to features extracted from the initial negative phase until 100 ms before the movement onset. T3 is ‘Complete MRCP’ which refers to features extracted from the complete MRCP. The number of classes is 2 in the initial six rows in the first column, while the number of classes is 4 in the remaining rows. The rightmost column contains the result of the post hoc tests. * = significantly different.

3.3. System performance

Estimates of system performance, when combining detection with classification, are presented in table 3. Six results are presented: I) Correct detection and correct classification and II) Correct detection and incorrect classification for ‘T1’, ‘T2’ and ‘T3’, respectively. The highest system performance (two classes) was ‘Fast 60% MVC vs. Slow 60% MVC’ for all of the timings. For these 2-class systems 67±13, 68±13 % and 74±12 % of the movements were correctly detected and classified. For task pairs with low classification accuracies, the system misclassification was high; the same was observed for the 4-class system where system misclassification was even higher. The 4-class system was performing best using fast movements with 'Fast 20% MVC' being the best with 52±13, 58±17 % and 61±16 % of the movements being correctly detected and classified. The performance of the 2-class systems and the 4-class system improved when features from the complete MRCP were used in the classification ('T3').

All values presented in table 3 have high standard deviation indicating variable performance among the 12 subjects.

Task pair/task	**T1 (%)** **TPR*CA / *TPR*(1-CA)***	**T2 (%)** **TPR*CA / *TPR*(1-CA)***	**T3 (%)** **TPR*CA / TPR*(1-CA)**
Fast 20 vs. Fast 60	64±13 / 21±7	64±13 / 20±7	67±13 / 17±6
Fast 20 vs. Slow 20	62±9 / 17±5	64±10 / 16±4	67±12 / 12±3
Fast 20 vs. Slow 60	63±11 / 18±7	64±12 / 17±6	69±13 / 12±6
Fast 60 vs. Slow 20	65±12 / 16±7	67±11 / 14±5	72±11 / 9±3
Fast 60 vs. Slow 60	67±13 / 16±9	68±13 / 15±8	74±12 / 9±6
Slow 20 vs. Slow 60	58±8 / 19±6	58±7 / 19±5	57±7 / 21±6
Fast 20	52±13 / 31±9	58±17 / 24±9	61±16 / 22±9
Fast 60	48±18 / 39±16	55±17 / 31±13	60±15 / 26±11
Slow 20	41±9 / 35±10	45±10 / 30±11	49±9 / 27±8
Slow 60	29±10 / 50±13	36±15 / 44±15	42±10 / 38±11
	Mean±SD / Mean±SD	**Mean±SD / Mean±SD**	**Mean±SD / Mean±SD**

Table 3) Estimate of system performance based on the TPR and the classification accuracies for the three timings averaged across subjects. Different system performances were evaluated for the combination of task pairs (2-class systems) and for a 4-class system. In the three rightmost columns the percentage of correct detections and classifications are given as well as the percentage for correct detection and incorrect classification for features extracted with respect to the three timings, respectively.

4. **Discussion**

In the continuous EEG recordings four types of cued isometric dorsiflexions of the ankle were detected ~300 ms before the movement onset with an average TPR of ~80 % and less than 1.5 FPs/min. The classification accuracy was calculated for each task pair using only features from the initial negative phase of the MRCP until the point of detection where the difference in levels of speed had a higher classification accuracy (80±10 %) compared to that of force (75±9 %). When using features extracted from the data until 100 ms before the movement onset, and data from the complete MRCP, the classification accuracies improved with ~4 to 9 percentage points compared to the classification accuracies calculated at the point of detection. The system performance of a BCI with two classes, which predicts the movement intention, was in the range of 58-67 %. The results indicate that it is feasible to make a BCI system that can detect movements and discriminate between different levels of speed and force which can be applied for introducing task variability in a rehabilitation setting.

4.1. Detection and classification

This study focused on two aspects, detection and classification, to test the feasibility of implementing a BCI system with two or four classes for rehabilitation purposes.

The detection of movement intentions (prediction of voluntary movements) has been accomplished in different studies previously for: self-paced foot [13], arm [21] and wrist movements [22]. The movements were detected using the MRCP with which it was possible to detect them with limited detection latencies in the range from 100 to 600 ms before the movement onset. In this study, cued movements were detected with latencies (317±73 ms) and TPRs in the range of which has previously been reported [14, 21] even though the morphology of the MRCP is slightly different for cued and self-paced movements [6].

After the detection of the movement intentions, they were classified to obtain information about the level of speed and force of the forthcoming movement, which means that the BCI will contain two or more classes. Discrimination between several classes for BCI purposes (obtaining more degrees of freedom) has been investigated in several studies e.g. by discriminating between right and left hand, right foot and tongue movements from motor imagination [23]. However, the number of studies is limited in which the kinetics of the movement, such as speed and force, are decoded. MRCPs contain information about the speed and force of a movement [5] which can be extracted from the movement intention for imaginary [18] and executed plantar flexions of the ankle [17]. When using features from the initial negative phase ('T1' and 'T2'), the classification accuracies in this study were similar to or slightly lower than those obtained using the marginal distribution of an optimized wavelet [17]. When features from the complete MRCP are used, the classification accuracies were higher than those obtained for force and speed discrimination from imaginary movements [18]. The classification accuracy for four classes, two levels of force and speed, was lower compared to the discrimination of two classes, which was expected due to the similarities in the morphology of the MRCP in the different tasks (see figure 2). The theoretical chance level for the classification accuracies in the two-class paradigm is 50 % and 25 % in the four-class paradigm, but due to the limited number of trials in each class the chance level with a 95 % confidence interval is higher than 50 % and 25 %, respectively. The chance level with a 95 % confidence interval was around 60-65 % and 30-35 % in the two- and four-class paradigm, respectively [24]. The classification accuracies obtained in this study, however, were higher than the estimated chance levels in all cases.

The system performance was also investigated when using features extracted from the complete MRCP ('T3') to get an indication of the applicability of a multiclass system for communication purposes. The estimated system performance was moderate, but when only the detection was taken into account (on/off) the performance (TPR) was around 80 %. The performance decreased when the detected movement was classified according to the movement type, i.e. when the complexity of the system was increased.

4.2. Signal processing

As indicated by the performance of the detector the TPR may be correlated to the signal-to-noise ratio (SNR) which can be seen in table 1 and figure 2. The use of the common spatial pattern (CSP) filter has been applied in various BCI applications and used for improving the SNR for single-trial analysis [19]. In the work by Niazi *et al* (2011) different spatial filters (Large Laplacian, CSP and an optimized spatial filter) were applied where the TPR was obtained for each spatial filter. Given the amount of training data, the Large Laplacian and optimized spatial filter outperformed the CSP, with a slightly higher TPR for the optimized spatial filter compared to the Large Laplacian spatial filter. It should be investigated how the classification accuracies (and the system performance) will be affected when applying the optimized spatial filter. Other pre-processing techniques for improving the SNR should be investigated as well, e.g. denoising using wavelets [25] or blind source separation [26].

4.3. Feature extraction

For discriminating between the variations in force and speed only temporal features were used either from the initial negative phase ('T1' and 'T2') of the MRCP or the complete MRCP ('T3'). The classification accuracies were higher when adding the information from the reafferent potential, especially with variations in speed. This improvement is in agreement with previous studies that have found information about speed is encoded in the reafferent potential [5, 27, 28]. To improve the classification accuracy additional features could be implemented. The use of optimized wavelets as features alone has shown high classification accuracies for variations in force and speed [17, 18], but also the combination with spectral features could potentially improve the performance. The power in specific frequency ranges, corresponding to mu and beta rhythm, has been combined with temporal features from the MRCP for discrimination between levels of speed [27], as well as the combination of event-related synchronization and desynchronization with the Bereitschaftspotential for discrimination between left and right finger movements [29]. However, in BCIs where the device commands must be delivered with minimal latency with respect to the onset of the movement some features may not be applicable e.g. event-related synchronization which is observed after the movement onset. The combination of several types of features for discrimination between MRCPs associated with toe and finger movements has been applied [30]. In this study, temporal features as well as power spectral densities, auto regressive coefficients, mean frequencies and amplitudes were used as features. Different studies have also proposed that non-linear dynamics methods can be used for feature extraction in BCI applications e.g. using sample entropy to discriminate between different brain states [31]. As outlined in the previous section about pre-processing techniques for improving the SNR, different techniques are proposed for feature extraction as well. Future studies could elucidate the optimal pre-processing techniques to be used in similar applications as well as the combination of features to use for discrimination between various levels of force and speed.

4.4. System performance in relation to neuromodulation

In this study, the system performance was estimated when detecting movement intentions and decoding two levels of force and speed. The system consisting of two classes correctly detected and classified the movements between 58-67 % of the time ('T1'). When the number of classes was increased to four, the number of correctly detected and classified movements was in the range of 29-58 %. The system performance was higher when using features from the complete MRCP when the number of classes was two and four, respectively. The purpose of this study was to estimate the system performance to find out if it was good enough to be used for neuromodulation for rehabilitation purposes. In general, the BCI system performance required for inducing plasticity is not known as reported by Grosse-Wentrup *et al* (2011). However, it has been shown that at a moderate level of BCI performance it is possible to induce plasticity when using the protocol proposed by Mrachacz-Kersting (2012) [32]. Also, in another study using a similar protocol the system performance (TPR, only detection of movement intentions) was 67 %, which led to a significant increase in the excitability of the cortical projection to the target muscle [13]. It was found that the ratio between the TPR and FPs was correlated to the changes in excitability with better performance leading to higher excitability. With respect to the work of Niazi *et al* (2012), the system performance (detection and classification), with two classes, is in the range of application for neuromodulation, while the performance of the system with four classes is lower. However, the lower limit for the system performance to be used for neuromodulation is not known [12]. To improve the system performance, the system can be optimized as described in the previous sections, or the user can be trained. Subject training is expected to improve the system performance since BCI use is a skill [10], and the subjects were naive BCI users. With practice the signal strength may be improved [33], so better system performance is obtained. By training the system and the subjects, it was found that the online performance of the subjects improved from the first to the last session [34].

4.5. Implications

A BCI system that is able to detect and decode movement intentions, with respect to the timing necessary for neuromodulation [15], could potentially control FES or robot-assisted movements. By decoding various levels of force and speed, task variability could be introduced while the efferent activity matches the afferent feedback from different types of movements, which could be very important for patient-driven rehabilitation and retention of relearned movements in stroke victims.

4.6. Limitations

In this study the signals (from healthy subjects) were processed offline, and the performance of the detector and classifier were evaluated separately. The system performance was calculated as a probability given the two events, detection and classification, were independent. In an online system the amount of information for feature extraction will vary depending on the point of detection, which was seen from the results in table 2. Movement intentions were detected 317±73 ms before the movement onset, but the findings by Mrachacz-Kersting *et al* (2012) suggest that afferent feedback should reach the cortical level at the peak of maximum negativity to have an effect on the excitability. In practice, the detection time relative to the peak of maximum negativity is not known, but the detection threshold could be increased leading to a lowering of the detection latency. The detector has been tested online [13], but the combination of detection and classification, needs to be tested. However, it is anticipated that online classification is feasible due to the simplicity of the feature extraction and classification. The time it took for extracting and classifying the features was approximately 11 ms, obtained using the timer function in MATLAB 2010b on a computer with an Intel® CoreTM i7-720QM processor (1.6GHz, 6MB L3 cache) and 4 GB DDR3 Memory.

The morphology [6] and the neural generators [35] are different when movements are externally cued compared to self-paced. In this study, however, the movements were cued to have precise control on the levels of force and speed across trials and subjects, so that the results were as comparable as possible.

Another limitation of this study is the inclusion of only healthy subjects while the intended user group consists of patients with motor impairments. The system performance is not known when the user is a patient. It is reasonable to hypothesize that the performance will decrease to some extent, which was shown in a study where the detection of attempted movements from stroke patients was compared to the detection of movements from healthy subjects [14]. However, the amplitudes of the different phases of the MRCPs associated with attempted movements were similar in acute stroke patients compared to those obtained for healthy subjects [36]. The decline in performance will depend on various factors such as severity of the motor impairments, mood and amount of BCI training.

5. Conclusion

This study demonstrates the feasibility of implementing a BCI system, with two or four classes, that detects movement intentions and decodes levels of force and speed from these. The results are relevant for BCI systems that can be applied with assistive technologies in rehabilitation where meaningful afferent feedback can be provided according to the efferent activity.

Acknowledgments

This work was supported by the Danish Technical Research Council.

The authors declare no competing financial interests.

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