Upper Limb Complex Movements Decoding From Pre-Movement EEG Signals Using Wavelet Common Spatial Patterns

Mohseni, Mahdieh; Shalchyan, Vahid; Jochumsen, Mads; Niazi, Imran Khan

Published in:
Computer Methods and Programs in Biomedicine

DOI (link to publication from Publisher):
10.1016/j.cmpb.2019.105076

Publication date:
2020

Document Version
Accepted author manuscript, peer reviewed version

Citation for published version (APA):
Mohseni, M., Shalchyan, V., Jochumsen, M., & Niazi, I. K. (2020). Upper Limb Complex Movements Decoding From Pre-Movement EEG Signals Using Wavelet Common Spatial Patterns. *Computer Methods and Programs in Biomedicine*, *183*, Article 105076. Advance online publication. https://doi.org/10.1016/j.cmpb.2019.105076

Highlights

- Pre-movement EEG data in planning and preparation time-period can be used for accurate classification of complex movement.
- Spatio-spectral features are extracted using a combination of stationary wavelet transform and common spatial patterns.
- The gamma and beta frequency bands had the most contribution in the classification of complex movements
- A subset the most effective EEG channels for the complex movement classification is distributed over the prefrontal and frontal areas of the brain.

Upper Limb Complex Movements Decoding From Pre-Movement EEG Signals Using Wavelet Common Spatial Patterns

Mahdieh Mohseni[a], Vahid Shalchyan[a*], Mads Jochumsen[d], Imran Khan Niazi[b, c, d*]

a- Neuroscience and Neuroengineering Research Lab, Biomedical Engineering Department, School of Electrical Engineering, Iran University of Science & Technology (IUST), Narmak, Tehran, Iran

b- Centre for Chiropractic Research, New Zealand College of Chiropractic, Auckland, New Zealand

c- Faculty of Health & Environmental Sciences, Health & Rehabilitation Research Institute, AUT University, Auckland, New Zealand

d- Centre for Sensory-Motor Interactions (SMI), Department of Health Science and Technology, Aalborg University, Aalborg, Denmark

*Shared Corresponding Authors Emails: Shalchyan@iust.ac.ir (V. Shalchyan), Imran.niazi@nzchiro.co.nz (I.K. Niazi)

Abstract

Background and Objective: Decoding functional movements from electroencephalographic (EEG) activity for motor disability rehabilitation is essential to develop home-use brain-computer interface systems. In this paper, the classification of five complex functional upper limb movements is studied by using only the pre-movement planning and preparation recordings of EEG data.

Methods: Nine healthy volunteers performed five different upper limb movements. Different frequency bands of the EEG signal are extracted by the stationary wavelet transform. Common spatial patterns are used as spatial filters to enhance separation of the five movements in each frequency band. In order to increase the efficiency of the system, a mutual information-based feature selection algorithm is applied. The selected features are classified using the k-nearest neighbor, support vector machine, and linear discriminant analysis methods.

Results: K-nearest neighbor method outperformed the other classifiers and resulted in an average classification accuracy of 94.0±2.7% for five classes of movements across subjects. Further analysis of each frequency band's contribution in the optimal feature set, showed that the gamma and beta frequency bands had the most contribution in the classification. To reduce the complexity of the EEG recording system setup, we selected a subset of the 10 most effective EEG channels from 64 channels, by which we could reach an accuracy of 70%. Those EEG channels were mostly distributed over the prefrontal and frontal areas.

Conclusions: Overall, the results indicate that it is possible to classify complex movements before the movement onset by using spatially selected EEG data.

Keywords. EEG, Movement Classification, Wavelet Transform, k-nearest neighbors, Common spatial patterns, brain-computer interface.

Introduction

In recent years, brain-computer interfaces (BCIs) have been proposed as a means for neurorehabilitation after e.g. stroke [1, 2]. The BCI has been shown to artificially close the motor control loop that is disrupted by the lesion. The BCI can decode attempted movements through the EEG and trigger a device such as an exoskeleton or electrical stimulation that can provide relevant somatosensory feedback in response to the attempted movement [3-6]. By pairing the cortical activity associated with the attempted movement and the somatosensory feedback, it is hypothesized that Hebbian-associated plasticity is induced [7]. The clinical effect of using BCIs for stroke rehabilitation has been outlined in several studies where there is a general tendency that plasticity is induced in the patients and that they improve that motor function [8-11]. To further refine the use of BCI in motor disability rehabilitation, the next step could be to decode functional movements that are more complex and clinically relevant than simple isolated movements, although they are important too. These complex movements can also be more easily executed with modern exoskeletons that have become more sophisticated. However, the limitation could be the decoding of the functional movements from single-trial EEG since the electrical activity that is recorded is a blurred image of the underlying activity due to e.g. volume conduction [12]. In previous studies, it has been shown that different movement types with different kinetic profiles can be decoded [4, 6, 13, 14], but this is primarily simple isolated movements such as dorsiflexion of the ankle joint or wrist extension/flexion. Moreover, different movement types of the same limb have been decoded as well [15, 16]. It has also been shown that more complex movements can be detected from the EEG such as in [17], but to be used in rehabilitation where plasticity is induced only pre-movement activity should be used to fulfill the strict temporal association between efferent activity and somatosensory feedback [18]. It is expected that the somatosensory feedback should arrive at the cortical level <200-300 ms after the maximal efferent activity [7], which is at the time point where the motor control signal is sent to the spinal cord. This limits the amount of discriminative information that can be used to decode the intended movements. Despite the limited spatial resolution of the EEG, the hardware (amplifiers and electrodes) and the signal processing techniques improve and it may be possible to decode complex functional movements from single-trial EEG.

The time-frequency analysis of non-stationary EEG signals using wavelet transform is a widely used feature analysis technique in BCI systems [19-22]. Mousavi et al. have used wavelet packets (WP) decomposition, followed by common spatial pattern (CSP) filtering to analyze BCI signals [21]. CSP is commonly used in a two-class problem in BCI studies, but it can be used in multi-class problems as well [12, 23-25]. It finds a linear combination of the band-pass filtered EEG channels to increase the separability of two different classes of movements. It attempts to increase the variance of one class and simultaneously decrease the variance of the other class. This methodology is very useful in the BCI systems because the variance of a band-pass filtered signal is equal to its band-power. In [22], the discrete wavelet decomposition (DWT) was employed before a regularized CSP filtering for classification of simple center-out movements in four different directions. However, the time segment extracted for their analysis was one second before and after the movement cue. In other words, they have used the EEG data for the time of movement preparation, execution and a post-movement period, which is not well suited for the online BCI applications for inducing neural plasticity for neurorehabilitation.

The aim of this study is to decode five different complex functional upper limb movements that are trained in rehabilitation clinics by using only the EEG data corresponds to the pre-movement planning and preparation period. Here, we used the stationary wavelet transform (SWT) to decompose EEG signals into various sub-bands following by CSP filtering for classification of five different complex movements. Moreover, it is investigated what the effect of the number of channels is as well as the spectral contribution to the decoding. This will provide an estimate of the feasibility of developing a 5-class BCI that can decode functional movements from single-trial EEG using only motor planning activity. A brief review of the advantages and disadvantages of the current and previous similar studies is presented in Table 1.

Table 1. Comparison of the advantages and disadvantages for the current and previous studies.

Study	Task	Advantages	Disadvantages
[4]	Motor execution/imagery of four isometric palmar grasps	Using signals only 2 s before movement Employing stroke patients	Mean accuracy of 40% in four classes
[17]	Reaching and grasping the objects in a horizontal plane	Studying different numbers of channels	Mean accuracy of 65.9% in four class Using signals after movement onset
[22]	Center-out movement in four orthogonal directions in 2D horizontal plane	Mean accuracy of 80.2 % in four classes	Simple movements limited to the 2D horizontal plane Using signals after movement onset
[15]	Upper-limb gestures (elbow flexion/extension, arm supination/pronation and hand open/close)	Six classes of different kind of upper-limb gestures in the 3D space	Using signals after movement onset Mean accuracy of 55% in six classes
[46]	Foot reach to maximum voluntary contraction with fast+high and slow+low forces	Using signals only 2 s before movement Employing stroke patients	Two classes of simple movements Mean ACC of 57% in 2 class
[47]	Open and close the affected hand in stroke patients	Employing stroke patients	Mean accuracy of 69.5% for two classes Using signals after movement onset
*This Study	Five different complex functional upper-limb movements	Using signals only 3s before movement Mean accuracy of 94.0 % in five classes Studying different numbers of channels	Employing only healthy subjects

Methods

A. Subjects

Nine right-handed healthy volunteers participated in this study (5 male and 4 female, age: 23±3 years). All procedures were approved by the local ethics committee (N-20130081), and the experiments were conducted according to the Helsinki Declaration. All subjects gave their written informed consent prior to participation.

B. Experimental protocol

Initially, the subject was seated in a chair and a 64-channel active EEG cap using the 10-10 system was mounted (g.GammaCap, Guger Technologies, Austria). The EEG was amplified (g.HIamp, Guger Technologies, Austria) and referenced to the left and right ear lobe. The EEG was recorded with a sampling frequency of 512 Hz. Continuous EEG was recorded while the subject performed five different functional tasks of the upper extremities, each of the five functional tasks was performed 50 times in total. The movements were performed in blocks of 10 movements of the same task; the order of the blocks was randomized. Each movement was verbally cued by the experimenter who indicated the initiation of the movement by counting down from three, after which the experimenter placed a marker in the continuous EEG. This was used to synchronize the EEG into epochs in the processing. During this pre-movement period, and during the movement execution, the subject was instructed to sit as still as possible and avoid blinking. Each movement was separated by ~5-10 s. The starting and ending position for each movement was when the subject rested both hands in the lap. The five different movements were: 1) Reaching out and picking up an empty glass from a table with the right hand, raise the glass to the mouth and place it on the table again (the position of the glass was fixed), 2) a ball toss from the right to the left hand, 3) lifting a tray ~20 cm up from the table with both hands and placing it on the table again, 4) push a glass forward from one position to another on the table with the right hand (the distance between the positions was 20 cm), 5) pick up a pen and write the letter "H" using the right hand.

C. Preprocessing

First, the EEG data were filtered between 0.3 Hz to 70 Hz by means of a 4th order zero-phase Butterworth filter to remove the direct current shifts and to remove the high-frequency noise components in the signal. In addition, the power-line interference was suppressed with a notch filter at 50 Hz. To remove artifacts caused by eye-blinks, eye movements, and muscle activities from the face, neck and shoulder movements a SOBI blind Source Separation algorithm [27] from the automatic artifact removal (AAR) toolbox as an EEGLAB plug-in [28] was used. Afterward, we re-referenced the data to a common average reference where the average across all channels as an estimate of common noise reference was removed from each channel independently [29]. In this study, we only used the EEG signals in a three seconds time-window before the physical movement. Therefore, the continuous EEG data were segmented into three seconds trials leading to the movement initiation. Fig. 1 shows an example of single-trial EEG data in a three seconds time-window before the movement for 5 different movement types in selected channels from frontal, central and parietal lobes. After the pre-processing step, the data is further processed using the proposed algorithm as described in the following sections. An overview of the proposed algorithm as a block diagram is presented in Fig. 2.

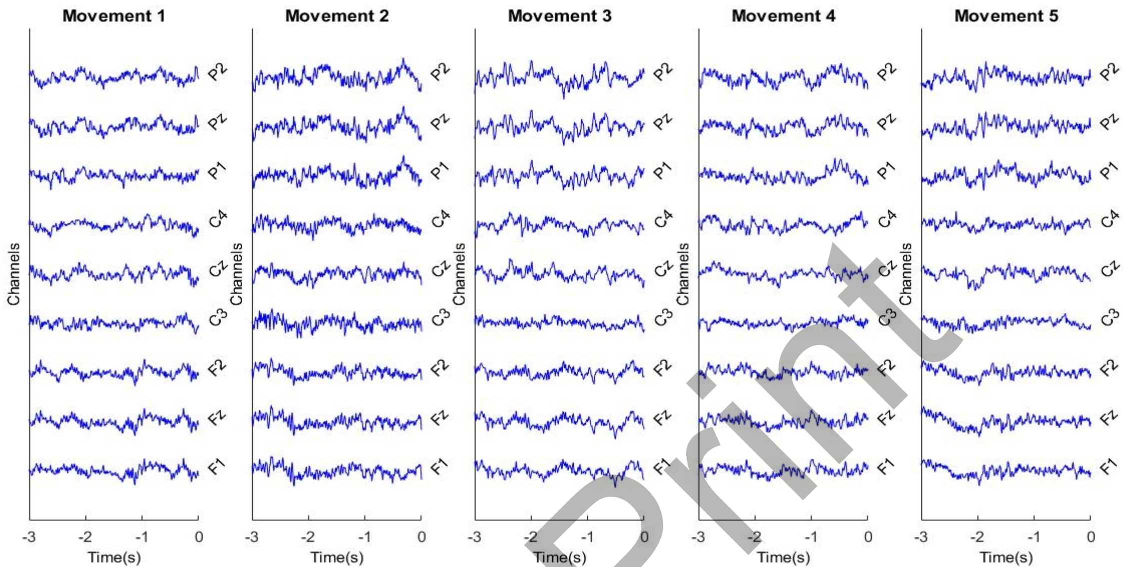

Figure 1. Single-trial pre-movement EEG signals after preprocessing in F1, Fz, F2, C3, Cz, C4, P1, Pz and P2 channels in 5 movements.

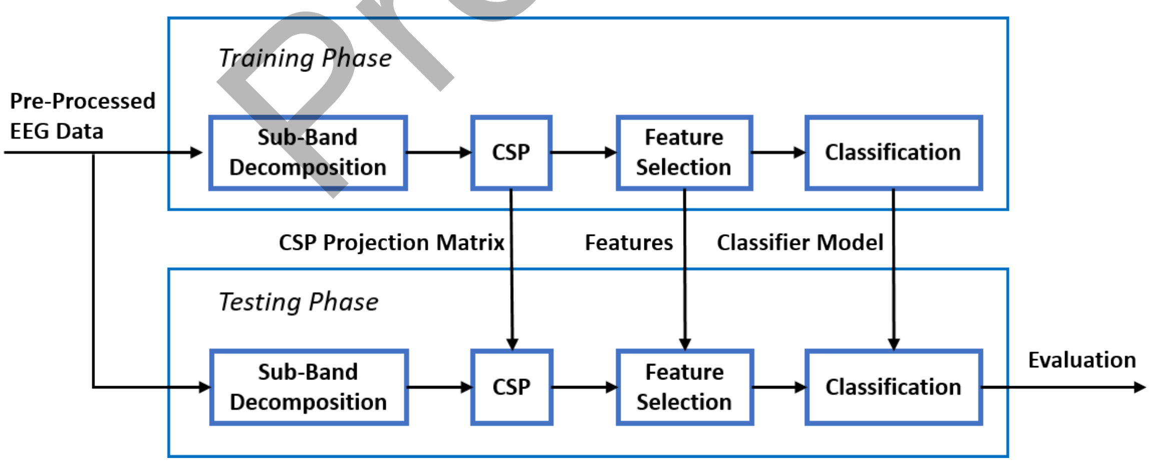

Figure 2. The block diagram of the proposed algorithm for classification of hand movements. Splitting the pre-processed data into training and testing folds during the cross-validation is indicated. After frequency sub-band decomposion, the training data create the best CSP filters, select the best features and train the classifier model. The learned CSP matrix, best features, and classifer model are used in the testing phase for the evaluation.

D. Feature extraction

D.1.Wavelet decomposition analysis. Here, we used the stationary wavelet transform (SWT) to decompose EEG signals into various sub-bands. The SWT can overcome the problem of shift-variance that exists in the DWT by removing the decimation step at each decomposition level [30]. Daubechies mother wavelets have resulted in more accurate BCI systems in other studies [31, 32]. Hence, in this study, we used the db4 mother wavelet for SWT decomposition. By applying eight levels of SWT decomposition on the filtered EEG signals, eight wavelet details and one wavelet approximation sub-bands were created (Fig. 3). According to 256 Hz sampling rate of the signal, after the decomposition, the following frequency sub-bands were created: 64-128 Hz, 32-64 Hz, 16-32 Hz, 8-16 Hz, 4-8 Hz, 2-4 Hz, 1-2 Hz, 0.5-1 Hz, 0.25-0.5 Hz, and 0-0.25 Hz. The highest frequency sub-band was not used because the signal has been previously filtered up to 70 Hz in the preprocessing step. Therefore, we had nine sub-bands to produce features. For comparison, we

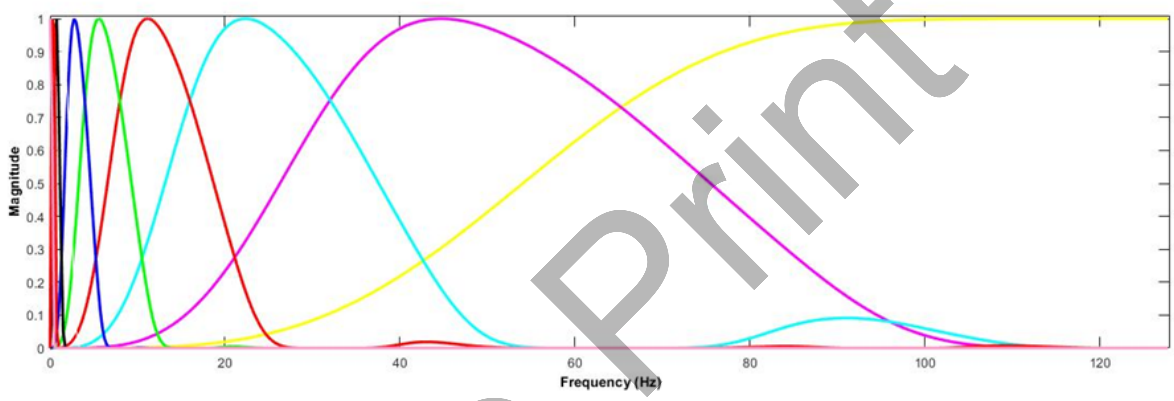

Figure 3. Magnitude frequency responses for SWT sub-band decomposition filters based on db4 mother wavelet.

also used the filter-bank and DWT method with the same frequency sub-bands as the SWT. The filter-bank decomposition was made by using 4th order zero-phase Butterworth band-pass filters with the cut-off frequencies of 32-64 Hz, 16-32 Hz, 8-16 Hz, 4-8 Hz, 2-4 Hz, 1-2 Hz, 0.5-1 Hz, 0.25-0.5 Hz, and 0-0.25 Hz.

D.2.Spatial filtering. In the next step, we spatially filtered each filter bank or wavelet sub-band using a CSP spatial filter. In this research, we applied a CSP in each sub-band over all EEG channels to increase the difference between various movement classes. The one-versus-all (OVA) scheme was used to obtain multiple binary CSPs for this multi-class problem. If the band-pass filtered EEG data denoted as $\mathbf{S}$, the normalized covariance matrix is calculated as follows:

$$C = \frac{SS^T}{trace(SS^T)} \qquad (1)$$

Where "T" denotes the transpose operator and the trace (.) is the sum of the diagonal elements of a matrix. For each of the binary classes, the class covariance (i.e., C_1 or C_2) is calculated by averaging the covariance matrix over the trials of each class. Considering $C_c = {C_2}^{-1} C_1$, the Eigen decomposition of the Cc results in $C_c = U$□□U^T, where U is the eigenvector matrix and □

is the diagonal eigenvalue matrix with the eigenvalues are sorted in descending order. The CSP filter is comprised of the first m columns of eigenvector matrix associated with the m highest eigenvalues of the C_c matrix. The feature vector of $(m \times 5 \times 9)$ dimensions was obtained from the logarithm of variance over the first m outputs from five OVA-CSPs in nine wavelet sub-bands. For setting the parameter m, we obtained the accuracies over all subjects for training data containing the first recorded session with different values of m in one loop. The highest accuracy was obtained when using m=17.

E. Feature selection

A high dimension feature space is usually associated with a higher data collection cost, more difficulty in model interpretation, a higher computational cost for the classifier, and decreased accuracy of the system. Therefore, one of the important parts of the system is selecting an informative feature subset. The mutual information (MI) based feature selection methods have been successfully used with the filter-bank CSP (FBCSP) approach in BCI studies to select the best subset of features that maximize the MI between class labels and feature sets [22, 33, 34]. In this study, we used the MI [35] to choose a subset of features that provide the most discrimination in classes, produce higher classification accuracy and increase the efficiency of the system. Regarding the selection of $m=17$ in this study, over the total number of 765 features, we selected the first N=95 features for each subject. This parameter (i.e. N) was obtained by an optimization process on the training data across all subjects. The training data of each subject were divided into the estimation and the evaluation subsets based on 10-folds cross-validation. The MI criterion was used to sort the features in the estimation subset in descending order while the accuracy was calculated when using the first N features from the sorted list on the evaluation subset. The average accuracy across all folds and all subjects was optimized by varying the N parameter. The best result was obtained when using the first N=95 features.

F. Classification

To discriminate between these five classes, the k-nearest neighbors (K-NN) classifier was employed. This classifier assigns the class label of new data based on the class with the most occurrences in a set of k nearest training data points usually computed using a distance measure [34]. In this study, we used the Manhattan (L1-Norm) distance and $K=1$ for K-NN implementation. To compare the efficiency of K-NN, we also used support vector machine (SVM) and linear discriminant analysis (LDA) as other commonly used classifiers in similar studies [4, 6, 14, 15, 22]. To apply LDA and SVM binary classifiers to our multi-class problem, the one-versus-one technique is used.

G. Evaluation

The following three performance parameters were calculated in order to quantify the classification performance for different methods: Accuracy (in %) - correctly predicted observations with respect to all observations. Precision (in %) - correctly predicted positive observations with respect to all predicted positive observations. Recall (in %) - correctly predicted positive observations with respect to the total observations. For calculation of the classification performance parameters, the data set of each subject is divided into a training and test set. The training set is used for training the classifier model and selecting the best features, whereas the test set was used for evaluating the classification. For this aim, 10-fold cross-validation is used.

Paired-wise *t*-test is used for statistical comparison of the performance parameters of different methods. The level of significance was considered as P=0.05.

In BCI problems, information transfer rate (ITR) or bit rate (i.e. bits/min) is usually a matter of concern. As described in [12], the number of bits, or *B*, transmitted per a single-trial of multi-class selection can be calculated as:

$$B = \log(N) + P\log(P) + (1-P)\log\left(\frac{1-P}{N-1}\right) \qquad (2)$$

Where *N* is the number of possible classes and *P* is the classifier accuracy. *ITR* or bits/min can then be computed by dividing *B* by the trial duration in min.

Although the online classification was not included in the scope of this work, in order to evaluate the overall feasibility of the proposed method for later investigations in online mode, we calculated the computational cost for running one trial movement classification. The computational cost was defined as the time needed for extracting selected features and obtaining the class labels using the trained classifier in a single-trial. To obtain this execution time, we used the MATLAB® R2016a on a PC with an Intel Core i7 CPU.

Results

In this paper, we studied the classification of five different kinds of movements with the upper extremities on the time segment of 3s before the movement using wavelet decomposition and CSP filtering. The broad frequency range of the EEG signal was decomposed to several frequency sub-bands. In this study, we used all sub-bands between 0.3-70 Hz that includes the full EEG spectrum. The classification results and efficiency of these sub-bands and various supporting analyses are provided in this Section.

A. Mother wavelet selection

The choice of the mother wavelet is an important issue and can affect classification performance. In this study, the classification accuracies were based on seven different mother wavelet functions: db3, db4, db6, coif3, Bior2.2, sym3, and sym4. The obtained results are shown in Fig. 4. Although there is not any significant difference between the accuracies obtained from different mother wavelets, the db4 mother wavelet outperformed others on average, and therefore it was used for all calculations in this paper.

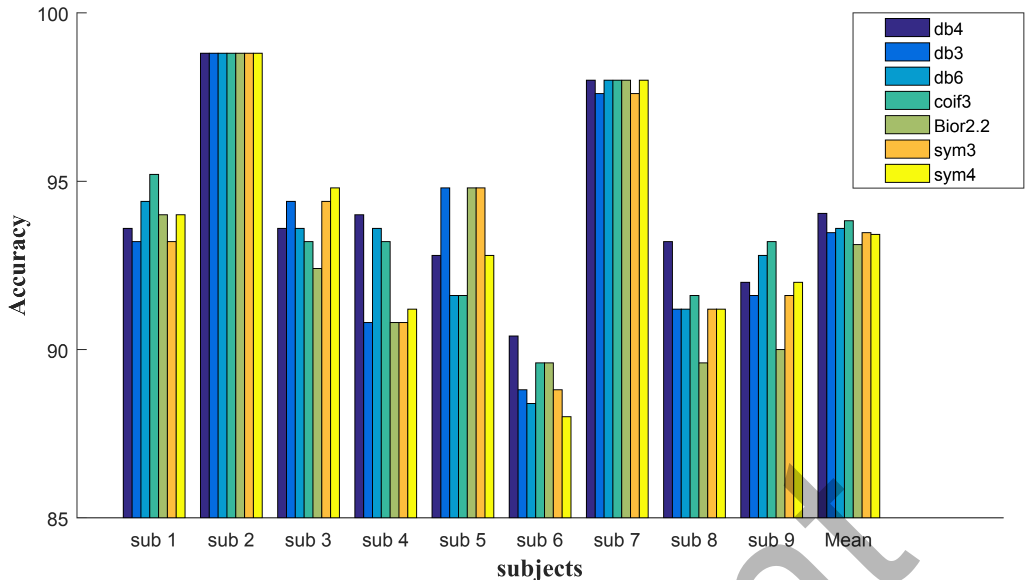

Figure 4. Classification accuracies based on seven different mother-wavelet functions including db4, db3, db6, coif3, bior 2.2, sym3, and sym4.

B. Classification results

The summary of the classification performance parameters achieved across all subjects for the FBCSP, the DWT-CSP and the SWT-CSP with K-NN, SVM, and LDA classifiers are shown in Table 2. Performance parameters include accuracy, precision, and recall. We obtained an average (± standard deviation) classification accuracy of 94.0±2.7% using SWT-CSP followed by K-NN classification for 5-class movement discrimination. With the same features, the average accuracies of 88.9±7.4 and 60.0±14.7 were calculated with SVM and LDA, respectively. Because of the better performance of K-NN in comparison to SVM and LDA, K-NN was used for further analysis. When using K-NN as the classifier, different feature extraction methods are compared in the first three rows of Table 2. The results showed that SWT-CSP in terms of all performance parameters significantly outperformed (p-value < 0.01) both DWT-CSP and FBCSP. On the other hand, with the fixed K-NN classifier, the average (± standard deviation) ITR of 5.2± 4.3, 12.14±3.7 and 13.5± 1.2 Bit/min were obtained for FBCSP, DWT-CSP and SWT-CSP feature extraction methods, respectively. This shows the superiority of SWT-CSP over FBCSP and DWT-CSP in terms of ITR criterion. Therefore, The SWT-CSP feature extraction method was selected to be used for further analyses.

The results of classification accuracy performances for all subjects using different feature extraction methods including, SWT-CSP, FBCSP, and DWT-CSP with K-NN classifier are presented as bar charts in Fig. 5. Subject 2 showed the best classification result (accuracy of 98.8±1.9%), while the worst accuracies were obtained for subjects 6 and 9 (90.4±9.3% and 92±6.2%, respectively).

Table 2. Summary of the average (± standard deviation) classification performance parameters obtained across all subjects for three feature extraction methods of FBCSP, DWT-CSP, and SWT-CSP and three classification methods of K-NN, SVM and LDA.

Classification	Feature Extraction	Accuracy	Precision	Recall
K-NN	FBCSP	62.6±17.8	61.2±22.1	58.9±21.6
	DWT-CSP	89.0±9.9	89.1±18.7	89.0±16.3
	SWT-CSP	94.0±2.7	95.1±2.1	94.0±2.7
SVM	FBCSP	58.1± 10.3	61.0± 12.0	58.1± 22.3
	DWT-CSP	88.7±8.0	91.0±8.6	88.7±10.2
	SWT-CSP	88.9± 7.4	90.6± 6.3	88.9± 7.4
LDA	FBCSP	45.6± 11.9	43.1± 12.5	45.6± 11.7
	DWT-CSP	56.6±16.7	54.1± 22.9	56.4±22.2
	SWT-CSP	60.0± 14.7	58.0± 12.8	60.0± 11.4

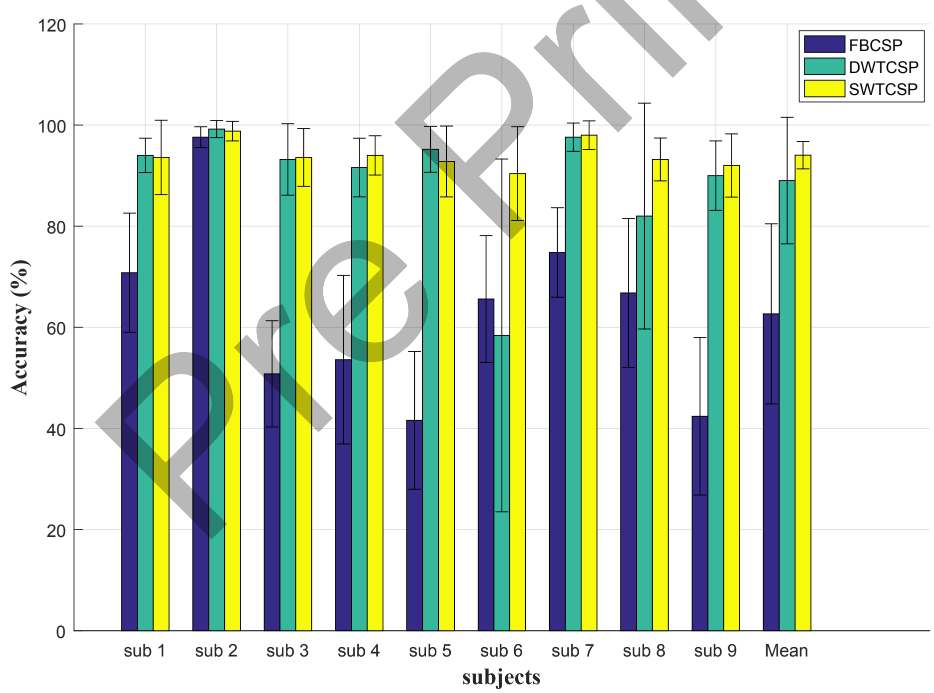

Figure 5. K-NN classification accuracies of all subjects for three feature extraction methods: FBCSP, DWT-CSP and SWT-CSP.

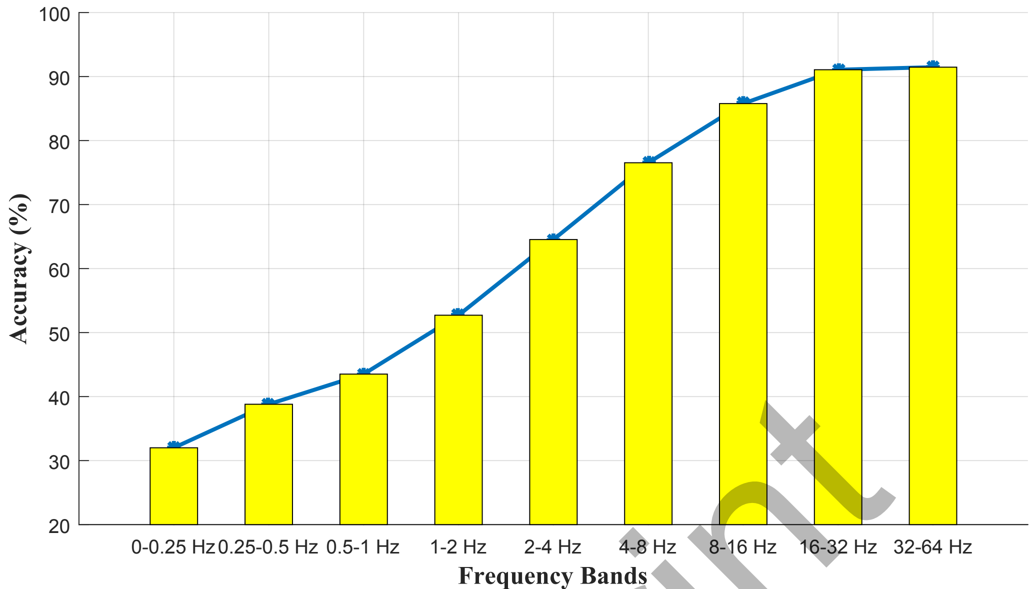

Figure 6. Average performance accuracy of all subject in different frequency ranges.

C. Contribution of different frequency sub-bands

In this part, we studied the contribution of different wavelet frequency sub-bands in the classification performance. For this purpose, the classification accuracy was obtained for each frequency band alone. The calculation was performed without using feature selection. The results are reported in Fig. 6. According to the obtained results, high-frequency sub-bands had better performance compared to low frequency. The results showed that using either the beta (16-32 Hz) or the gamma (32-64 Hz) sub-bands, a classification accuracy over 90% can be obtained.

In order to investigate the contribution percent of different frequency sub-bands in MI-based feature selection, the average number of the selected features of each frequency sub-band obtained by MI selection across subjects and 10-folds of cross-validation was calculated and divided by the total number of features. Fig. 7 demonstrates these percent's contribution for each frequency sub-band. This figure shows that more than 70% of the MI-based selected features belong to the alpha, beta and gamma sub-bands.

D. Channel selection

According to [37], many of the EEG channels may represent redundant information. This means that there is no need to analyze all 64 EEG channels [38]. On the other hand, recording from a large number of EEG channels involves high costs, user difficulties and timely procedure for setting up, which makes it unsuitable for online applications and clinical applications. Therefore, in this work, we aimed to study how to select a small subset of EEG channels while keeping the high classification performance to reduce the complexity of the system. For this purpose, the absolute channel weight values of the corresponding CSP filters for the best 10 selected features

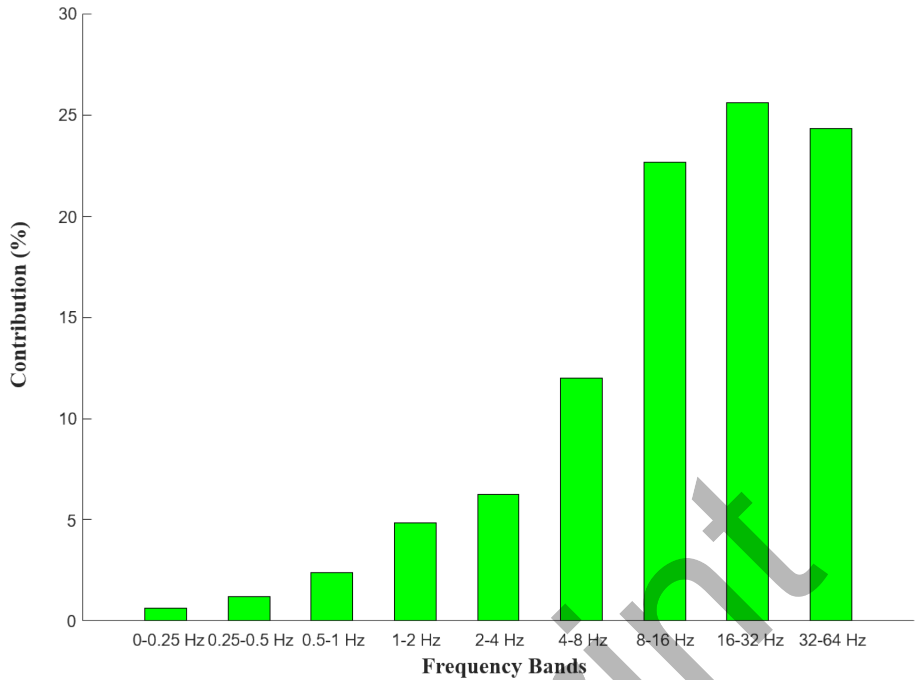

Figure 7. Average number of selected features in each frequency sub-band with MI feature selection criterion across subjects and cross-validation folds.

in each subject were normalized into the range (0, 1). The obtained normalized channel weight vectors were averaged across 10 folds and across subjects. Fig. 8 depicts the topographic distribution of the averaged channel weight vector for all 64 channels. This topography map shows the representative contribution of the prefrontal and frontal EEG channels in the classification of

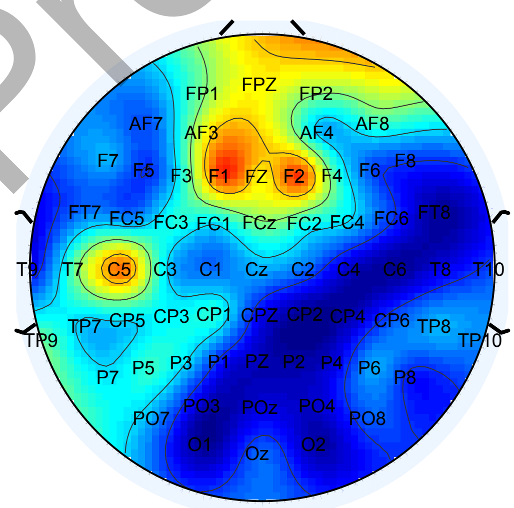

Figure 8. The topographic distribution of the averaged channel weight vectors across the selected features and across subjects.

different movement tasks during movement preparation and planning period. Also, some electrodes in the central and temporal areas have considerable weights on the map.

For selecting the best subset of important channels, the channels were sorted according to their averaged channel weight vector in the descending order. Fig. 9 represents the average classification accuracies obtained when only the *n* first number of the EEG channels from the sorted list were used in the proposed algorithm. According to this figure, by using only 10 first channels, we can reach a classification accuracy close to 70%. Comparing this result with the previous results obtained when using all 64 channels, shows nearly 24% of accuracy loss in return for an 85% reduction in the number of used channels. The average computational cost of the proposed method for a single-trial movement feature extraction and classification using all 64 channels was 0.93±0.03 sec, whereas after reducing the number of channels into 10 channels, the average computational cost was reduced to 0.72±0.02 sec.

Discussion

In this paper, five complex movements of the upper limb are classified using the combination of CSP and SWT. On the contrary to many other studies, only the EEG signal before the start of movement was used to classify these movements. Applying this processing limitation makes it possible to implement the application and use it in BCI systems for neurorehabilitation where neural plasticity is induced. In addition, another goal of this study was to analyze the effect of reducing the number of recorded channels on classification accuracy of the system, so that it can be used for online applications and it is feasible to use in a clinical setting. In the previous sections,

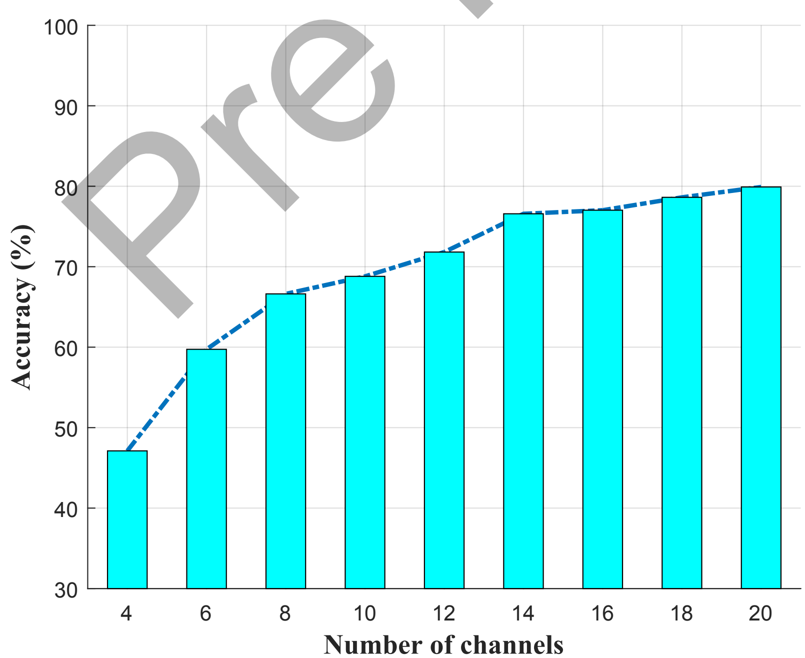

Figure 9. Average classification accuracies for different number of channel subsets.

signal processing techniques were used and the results of them presented. In this section, we will discuss the results obtained.

A. Major findings

A multi-class complex movement decoding problem is successfully addressed by combining the method of extracting the SWT and CSP features with 9 healthy users. In addition, FBCSP and DWT-CSP methods, which have been previously employed in motor imaginary/execution classification [22, 33, 39], are used with the same frequency bands. The results of this work showed that SWT-CSP outperformed both FBCSP and DWT-CSP in all classification performance parameters and in information transfer rate. The reason may lie in the over complete representation of the SWT which comes from overlaps between adjacent frequency sub-bands. By applying a proper method to select the appropriate features, as used in this paper, the probability of extracting the optimal features from this over complete representation is increased. Our focus on this paper was proposing a method for advanced feature extraction and classification of the complex movements from pre-movement EEG signals. Hence we chose the K-NN algorithm because it's useful and simple application in multi-class problems. Other advantages of this classification method are that it needs only one hyperparameter setting and has a low computational cost. In our analysis, we compared K-NN classifier with both LDA and SVM algorithms and it outperformed both of the compared methods.

With the evaluation of different frequency bands, the gamma, beta, and alpha bands had major contributions in the MI-based selected subset of features (Fig. 7). Also, when the accuracy of the classification was calculated by using single-frequency sub-bands, the beta and gamma bands led to the highest accuracies (Fig. 6). In previous studies, BCI systems that use motor execution or motor imagery classification have often reported the significant role of the mu and beta bands in the production of sensory-motor rhythms [12]. Although most of these studies have used the signal from before to after the movement or motor imagery, we only used the time before the start of the movement. In line with these results, the power modulation of the beta and gamma bands during motor execution was reported in [40], and also the effect of the gamma band during movement preparation and planning period has been emphasized in [41].

One of the objectives in this study was to reduce the number of EEG channels, so the system complexity is reduced in terms of setup time and cost, and potentially the user-friendliness for home users. For this objective, a subset of the best channels was selected by employing the MI criterion. Studying the MI-based selected channels showed a spatial distribution of them over the prefrontal and frontal areas (Fig. 8). In [42], the anatomy of the cortex has been studied in different areas related to the direction of arm movement. They reported the gamma band from the frontal and central areas had the most contribution to the movement direction. According to the functional actions of the frontal area that carries out many activities, such as planning, decision-making, and movement execution, these results are expected. The function of the system has been recalculated using only this selected subset of channels. With the results obtained, only by using 10 channels, we could achieve the 70% accuracy and reducing 22% runtime of the algorithm. Moreover, the setup time will be reduced. To design a more practical BCI system, a higher computational speed, a lower complexity of the method and reducing setup time has great importance.

B. Limitations

In the current study, all steps including the feature extraction, model learning, and classification were implemented offline. However, for a more practical BCI system, which was not the scope of this study, there is a need to develop an online system and reduce the computational time for classification further to obtain the strict timing needed for neurorehabilitation purposes. In future studies, the reduced number of channels can be used in areas that are specific for movement, so that more information can be obtained. On the other hand, this test has been performed only on healthy subjects, while one of the requirements for the development of the uses of this classification for BCI applications is to help people with motor disabilities while they attempt to do the movement. By doing this, the results can be generalized to patient groups. On the other hand, in some cases the EEG activity after a stroke because of damage the motor cortex makes a challenge to detect movement intentions. In this case, adding other signal related to movement like EMG can be useful [47].

There are, of course, many other useful features that can be extracted from the EEG signals for classification of movements such as higher-order moments or other nonlinear statistical features that have not been tested in this work. However, our initial intention was to focus on combining the CSP as a powerful spatial filter with wavelet or filter-bank spectral features for the classification of movements. Other features as indicated can also be further studied in future works.

Conclusion

In this paper, the classification of five different complex functional upper limb movements using only time segment before the start of movement was studied. For this purpose, a time-frequency feature obtained by SWT, combined with CSP was extracted. Overall, the K-NN algorithm performed better as compared to LDA and SVM. According to the results, this method has been able to classify 5 different movements successfully with obtaining a mean accuracy of 94%. To study different frequency bands, gamma and beta had the most contribution to performance, which can indicate the relationship between activity related to movement planning time and these frequency bands. On the other hand, by studying the effect of different channels selected by mutual information, most of the selected channels were placed on the frontal area. According to the above results, it is possible to use only gamma and beta bands of the frontal area and obtain similar results. Considering that only the time before the movement was extracted it can be used to design online BCI systems for neurorehabilitation.

References

[1] Van Dokkum L, Ward T, Laffont I. Brain computer interfaces for neurorehabilitation–its current status as a rehabilitation strategy post-stroke. Annals of physical rehabilitation medicine. 2015;58:3-8.

[2] Daly JJ, Wolpaw JR. Brain–computer interfaces in neurological rehabilitation. The Lancet Neurology. 2008;7:1032-43.

[3] Niazi IK, Mrachacz-Kersting N, Jiang N, Dremstrup K, Farina D. Peripheral electrical stimulation triggered by self-paced detection of motor intention enhances motor evoked potentials. IEEE transactions on neural systems rehabilitation engineering. 2012;20:595-604.

[4] Jochumsen M, Niazi IK, Taylor D, Farina D, Dremstrup K. Detecting and classifying movement-related cortical potentials associated with hand movements in healthy subjects and stroke patients from single-electrode, single-trial EEG. Journal of neural engineering. 2015;12:056013.

[5] Xu R, Jiang N, Mrachacz-Kersting N, Lin C, Prieto GA, Moreno JC, et al. A closed-loop brain-computer interface triggering an active ankle-foot orthosis for inducing cortical neural plasticity. IEEE Trans Biomed Engineering. 2014;61:2092-101.

[6] Jochumsen M, Niazi IK, Mrachacz-Kersting N, Jiang N, Farina D, Dremstrup K. Comparison of spatial filters and features for the detection and classification of movement-related cortical potentials in healthy individuals and stroke patients. Journal of neural engineering. 2015;12:056003.

[7] Grosse-Wentrup M, Mattia D, Oweiss K. Using brain–computer interfaces to induce neural plasticity and restore function. Journal of neural engineering. 2011;8:025004.

[8] Mrachacz-Kersting N, Jiang N, Stevenson AJT, Niazi IK, Kostic V, Pavlovic A, et al. Efficient neuroplasticity induction in chronic stroke patients by an associative brain-computer interface. Journal of neurophysiology. 2015;115:1410-21.

[9] Ang KK, Chua KSG, Phua KS, Wang C, Chin ZY, Kuah CWK, et al. A randomized controlled trial of EEG-based motor imagery brain-computer interface robotic rehabilitation for stroke. Clinical EEG neuroscience. 2015;46:310-20.

[10] Ang KK, Guan C, Phua KS, Wang C, Zhou L, Tang KY, et al. Brain-computer interface-based robotic end effector system for wrist and hand rehabilitation: results of a three-armed randomized controlled trial for chronic stroke. Frontiers in neuroengineering. 2014;7:30.

[11] Frolov AA, Mokienko O, Lyukmanov R, Biryukova E, Kotov S, Turbina L, et al. Post-stroke rehabilitation training with a motor-imagery-based brain-computer interface (BCI)-controlled hand exoskeleton: a randomized controlled multicenter trial. Frontiers in neuroscience. 2017;11:400.

[12] Blankertz B, Tomioka R, Lemm S, Kawanabe M, Muller K-RJISpm. Optimizing spatial filters for robust EEG single-trial analysis. IEEE Signal processing magazine. 2008;25:41-56.

[13] Gu Y, Dremstrup K, Farina D. Single-trial discrimination of type and speed of wrist movements from EEG recordings. Clinical Neurophysiology. 2009;120:1596-600.

[14] Farina D, Do Nascimento OF, Lucas M-F, Doncarli C. Optimization of wavelets for classification of movement-related cortical potentials generated by variation of force-related parameters. Journal of neuroscience methods. 2007;162:357-63.

[15] Ofner P, Schwarz A, Pereira J, Müller-Putz GR. Upper limb movements can be decoded from the time-domain of low-frequency EEG. PloS one. 2017;12:e0182578.

[16] Jochumsen M, Niazi IK, Dremstrup K, Kamavuako EN. Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation. Medical biological engineering computing. 2016;54:1491-501.

[17] Schwarz A, Ofner P, Pereira J, Sburlea AI, Müller-Putz GR. Decoding natural reach-and-grasp actions from human EEG. Journal of neural engineering. 2017;15:016005.

[18] Mrachacz-Kersting N, Kristensen SR, Niazi IK, Farina D. Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity. The Journal of physiology. 2012;590:1669-82.

[19] Qin L, He B. A wavelet-based time–frequency analysis approach for classification of motor imagery for brain–computer interface applications. Journal of neural engineering. 2005;2:65.

[20] Yang B-h, Yan G-z, Yan R-g, Wu T. Adaptive subject-based feature extraction in brain–computer interfaces using wavelet packet best basis decomposition. Medical engineering physics. 2007;29:48-53.

[21] Mousavi EA, Maller JJ, Fitzgerald PB, Lithgow BJ, Control. Wavelet common spatial pattern in asynchronous offline brain computer interfaces. Biomedical Signal Processing. 2011;6:121-8.

[22] Robinson N, Guan C, Vinod A, Ang KK, Tee KP. Multi-class EEG classification of voluntary hand movement directions. Journal of neural engineering. 2013;10:056018.

[23] Grosse-Wentrup M, Buss M. Multiclass common spatial patterns and information theoretic feature extraction. IEEE transactions on Biomedical Engineering. 2008;55:1991-2000.

[24] Ramoser H, Muller-Gerking J, Pfurtscheller G. Optimal spatial filtering of single trial EEG during imagined hand movement. IEEE transactions on rehabilitation engineering. 2000;8:441-6.

[25] Hernández LG, Antelis JM. Self-paced movement intention recognition from EEG signals during upper limb robot-assisted rehabilitation. 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER): IEEE; 2019. p. 69-72.

[26] Yan T, Jingtian T, Andong G. Multi-class EEG classification for brain computer interface based on CSP. 2008 International Conference on BioMedical Engineering and Informatics: IEEE; Vol. 2. 2008. p. 469-72.

[27] Yeredor A. Blind separation of Gaussian sources via second-order statistics with asymptotically optimal weighting. IEEE Signal Processing Letters. 2000;7:197-200.

[28] Gómez-Herrero G. Automatic artifact removal (AAR) toolbox v1. 3 (Release 09.12. 2007) for MATLAB. Tampere University of Technology. 2007.

[29] Foodeh R, Khorasani A, Shalchyan V, Daliri MR. Minimum noise estimate filter: A novel automated artifacts removal method for field potentials. IEEE transactions on neural systems rehabilitation engineering. 2017;25:1143-52.

[30] Nason GP, Silverman BW. The stationary wavelet transform and some statistical applications. Wavelets and statistics: Springer; 1995. p. 281-99.

[31] Li D, Pedrycz W, Pizzi N. Fuzzy wavelet packet based feature extraction method and its application to biomedical signal classification. IEEE transactions on Biomedical Engineering. 2005;52:1132-9.

[32] Yang B-h, Yan G-z, Wu T, Yan R-g. Subject-based feature extraction using fuzzy wavelet packet in brain–computer interfaces. Signal processing. 2007;87:1569-74.

[33] Zhang H, Ang KK, Guan C, Wang C. Spatio-spectral feature selection based on robust mutual information estimate for brain computer interfaces. Engineering in Medicine and Biology Society, 2009 EMBC 2009 Annual International Conference of the IEEE: IEEE; 2009. p. 4978-81.

[34] Ang KK, Chin ZY, Zhang H, Guan C. Filter bank common spatial pattern (FBCSP) in brain-computer interface. Neural Networks, 2008 IJCNN 2008(IEEE World Congress on Computational Intelligence) IEEE International Joint Conference on IEEE; 2008. p. 2390-7.

[35] Zhang H, Guan C, Li Y. A linear discriminant analysis method based on mutual information maximization. Pattern Recognition. 2011;44:877-85.

[36] Li D, Pedrycz W, Pizzi NJJITobe. Fuzzy wavelet packet based feature extraction method and its application to biomedical signal classification. IEEE Transactions on biomedical engineering 52.6; 2005;52:1132-9.

[37] Sleight J, Pillai P, Mohan S. Classification of executed and imagined motor movement EEG signals. Ann Arbor: University of Michigan. 2009:1-10.

[38] Alomari MH, Samaha A, AlKamha K. Automated classification of L/R hand movement EEG signals using advanced feature extraction and machine learning. arXiv preprint arXiv. 2013.

[39] Ang KK, Chin ZY, Wang C, Guan C, Zhang H. Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b. Frontiers in neuroscience. 2012;6:39.

[40] Pfurtscheller G, Graimann B, Huggins JE, Levine SP, Schuh LA. Spatiotemporal patterns of beta desynchronization and gamma synchronization in corticographic data during self-paced movement. Clinical neurophysiology. Clinical neurophysiology 114.7 ;2003; 1226-1236.

[41] Thürer B, Stockinger C, Focke A, Putze F, Schultz T, Stein T. Increased gamma band power during movement planning coincides with motor memory retrieval. Neuroimage. 2016;125:172-81.

[42] Ball T, Schulze-Bonhage A, Aertsen A, Mehring C. Differential representation of arm movement direction in relation to cortical anatomy and function. Journal of neural engineering. 2009;6:016006.

[43] Park C, Plank M, Snider J, Kim S, Huang HC, Gepshtein S, et al. EEG gamma band oscillations differentiate the planning of spatially directed movements of the arm versus eye: multivariate empirical mode decomposition analysis. IEEE transactions on neural systems rehabilitation engineering. 2014;22:1083-96.

[44] Darvas F, Scherer R, Ojemann JG, Rao R, Miller KJ, Sorensen LB. High gamma mapping using EEG. Neuroimage. 2010;49:930-8.

[45] Pfurtscheller G, Graimann B, Huggins JE, Levine SP, Schuh LA. Spatiotemporal patterns of beta desynchronization and gamma synchronization in corticographic data during self-paced movement. Clinical neurophysiology. 2003;114:1226-36.

[46] Jochumsen M, Khan Niazi I, Samran Navid M, Nabeel Anwar M, Farina D, Dremstrup K. Online multi-class brain-computer interface for detection and classification of lower limb movement intentions and kinetics for stroke rehabilitation. Brain-Computer Interfaces. 2015;2:202-10.

[47] Lóopez-Larraz E, Birbaumer N, Ramos-Murguialday A. A hybrid EEG-EMG BMI improves the detection of movement intention in cortical stroke patients with complete hand paralysis. 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC): IEEE; 2018. p. 2000-3.

There is no conflict of interests to be declared.