Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation

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Abstract

Brain-computer interfaces can be used for motor substitution and recovery; therefore, detection and classification of movement intention is crucial for optimal control. In this study, palmar, lateral and pinch grasps were differentiated from the idle state and classified from single-trial EEG using only information prior the movement onset. Fourteen healthy subjects performed the three grasps 100 times while EEG was recorded from 25 electrodes. Temporal and spectral features were extracted from each electrode, and feature reduction was performed using sequential forward selection (SFS) and principal component analysis (PCA). The detection problem was investigated as the ability to discriminate between movement preparation and the idle state. Furthermore, all task pairs and the three movements together were classified. The best detection performance across movements (79±8%) was obtained by combining temporal and spectral features. The best movement-movement discrimination was obtained using spectral features; 76±9% (2-class) and 63±10% (3-class). For movement detection and discrimination, the performance was similar across grasp types and task pairs; SFS outperformed PCA. The results show it is feasible to detect different grasps and classify the distinct movements using only information prior to the movement onset; which may enable brain-computer interface-based neurorehabilitation of upper limb function through Hebbian learning mechanisms.

Keywords: Hand grasp, brain-computer interface, movement-related cortical potential, movement intention, signal processing.

1. Introduction

Stroke is the leading cause of acquired disability among adults, and up to 17 million people per year suffer a stroke [9]. Out of those that survive the initial injury, up to 85% are initially left with motor disabilities such as a hemiplegic arm. Despite the rehabilitation efforts, 55-75% of the patients remain with some disability 3-6 months after the injury [10]; therefore, there is an incitement to optimize the rehabilitation process, e.g. by introducing new interventions to add to the current therapies, to maximize the outcome of the rehabilitation. Over the recent years, brain-computer interface (BCI) technology has been proposed for neurorehabilitation by inducing cortical plasticity which is the proposed mechanism for motor learning/recovery [5, 7, 11, 34]. Recently, a protocol for inducing cortical plasticity was established based on Hebbian learning mechanisms and the concept of paired associative stimulation [15, 29, 39]. In this protocol, somatosensory feedback from the target muscle was timed to coincide at the cortical level during maximal cortical activation from the cortex associated with that muscle [29]. In the time domain, the cortical activation is seen as a slow negative shift in the electroencephalography (EEG) recording [29]; this is known as a movement-related cortical potential (MRCP) [24, 38, 43]. It was obtained by imagining the kinaesthetics of the muscle contraction (imagining a movement) with its maximum being the onset of the imaginary movement. The MRCP associated with the imaginary movement was detected with a BCI that triggered an external device to provide sensory feedback from e.g. electrical stimulation or robot assisted movements [17, 28, 29, 33, 46]. In this type of protocol, timing is crucial for the usability [29]. The MRCP must be detected with short latency (i.e. before the onset of the movement), so the external device can provide the sensory feedback, and the feedback has time to propagate to the cortex. In these studies, MRCPs have been detected and an external device triggered, but potentially the protocol may be further improved by matching the sensory feedback to the efferent activity of the brain. Recently, it was demonstrated that MRCPs associated with movements performed with different levels of force and speed of the same body part (wrist and foot movements) could be decoded from the EEG using only information prior to the onset of the movement [13, 14, 21]. Also, different movement types have been classified such as hand grasping, opening and reaching [1, 2, 4], movement direction and kinematics (see [19] for a recent review), wrist movements [12, 40-42], shoulder and elbow movements [8, 47-49] and finger movements [26, 27, 44]. Information prior to and after the movement onset was used in the analysis in these studies. Moreover, the use of different features, from the time and frequency domain, has been used. The features have been derived from bandpass filtered data where different cutoff frequencies have been applied; some data are filtered with a narrow passband at low frequencies (for MRCP analysis), and some data are filtered, so spectral analysis can be performed on the full-band EEG.

By detecting the intention to move and decode various movement types, it may be possible to control e.g. a rehabilitation robot or functional electrical stimulation that are examples of technologies that have been used in neurorehabilitation [36], such that various movement types can be practiced in the same session. Task variability has been shown to improve the performance in subsequent sessions and maximize the retention of relearned movements [25].

In this study, the aim was to provide an estimate for the performance of a detector that can differentiate between the idle state (background EEG) and three different hand movements. The following movement types were performed: palmar, pinch and lateral grasps since they are used in ~95% of all daily functions [37]. In addition, classification was performed to discriminate between the three movement types. The analysis was performed on features extracted from the time domain, frequency domain and the combination of both. The temporal features were derived in two ways; 1) from data that were bandpass filtered in the frequency range of the MRCP and 2) full-band EEG. Only data recorded prior to the onset of the movement were used in the analysis to fulfill the temporal association needed for neurorehabilitation based on Hebbian learning mechanisms.

2. Methods

2.1. Subjects

Fourteen healthy subjects (7 women and 7 men: 24±1 years old) participated in this study; they were all naïve to BCI experiments. All subjects gave their written informed consent. The procedures were approved by the local ethical committee (N-20130081).

2.2. Experimental protocol

The subjects were seated in a comfortable chair with their right arm resting on an adjustable table in front of them. A hand grip dynamometer was placed to register the force produced. At the beginning of the experiment, the maximum voluntary contraction (MVC) was determined; this value was used in the three different tasks the subject performed. The tasks were 0.5 s to reach 5% MVC (figure 1) of palmar, lateral and pinch grasps (see figure 2). Each task was performed 4x25 times (100 in total) with 1 min rest in between each block of 25 movements; two consecutive movements were separated with 9 s. The order of the movements was performed in blocks. The order of the block was randomized. The subjects were visually cued (figure 1) by a custom made program (SMI, Aalborg University). The produced force was used as input to the program, so visual feedback was provided continuously. The subjects were instructed to time the onset of the movement and use 0.5 s to reach the ~5% MVC and minimise eye and body movements around the onset of the movements. It was not critical that they matched 5% MVC exactly; this level was chosen to avoid fatigue. ~5 min of practice were given for the subjects to familiarize with the setup and the tasks to be performed.

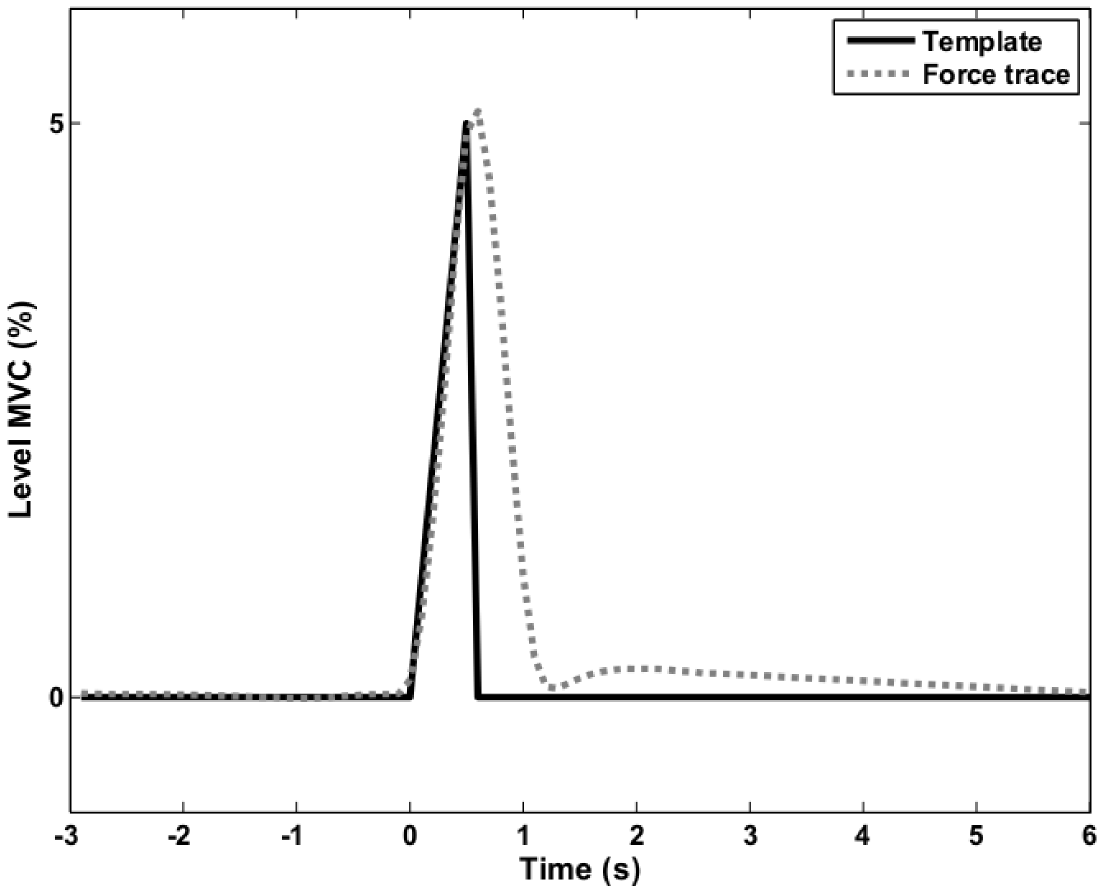

Fig. 1 The black force template was shown to the subjects while a moving cursor was controlled by the produced force (dashed line). This is a lateral grasp from a representative subject. Time 0 is defined as the movement onset

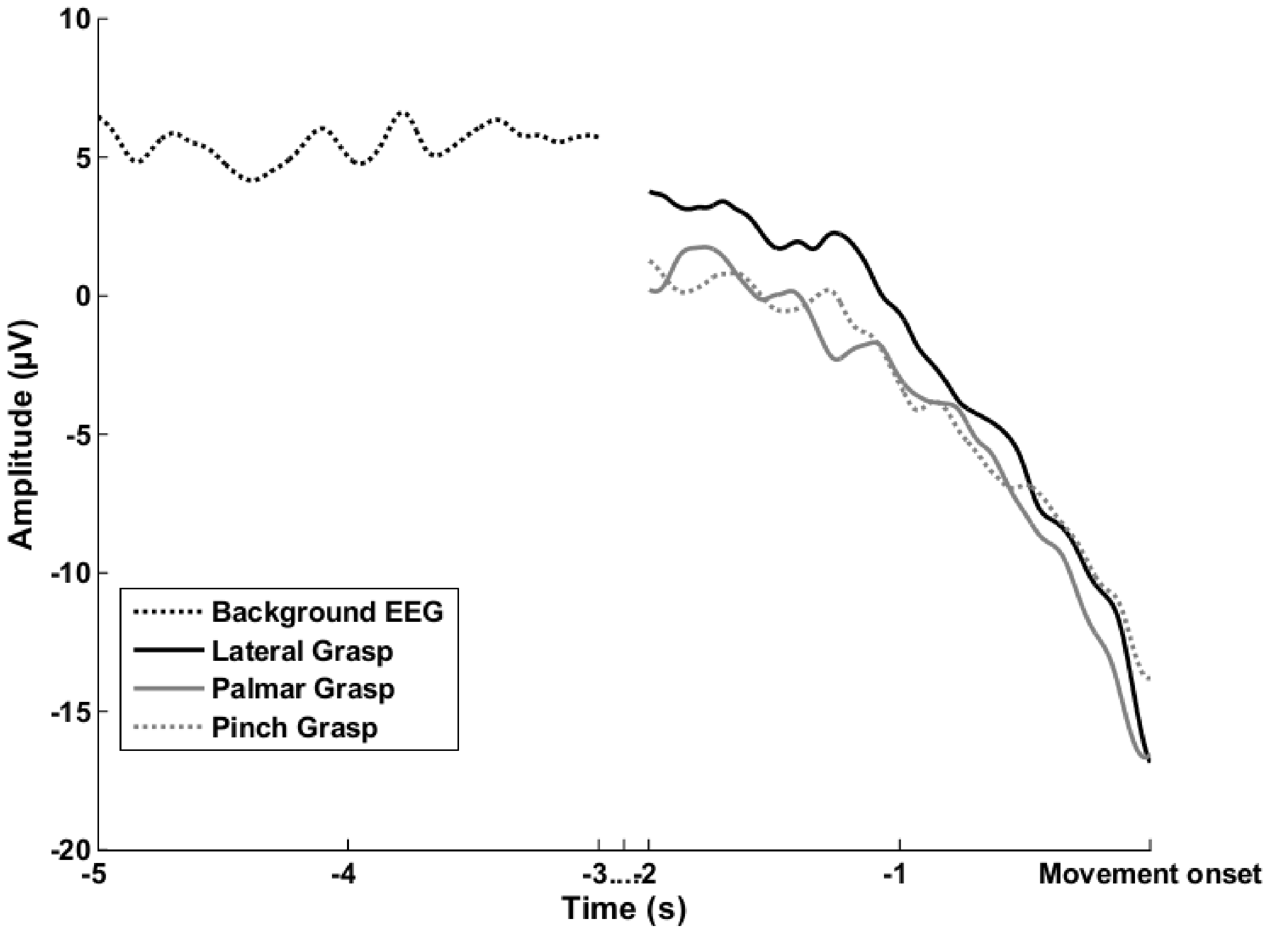

Fig. 2 Average of the movement and background EEG epochs from a representative subject. This data are bandpass filtered from 0.05-5 Hz

2.3. *Signal acquisition*

2.3.1.EEG

26 monopolar channels (Ag/AgCl ring electrodes) of continuous EEG were recorded (Neuroscan and EEG Amplifiers, Nuamps Express, Neuroscan) over the left cortical hemisphere from the following positions according to the international 10-20 system: FP1, F7, F5, F3, F1, Fz, FT7, FC5, FC3, FC1, FCz, T7, C5, C3, C1, Cz, TP7, CP5, CP3, CP1, CPz, P7, P5, P3, P1 and Pz. The signals were grounded at nasion and referenced to the right earlobe. Electrooculography (EOG) was extracted from FP1, thus only 25 EEG channels were used for analysis. All signals were sampled at 500 Hz. During the experiment, the electrode impedance was below 5 kΩ.

At the beginning of each trial (t=-3 s in figure 1), a digital trigger was sent from the visual cuing interface for epoching the continuous EEG in the offline analysis.

2.3.2.Force and MVC

Force was used as input (to provide visual feedback) and recorded with the custom made software ‘Follow Me’ (Knud Larsen, SMI, Aalborg University). It was sampled with 2000 Hz and recorded with a Jamar handgrip dynamometer (Noraxon USA, Inc., Scottsdale, Arizona). Three MVCs were performed, each separated with 60 s, where the highest value of the three was used throughout the experiment as reference.

2.4. Signal processing

The signals were processed in two ways depending on the feature extraction technique that was applied. The signals were bandpass filtered with a 2nd order Butterworth filter either from 0.01-5 Hz (MRCP frequency range) or 0.01-45 Hz (full-band EEG frequency range). The filtered continuous signals were then divided into two types of epochs; movement epochs and background EEG epochs. A movement epoch was extracted from the movement onset and 2 s prior this point. Background EEG epochs were extracted from 5-3 s prior the movement onset to avoid the start of the movement preparation phase. Epochs containing EOG activity (peak-peak amplitude in FP1 >125 µV) were discarded from further analysis. Moreover, epochs where one or more channels were saturated or drifted were removed from the analysis as well.

2.5. Feature extraction and feature reduction

2.5.1.Feature extraction

Different features were extracted from the epochs. Temporal features were extracted from the epochs that were bandpass filtered from 0.01-5 Hz and from 0.01-45 Hz. The mean amplitude was extracted from a 1 s window that was shifted 200 ms; this was done for each of the 25 EEG channels (leading to 6x25 features). In addition, from the epochs filtered from 0.01-45 Hz spectral features were extracted. The average power was calculated from the power spectral density in 5 Hz frequency bins from 0 to 45 Hz (0-5 Hz, 5-10 Hz etc.) for each channel (leading to 9x25 features).

2.5.2.Feature reduction

The dimensionality of the feature vector was reduced using sequential forward selection (SFS). The features from the training data were ranked individually by their ability to separate two groups (e.g. palmar grasps from pinch grasps for each subject) based on a Mann-Whitney test. The classification accuracy was calculated based on the feature associated with the highest u-statistics using leave-one-out cross-validation. After this, the 2nd most discriminative feature was added (2nd highest u-statistics). If it improved the classification accuracies it was saved; otherwise it was discarded. This procedure was repeated until all features were evaluated (see figure 3).

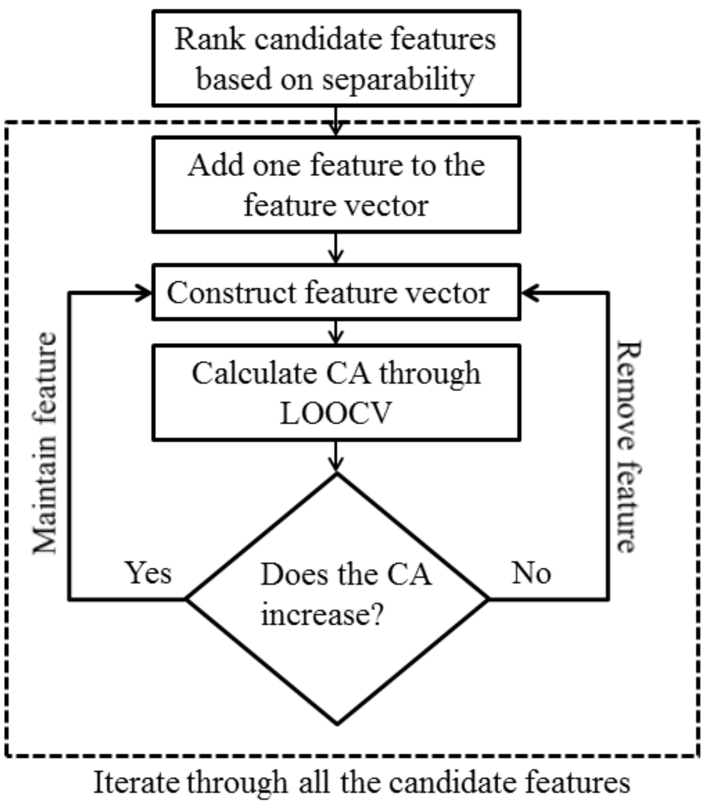

Fig. 3 Flowchart of the SFS procedure. The candidate features are ranked based on their separability using a Mann-Whitney test. Then one feature is added at the time to the feature vector starting with the feature with the highest separability. ‘CA’ is classification accuracy, and ‘LOOCV’ is leave-one-out cross-validation

This approach was extended when three groups were included in the analysis by calculating the optimal feature set for each task pair (as described above). The optimal features associated with each task pair were compiled, and additional feature selection was performed on this feature set to optimize the 3-class performance on the training data by adding and removing features from the compiled feature set.

Principal component analysis (PCA) was also performed to reduce the dimensionality of the feature vector to compare the classification accuracies obtained with SFS and PCA. The same number of principal components and features (determined by the SFS) was used in the analyses.

2.6. Classification

The epochs were divided into ten parts; nine parts were used for training and the last part for testing. The optimal features were determined through leave-one-out cross-validation on the training data. The optimal feature set was used on the testing set. The average of the classification accuracy for each testing set was calculated. The features were classified using linear discriminant analysis (LDA). Four evaluations were performed for each feature reduction technique using; I) temporal features bandpass filtered from 0.01-5 Hz, II) temporal features bandpass filtered from 0.01-45 Hz, III) spectral features and IV) combination of spectral features with temporal features bandpass filtered from 0.01-45 Hz.

2.6.1.Movement versus background EEG discrimination

To obtain an estimate for a BCI that can discriminate between the three movement types and background EEG, all the movement epochs were compiled into one class, and background EEG epochs were compiled in another class. Also, each movement type and the associated background EEG were classified individually.

2.6.2.Movement versus movement discrimination

The classification accuracies were calculated for each task pair (pinch versus palmar grasp, pinch versus lateral grasp, and lateral versus palmar grasp). In addition, classification accuracies were obtained for the 3-class problem as well.

2.7. Statistics

The classification accuracies for the movement versus background EEG (detection) were tested using a 2-way repeated measures analysis of variance (ANOVA) with 'feature type' (4 levels: temporal (5 Hz), temporal (45 Hz), spectral and combination) and 'feature reduction' (2 levels: SFS and PCA) as factors. For the classification between the movement types, the averaged classification accuracies (across tasks) were tested with a 2-way repeated measures ANOVA with the same factor as above. Significant tests were followed up with post hoc test using Bonferroni correction. The level of significance was P=0.05 in all tests.

3. Results

The results are summarized in table 1 and 2 and in figure 5 and 6. On average 6±10 (palmar grasp), 6±10 (lateral grasp) and 7±15 (pinch grasp) epochs were removed per subject from the analysis due to EOG artefacts and saturated or drifting channels. A grand average for several electrodes can be seen in figure 4. On average, the feature space was reduced to 13±5 features (out of 150, 225 and 375).

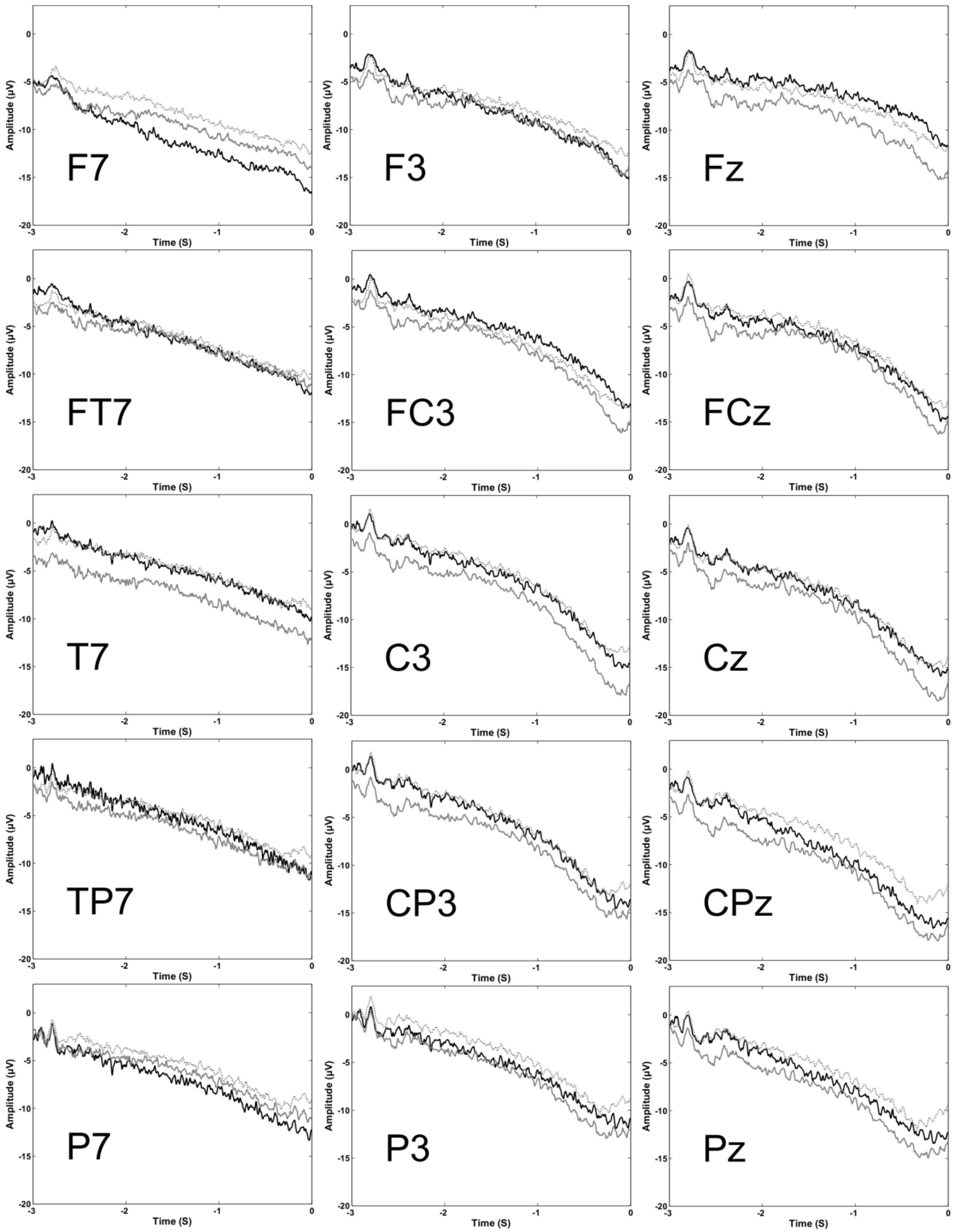
F7
F3
Fz
FT7
FC3
FCz
T7
C3
Cz
TP7
CP3
CPz
P7
P3
Pz
Amplitude (μV)
Time (S)

Fig. 4 Grand average across subjects for 15 electrodes. The solid black lines are lateral grasps, the solid grey lines are palmar grasps, and the light grey dashed lines are pinch grasps

3.1. Detection

The highest classification between movement and background EEG epochs was obtained when using the combination of temporal and spectral features (~80% classification accuracy). The performance was slightly lower when using temporal features (see table 1). The classification accuracies associated with the different grasps individually were similar.

Table 1: Movement versus background EEG classification using SFS and PCA for feature reduction. All classification accuracies are presented as mean ± standard deviation across subjects for the different features. 'Combination' refers to the combination of 'Temporal (45 Hz)' and 'Spectral'.

Temporal (5 Hz)				
	Lateral [%]	Pinch [%]	Palmar [%]	All [%]
SFS	75±11	75±11	73±11	77±8
PCA	72±13	72±10	73±12	72±10
Temporal (45 Hz)				
SFS	74±11	73±9	73±11	77±8
PCA	70±14	71±11	71±12	71±11
Spectral				
SFS	68±10	71±11	72±12	73±10
PCA	59±9	56±11	55±11	56±11
Temporal + Spectral				
SFS	77±11	77±8	78±8	79±8

PCA	67±13	66±12	65±12	66±12
	Mean±SD	Mean±SD	Mean±SD	Mean±SD

A 2-way repeated measures ANOVA revealed a significant interaction ($F_{(3,440)}$=7.4;P=0.000007) between the feature type and feature reduction technique that were used. The effect of feature type ($F_{(3,440)}$=17.5;P=$0.01*10^{-8}$) and feature reduction ($F_{(1,440)}$=57.2;P=$0.02*10^{-11}$) was significant. The performance obtained with spectral features was lower compared to the other features, and SFS outperformed PCA.

In general, the features are widely distributed over the different time windows, frequency ranges and channel locations (see figure 5). The largest fraction of the temporal features was selected from the time window containing the mean amplitude from -1 s to 0 s with respect to the movement onset although this fraction was only slightly higher compared to the others. For the spectral features, the largest fraction of features was found below 20 Hz. The largest fraction of features associated with the different channel locations varies for the different movement types and different features types.

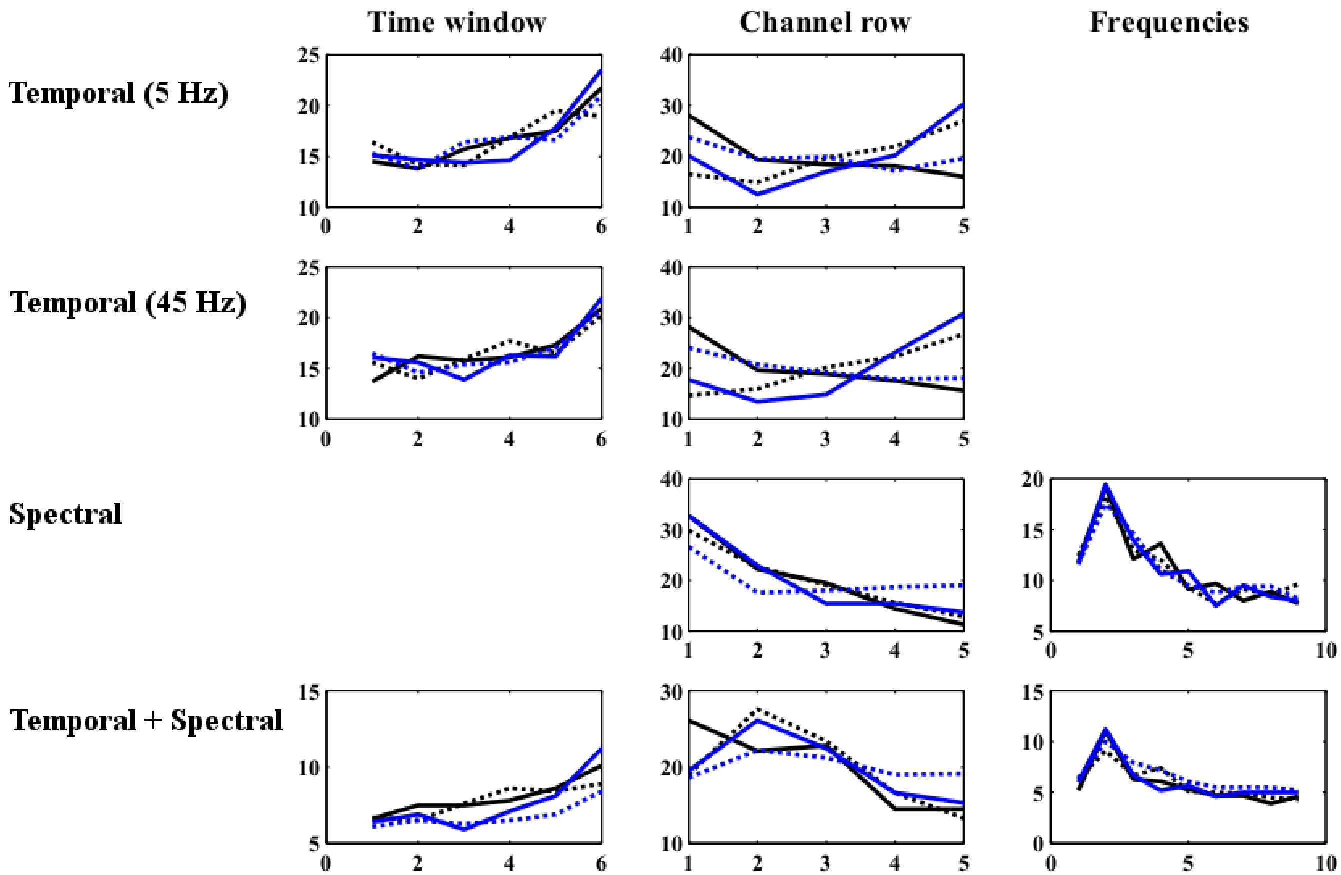

Fig. 5 Distribution of the features in time window, frequency range and channel location when using SFS for movement detection. All values on the y-axes are in percent. Legend: Palmar grasp (solid blue line), pinch grasp (dashed black line), lateral grasp (solid black line) and all grasps together (dashed blue line). The mean amplitude in 'Time window' has the following order (0 s is the movement onset): [-2 s to -1 s / -1.8 s to -0.8 s / -1.6 s to -0.6 s / -1.4 s to -0.4 s / -1.2 s to -0.2 s / -1 s to 0 s]. 'Frequencies' contain the average power in the following order: [0-5 Hz / 5-10 Hz / 10-15 Hz / 15-20 Hz / 20-25 Hz / 25-30 Hz / 30-35 Hz / 35-40 Hz / 40-45 Hz]. 'Channel row' contains 5 elements with 5 channels in each element: [(F7, F5, F3, F1, Fz) / (FT7, FC5, FC3, FC1, FCz) / (T7, C5, C3, C1, Cz) / (TP7, CP5, CP3, CP1, CPz) / (P7, P5, P3, P1, Pz)]

3.2. Classification

The highest classification accuracies to discriminate between the different movement types were obtained using spectral features. The classification accuracies were ~75% for the 2-class problems (see table 2). The classification accuracies decreased to 63% for the 3-class problem.

Table 2: Movement versus movement classification when using SFS and PCA for feature reduction. All classification accuracies are presented as mean ± standard deviation across subjects for the different features. 'Combination' refers to the combination of 'Temporal (45 Hz)' and 'Spectral'. 'Lat' is lateral grasp, 'Pal' is palmar grasp and 'Pin' is pinch grasp.

Temporal (5 Hz)				
	Lat vs. Pal [%]	Lat vs. Pin [%]	Pal vs. Pin [%]	3-class [%]
SFS	55±9	59±10	55±9	39±8
PCA	57±9	56±7	54±9	38±7
Temporal (45 Hz)				
SFS	55±9	58±9	54±7	39±6
PCA	57±10	55±8	54±8	38±6
Spectral				
SFS	75±7	76±9	75±9	63±10
PCA	67±6	67±6	68±4	52±6
Temporal + Spectral				
SFS	74±8	74±9	75±10	60±12
PCA	68±6	67±7	67±4	53±6
	Mean±SD	Mean±SD	Mean±SD	Mean±SD

A 2-way repeated measures ANOVA revealed a significant interaction between feature type and feature reduction technique ($F_{(3,440)}$=4.6;P=0.004) of the feature type that was used. The effect of feature type ($F_{(3,440)}$=84.4;P=0.04*10^{-41}) and feature reduction ($F_{(1,440)}$=17.7;P=0.00003) was significant The performance obtained with temporal features was significantly lower compared to the spectral features and the combination of temporal and spectral features. For the feature reduction, SFS outperformed PCA.

In general, the features are widely distributed over the different time windows, frequency ranges and channel locations (see figure 6).

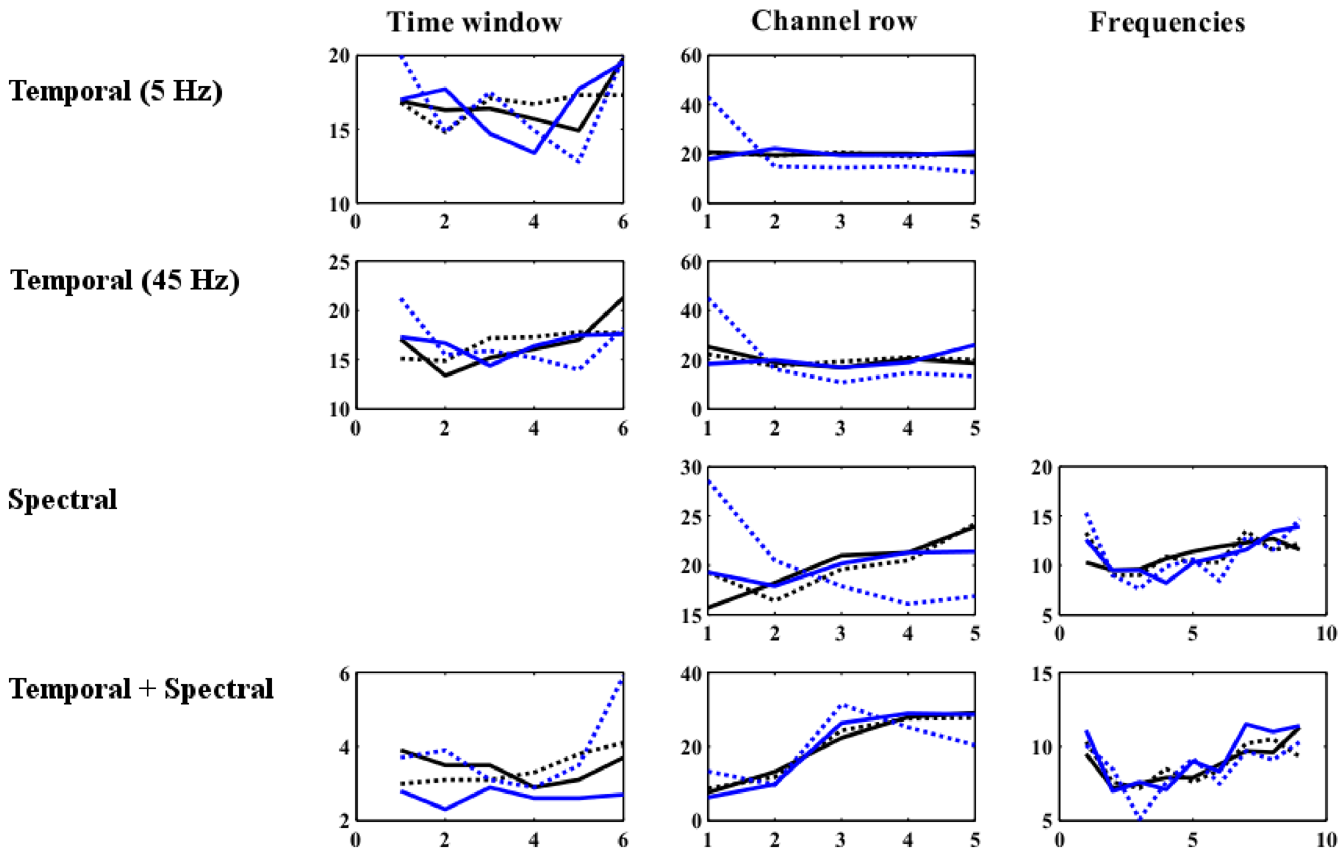

Fig. 6 Distribution of the features in time window, frequency range and channel location when using SFS for movement classification. All values on the y-axes are in percent. Legend: Palmar vs pinch grasp (solid blue line), lateral vs pinch grasp (dashed black line), lateral vs. palmar grasp (solid black line) and 3-class classification (dashed blue line). The mean amplitude in 'Time window' has the following order (0 s is the movement onset): [-2 s to -1 s / -1.8 s to -0.8 s / -1.6 s to -0.6 s / -1.4 s to -0.4 s / -1.2 s to -0.2 s / -1 s to 0 s]. 'Frequencies' contain the average power in the following order: [0-5 Hz / 5-10 Hz / 10-15 Hz / 15-20 Hz / 20-25 Hz / 25-30 Hz / 30-35 Hz / 35-40 Hz / 40-45 Hz]. 'Channel row' contains 5 elements with 5 channels in each element: [(F7, F5, F3, F1, Fz) / (FT7, FC5, FC3, FC1, FCz) / (T7, C5, C3, C1, Cz) / (TP7, CP5, CP3, CP1, CPz) / (P7, P5, P3, P1, Pz)]

4. Discussion

The three different hand movement types were discriminated from the background EEG with accuracies reaching 79±8% by combining temporal and spectral features. The performance of the classifier, when discriminating between the individual movement types, reached 76±9% correctly classified movements when using spectral features.

4.1. Detection

The features from the time domain combined with those from the frequency domain were best to differentiate the movement preparation from the idle state. This supports the findings in a recent study where it was found that a combination of temporal and spectral features was optimal for decoding MRCPs [22]. The combination of features was not significantly different compared to the use of temporal features from the MRCP frequency range (up to 5 Hz). One reason could be the distinct increase in negativity observed in the EEG prior the movement onset which is the initial negative phase of the MRCP (see figure 2); this is also reflected in the most discriminative features, which were derived from the time window from -1 s to 0 s with respect to the movement onset. The MRCP has been used previously for detection of movement intentions in continuous single-trial EEG recordings [21, 31-33, 45] where ~80% in true positive rates were obtained for the lower limb and ~75% for the upper limb [20]. The performance of the detector in the current study is similar to this; however, the methodology and movement types are different. In the current study, the signal was divided into epochs (based on a priori knowledge), and background EEG and movement epochs were classified contrary to online systems or simulated online systems [21, 31-33, 45]. When comparing this classification-based approach to discriminate between movement and background EEG, similar performance is obtained for other studies where the detection performance was 80-90% [3, 6, 23]. The spectral features that were most discriminative were in the MRCP frequency range (0-5 Hz), but also 5-15 Hz where sensorimotor rhythms are modulated by movement preparation [35].

4.2. *Movement discrimination*

The best classification accuracies between the different movement types were 76±9% for pairwise comparisons of each movement type and 63±11% for the 3-class problem; this was obtained using spectral features. The spectral features were better than the temporal features which may be explained by the similarities in the signal morphology in the time domain (see figure 2 and 4). Moreover, the spectral features may be less sensitive to variability than the extracted temporal features. The classification accuracies were above chance level for all comparisons, which is around 58% for a 2-class problem and 40% for a 3-class problem (calculated with a significance level of 0.05) [30].

When the redundant features were removed using SFS, the performance was ~75%, which is similar to other studies where movement of the same body part is performed e.g. individual finger movements [4], types of wrist movement [14, 41, 42], analytical upper limb movements [16], and variation in speed and force of foot movements [13, 21]. However, the performance was better compared to the findings in a recent study where force and speed were decoded from the MRCP associated with palmar grasps using a single electrode and a single Laplacian-filtered channel [20] suggesting that several electrodes are needed to obtain high classification accuracy. This is partly supported by the analysis where it was found that the selected features were distributed over a large area, which include the pre-frontal cortex, premotor cortex, supplementary motor area, primary motor and sensory cortices and the posterior parietal cortex that among other brain structures contribute to the generation of movement preparatory brain signals such as MRCPs and sensorimotor rhythms. However, one needs to be a bit cautious when interpreting the findings. In figure 5 and 6 the total number of features contributing to each channel location is reported, but the amount of discriminative information that each feature contains is not accounted for. Also, volume conduction of the electrical signals is affecting the analysis, and due to this phenomenon, only a blurred image of the underlying activity is obtained from the EEG. The classification accuracies obtained with features derived from the MRCP frequency range were lower compared to those obtained when using features from the full-band EEG frequency range. This suggests that MRCP-based binary switches for movement detection should use the full-band EEG features when extending binary switches to have more degrees of freedom by e.g. decoding movement type as well to optimize the system performance (detection and classification) [20, 22]. The best frequency range, or the one that was identified most times, varied as well as the time window for extracting the temporal features. This variation suggests that subject-dependent features must be extracted to obtain the best performance.

4.3. Limitations

It was shown that the movements could be classified with respect to each other and to background EEG, and it was used as an estimate of BCI performance. It is expected that the performance of an online BCI where movements are detected and classified in real-time will decrease due to the use of a priori knowledge in this study regarding the division of the signal into epochs. In this way, the optimal epoch for feature extraction (from the movement onset and 2 s prior this point) was selected for all movements whereas the point of detection will vary in an online system. If movements are detected earlier, the classification accuracy will decrease, however, if the movements are detected later, the classification accuracies may increase due to more discriminative information is included in the analysis [21]. A problem with early and late detections with respect to the movement onset, however, is that the effect of neuromodulation protocols will vary [29]. The extraction of spectral features was performed in 5 Hz bins; this was chosen to avoid a too large feature vector. The frequency bins could be smaller e.g. 2 Hz; this would increase the dimensionality of the feature vector (from 225 to 625 in this study). However, a better physiological description of the discriminative features could be obtained, especially with a finer spectral resolution around the frequency bands for sensorimotor rhythms (e.g. mu and beta) where movement discriminative information has been reported [35]. A better spatial resolution could be obtained with high density EEG and with spatial filters to correct for the blurring that volume conduction causes to the EEG.

The analysis was performed offline, but due to the simplicity of the feature extraction and the reduced size of the feature vector, it is expected that it can be implemented as an online BCI. The use of SFS led to better performance compared to PCA, but it should be noted that the SFS approach is more time consuming than PCA when calibrating the BCI system. For SFS approach it takes ~550 s to perform the calibration on the contrary to ~0.2 s for the PCA approach; this could be a limiting factor for the technology transfer from the laboratory to the end user.

In this study, healthy volunteers performed the movements, on the contrary to the intended user group which is stroke patients with hemiparesis. The system performance may decrease to some extent depending on the level of motor impairment and motivation, but it was previously shown that the amplitudes of the different phases of the MRCP were similar in healthy subjects and stroke patients in the acute phase [18].

4.4. Implications

Given the detection of movements and discrimination between different movement types are independent of each other, the performance of a system that can be used for detection and classification can be found by multiplying the performance of the detection and discrimination. This leads to a system performance where 60% (79% * 76%) of the movements are correctly detected and classified. This level of performance has been shown to be sufficient for inducing neural plasticity for neurorehabilitation [33]. By predicting the forthcoming movement, the movement can be assisted or replicated through electrical stimulation or rehabilitation robots to augment the afferent feedback. In addition, when different types of hand movements are decoded, it is possible to design training programs where task variability of the different movements can be incorporated; this could maximize the retention of relearned movements [25]. However, it needs to be investigated if it is necessary to provide correct sensory feedback to the decoded movement intention. Ultimately, such a BCI system could be used at home by patients who still have residual disability after their rehabilitation has ended, but before this goal can be reached the BCI could serve as a tool for rehabilitation specialists as an intervention in itself or as a priming tool prior to e.g. physiotherapy. Potentially, it could be used as an extra control channel for prosthetic control. In this scenario, it could be implemented as a hybrid BCI, where brain activity is supplemented by electrical activity from the muscles.

5. Conclusion

In this study, it was shown that three different hand movements can be discriminated from background EEG with high accuracy, which provides an estimate of the performance of a detector used in BCI. A combination of temporal and spectral features was optimal to use. It was possible to classify the three movement types where the optimal techniques to use were spectral features. This may be used in BCI control paradigms such as neurorehabilitation and prosthetic control.

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The authors declare no competing financial interests.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

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