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Determination of the Type of The Imagined Movement of Organs in People with Mobility Disabilities Using Corrected Common Spatial Patterns

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Abstract
In order to help people with disabilities, understanding presence of the coronavirus (covid-19) pandemic increasingly highlights the need for emerging technologies. As we know, brain computer interface (BCI) systems were hired to resolve the important challenges on the quality of life of people with disabilities and improve disabled person independent in performing daily activities. Therefore, in this work, BCI systems were furnished to study the type of movement of a person imagines from EEG signals. Before starting to analyze data, frequency bands and brain regions were first associated with motion imaging. Then, various types of spatial and frequency filters were applied to reduce signal noise, after that features were extracted by improving CSP algorithms like CSSP. Because the appropriate frequency band is not selected, the CSP results, which depend on frequency filtering, will not have the desired results, therefore CSSP method based on FIR filters is used. It means that we apply a frequency filter and frequency optimization occurred. The used data is standard data provided on bbci.de. In this database, 9 people have undergone EEG registration. Signal recording was performed in four visual classes including left-hand movement, right-hand movement, both feet, and language. To select the feature, we used the SFS feature algorithm. This algorithm achieved high accuracy by selecting six features together and using SVM classifier. In total, while the accuracy in the CSP method was 87.5%, in the CSSP method it reached 93.6 %.

Keywords: Brain-Computer Interface (BCI), EEG Signal Processing, CSP, CSSP, Feature Extraction, Classifier.

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1. INTRODUCTION

The coronavirus (covid-19) epidemic has far-reaching effects on all sections of the society, especially the disabled, and has placed more restrictions on this segment of society in daily activities. BCI systems based on brain signals are trying to find an opportunity to accelerate the development and implementation of innovative systems and assistive technologies to help these people with severe disabilities. In recent years, the BCI has rapidly established itself as an emerging technology, allowing brain signals for people with disabilities to interact with the outside world. Accordingly, the three main applications for the BCI system are the ability to move organs, the ability to speak and control various equipment to perform daily activities, and the analysis of physiological data, which has shown a lot of information about human function. When using EEG data, the time dimensions can be analyzed gradually and one by one, and different behaviors in different time frames or frequencies can be examined. The oscillating signals received from the brain are one-dimensional and change with time. When a person is in a normal state and is not engaged in any particular activity, brain signals can be received continuously and uniformly. The frequency of fluctuations of the received signal is in six different frequency ranges according to the level of consciousness and the level of concentration of the person and his mental and emotional state. Computer brain interfaces that use brain signals should be able to detect mental states from brain activity online. Different cortical areas in the brain are activated when thinking about different subjects such as mathematical calculations, imagined motion, and music. Information about these mental states can be recorded in a variety way. Each brain rhythm has a specific purpose and serves optimal brain function. The flexibility and ability of the human brain to switch between different brain rhythms play an important role in a person's success in daily activities such as controlling anxiety, focusing on homework, and having a good night's sleep [1,2]. The first attempts at human-computer interaction began with the discovery of EEG signals, and scientists sought to link these signals to brain activity [3]. However, because at first these signals were very disturbed and had noise, these signals were used only in medicine and only specialized doctors could use these signals based on experience. But gradually with the production of new devices and the ability to record these signals with better quality, more research was done in this field. At the first international conference in June 1999, a common definition for BCI was presented as follows: A brain-computer interface is a communication system that does not depend on the normal output pathways of the peripheral nervous system and muscles [4]. In 2012, Chen and colleagues used the causal connectivity network in the brain as a way to find features in BCI systems. Granger causality, including PDC and dDTF, was proposed in this paper and the PDC method was used. The accuracy of this method was 90% [5]. In a 2012 study by Ang et al., CSP was used to classify two classes of EEG data. They designed a filter bank for the CSP spatial model, FBCSP, and proposed its algorithm. The accuracy of 5 samples studied with the SVM classifier was 90.3% [6]. In a study presented by Mr.

Amanpour and colleagues in 2013, it was pointed out that an important issue in designing an interface is the choice of mental tasks to imagine. The notion of different types of mental tasks such as the notion of moving the limbs left, right, and tongue has been used. However, the mental perception of the practical actions of the BCI system is different. They used a wavelet converter and CSP filter to extract EEG signal properties [7]. In 2017, Dng et al. Classified multi-class motion-imaging signals using a hierarchical SVM system for a BCI system. The accuracy of this method was 64.4 ± 16.7% [8]. In a 2018 study by Rosalina Malahanti et al., Stroke patients were treated to improve their ability to move using BCI techniques. Functional connectivity in the functional model was used to extract the features and then machine learning techniques such as SVM were used to classify patients [9]. In another study conducted in 2018 by Yasumari Hashimoto, the development of a rehabilitation system was used. The brain-computer interface was evaluated for patients with unconscious stroke, who used ERD / ERS mapping to analyze the EEG signal [10]. In a 2019 study by Marie Corsi and colleagues, they used the aggregation of EEG and MEG signals to improve the classification of motor mental imagery from signals. For each sensor, the power spectrum between 4 Hz and 40 Hz with a frequency of 1 Hz was calculated. Next, a feature matrix containing the power spectrum was created for both the sensor and the corresponding frequency. The features used in the standard frequency bands θ, α, β and γ were extracted and the LDA classifier was used for classification. Examination of the classification results showed an improvement in BCI performance [11]. In a 2019 study, Natasha and her friends discussed the techniques and challenges of using EEG in motion-imaging studies. They pointed to the role of the EEG in brain-computer interactions during motion imaging. They compared them with a table of examples of aroused and spontaneous potentials. Extraction and selection of features due to the non-linearity and stability of the data as well as how to deal with EEG data, to reduce the size of the data, are parts of the challenges of BCI. Transforming laboratory studies into the real world is another challenge for BCI [12]. In 2019, Feng et al. pointed to a BCI hybrid system based on mental imagery and transient visual evoked potential. A combination of motor imaging and brain-computer interface technology can be very effective in rehabilitating patients. The transient visual evoked potential and the motor-mental imagery combined to create a BCI system. EEG signals are extracted according to their frequencies in the state of transient visual excitation and the state of motor mental imagery, and the desired features are extracted by wavelet transform. Then BP neural networks were used for classification. The mean diagnosis was 73%, which was different for each person and ranged from 70 to 85% [13]. In 2019, Feng in another study presented an optimized channel selection method based on the CSP algorithm for the BCI system based on motion imaging. Due to the additional information in multi-channel signals, the accuracy of BCI systems may greatly deteriorate. Channel selection methods can eliminate these task-independent signals and improve BCI system performance. However, in different frequency bands, the brain areas associated with motor mental imagery are not the same, leading to the inability of traditional channel selection methods to extract effective EEG features. To deal with the above problem, he proposes a new method based on the common spatial pattern or CSP which selects the channel rank for the multi-frequency EEG band. It uses a combination of signal analysis filter and CSP channel selection method to select meaningful channels and then uses LDA for classification. The accuracy of this method is much better than CSP [14]. Another study in 2019 by Pramod Gaur used a new method to improve the performance of a two-class BCI system based on motion imaging. EEG signals have poor time-frequency localization as well as unstable properties in the face of short Fourier time basis (STFT) or wavelet transform (WT) functions. In this study, they presented a preprocessing method for EEG signal reconstruction by selecting an intrinsic state (IMF) functions based on medium frequency measurements [15]. In a 2019 paper in the EURASIP journal, Javeria presented a way to classify multi-class EEG signals from motion imaging with sub-band spatial patterns. His goal is to improve the accuracy of multi-class classification for motion-imaging using a common subband band spatial pattern by the Sequential Feature Selection (SBCSP-SBFS) method. Bank filters, which have intermediate filters with different overlap cut-off frequencies, are used to separate noise signals from the EEG signal. The output of these filters is used to apply features by applying CSP and LDA algorithms. Then, three methods of SVM, NBPW, and KNN were used for classification. 86.5% accuracy was obtained for this project [16]. In a 2019 study, Mr. Kurhan examined the classification of EEG signals induced by motion imaging using the CSP method and convolutional neural networks. The results of this method were very interesting and while the CNN method alone had an accuracy of 43.12%, CNN and CSP together achieved an accuracy of 93.75% [17]. In a 2019 study by Zhang et al., Brain network features were used to increase classification accuracy in BCI systems. According to this paper, CSP has been used to extract features in most studies. Since CSPs are mainly derived from event-related programming (ERD) features, while the features created by the engine images are more than that, they created a Task-based brain network and coherence between channels. The EEG was calculated and with graph-based analysis found that the degree of nodules and clustering coefficients differed between the mental perception of left and right-hand movements. The results showed that these features perform better than CSP and the combination of brain network feature and CSP achieves higher accuracy [18]. In a 2020 study by Yau Guo et al., The FCCP method and the LDA classification were used, with an average accuracy of 82% for the samples [19]. In a study in 2021 by Jun Yang, he proposes a Multi-Time and Frequency Band Common Space Pattern (MTF-CSP)-based feature extraction and EEG decoding method. The MTF-CSP learns effective motor imagination features from a weak EEG, extracts the most effective time and frequency features, and identifies the motor imagination patterns. As a result, the average cross-session recognition accuracy of 78.7% was obtained [22]. In another study in June 2022 , Xiaozhong Geng presented that The EEG signals based on the BCI equipment is weak, non-linear, non-stationary and time-varying and an effective feature extraction as CSP method is the key to improve the recognition accuracy and the experimental results show that the EEG signals processed by the proposed method has obvious advantages in identifying and removing EOG and ECG artifacts and proposed method has higher classification accuracy than other algorithms [23]. In general, among the research that has been done in the BCI field for many years, we can imagine moving the right and left hand, moving the index fingers of both hands, performing five mental activities: resting position, writing letters, counting, mental multiplication. And the mental age, performing multiplication operations with varying complexity, listening to different types of music, performing emotional activities, and simulated driving, pointed out that many researchers have worked in each field and achieved acceptable results. Obtaining effective brain connectivity from the EEG signal generated by the motor imagery, is a new aspect that we will address. Some studies have used brain-based imaging techniques such as FMRI, which are costly, but using the EEG signal in this study is less expensive. Also, the EEG signal has a higher resolution time, which in itself can have a good effect on the accuracy of the results. Using upgraded CSP-based algorithms to find the features derived from these EEG signals will be another aspect of our innovation that, in combination with the connectivity pattern features, will provide stronger features. We found that special filters to improve the performance of the electrodes and eliminate noise between them will be other items under consideration. We used the SFS feature algorithm or sequential direct search for feature selection. SFS automatically select a subset of features that is most relevant to the problem. General structure of our BCI system presented in figure 1.

2. MATERIALS AND METHODS

In BCI, a motion picture is asked of a person imagining that a part of their body is moving. As a result of imagining movement, it activates the nervous system, as a result of which events occur in the brain. The task of the BCI system is to extract these events from the sampled EEG signals and to detect the type of motion based on them as presented in figure 2.

The preprocessing step is done for two reasons, the first reason is that since the EEG signal is a motion picture in the beta and mu bands, so first we need to filter the EEG signal so that only the band information is related to the moving image in the signal stay EEG. Figure 3 shows brain status in actual and mental motor imagery.

To do this, we use the Butterworth filter. After applying the filters, the reconstructed EEG signal will contain information about the 8 to 30 Hz band (mu and beta band). The second reason for filtering the EEG signal using spatial filters is to increase the localization property of the electrodes. Because each electrode is affected by other parts of the brain at the time of recording, the information that an electrode records is not specific to one area of the brain, thus reduces the performance of our model in the analysis. To solve this problem, a series of spatial filters such as car, large and small Laplace is applied.

In the EEG signal, in addition to event information, there is a series of information that is not related to our task and is practically not useful for our work, and has a large volume. This is common information that is common to all classes. This information is created in all classes and has a great impact on features and makes it difficult to

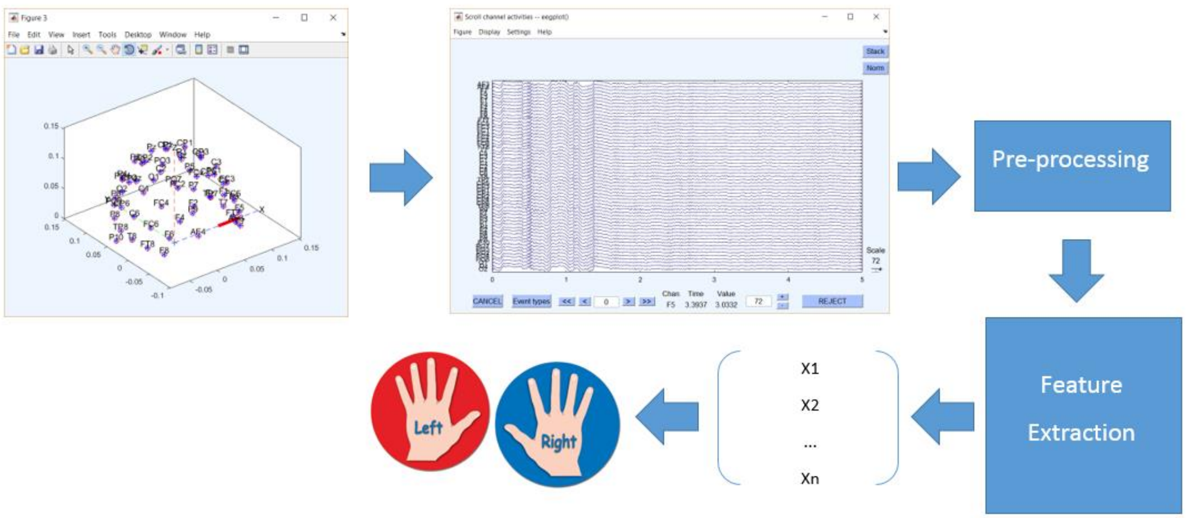

Fig. 1. General structure of BCI system.

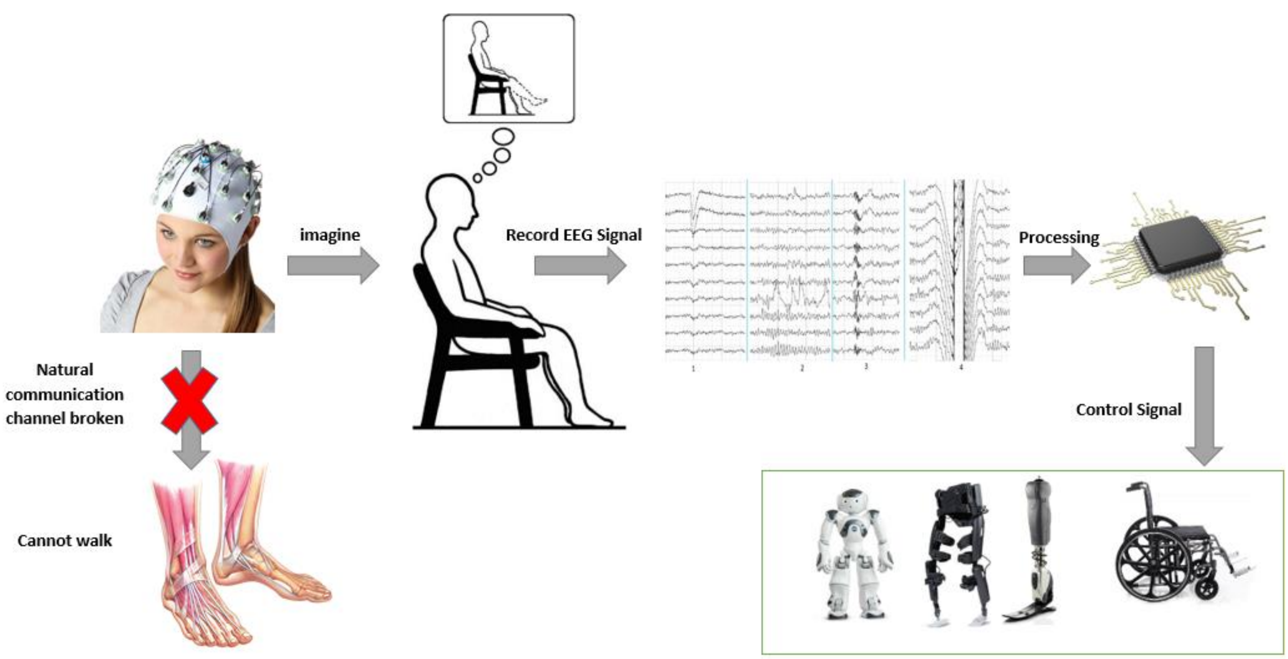

Fig. 2. Structure of our Motor imagery system.

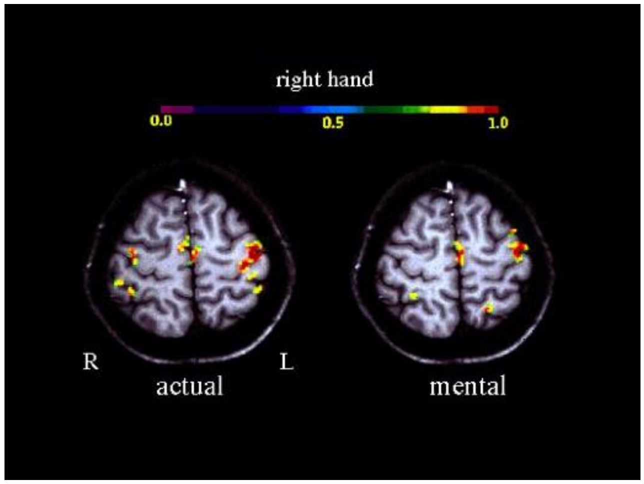

Fig. 3. Brain status in Actual and Mental Motor imagery status; Roth et al., 1996.

distinguish. This information can be seen more in the Mu and Beta rhythms. So, we have to put a band pass filter in the 8 to 30 Hz frequency band that only gives us this information and thus delete the common information. In the next step, for source localization, we can use CAR or Low Laplacian or High Laplacian filters. It is not mandatory in applying this section, but it is very effective in improving the result. Two basic factors are effective in designing an optimal BCI system that has high performance and accuracy:

First, it depends on people's ability to control the rhythm of the Mu, and it has been proven that people can control the rhythm of the Mu with training. Second, the noise signal is high and the signal noise is low. The less noise, the better the model performance.

In general, there are two categories of noise, some related to EEG and some non-EEG, such as EMG and eye movement, etc., which are created when recorded and added to the EEG. EMG, which has a frequency above 30 Hz, is not very common in motion imaging. Eye movement that is less than 5 Hz has nothing to do with Mu. The alpha rhythm, which is also the EEG frequency and is in the frequency of 8 to 12 Hz, its position varies and is very common in the occipital part and does not include the subject. Alpha occurs mostly in rest and meditation. EEG has a good temporal resolution but not a good spatial resolution. Due to the placement of the electrodes on the scalp and the recording of the activity of millions of neurons, many areas are affected on one electrode. Given that spatial filters can increase the SNR, we are looking for each electrode to have its area information and no other areas to be affected. With Source Localization, we increase the spatial resolution.

The CAR or Common Average Reference filter subtracts the information of one electrode from the average of the information of all other electrodes. If it is assumed that all the electrodes cover the head at the same distance and each electrode records the same part, the CAR filter will zero the average channels and cause Source Localization to occur.

$$x_i^{CAR}(t) = x_i(t) - \frac{1}{c}\sum_{j=1}^{c} x_j(t) \tag{1}$$

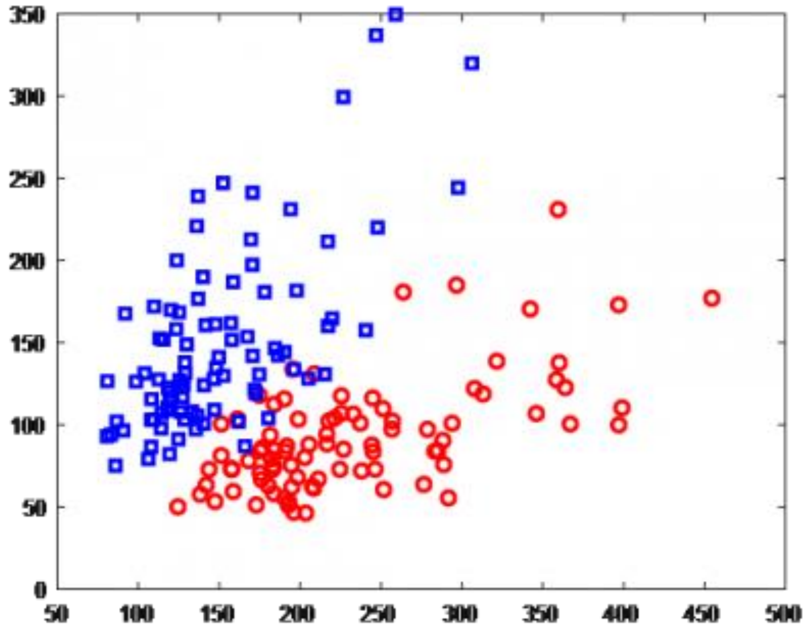

Fig. 4. EEG trials after applying CSP and feature extraction.

Of course, in practice mode, such electrodes are not spread and do not zero, and as a result, it becomes close to the reference-free state, which acts as a high-pass filter and removes low-frequency information. It eliminates the common noise between the electrodes.

2.1. Common Spatial Patterns (CSP)

The Common Spatial Patterns (CSP) algorithm was first used to detect abnormal EEG signals.

It was then used to distinguish between classes related to brain and computer interfaces and two-class movement patterns. Due to its multi-channel nature, this method is widely used for EEG signals. The CSP method, by applying space filters to the inputs, maximizes the variance of the signals in the first class and minimizes them in the other class at the same time. It then extracts first-class properties from the filtered signals. [20] This also happens in reverse.

A series of spatial filters maximizes signal variance in the second class and minimizes in the first class at the same time. It then extracts the second-class properties using filtered signals. After applying the CSP algorithm to the data, the number of channels is reduced to two channels and from each channel, the data variance is extracted as a feature and presented to the classification algorithm to detect the data class. After extracting the data feature in two-dimensional space, it looks like this:

$$w = argmax_w \frac{||wX_1||^2}{||wX_2||^2} \qquad (2)$$

And by calculating the covariance matrix we have:

$$R_1 = \frac{X_1 X_1^T}{t_1} \quad (3)$$

$$R_1 = \frac{X_2 X_2^T}{t_2} \quad (4)$$

From this cost function, we derive the weights and compute the patterns of the common space. After applying the CSP algorithm to the data, the number of channels is reduced to two channels and from each channel, the data variance is extracted as a feature and presented to the classification algorithm to detect the data class. Each point is equivalent to an EEG trial, which is as follows after extracting the feature as presented in figure 4.

2.2. Common Spatio-Spectral Pattern (CSSP)

If the appropriate frequency band is not selected, the CSP results, which depend on frequency filtering, will not have the desired results [21]. To solve this problem, S. Lemm proposed the CSSP method based on FIR filters. The basis of these filters is based on a constant amount of data movement time. In this method, space filters are obtained simultaneously with frequency filters. Since in motion-imaging, most of the two frequency bands are meow and beta, and other disturbances occur in other bands, it is better to limit the frequency bands. On the other hand, since the focus is on different frequency bands for different people, it is possible to select the best filter for each person by changing the τ parameter. The following conversion is considered in CSP:

$$\mathbf{S} = \mathbf{W}^{T}\mathbf{E} \quad \text{یا} \quad \mathbf{s}(t) = \mathbf{W}_{T}\, \mathbf{e}(t) \quad (5)$$

But in CSSP it is as follows:

$$S = W^T E + W_\tau^T E_\tau = \widehat{W}^T \binom{E}{E_\tau} \quad (6)$$

$$s(t) = W^T e(t) + W_\tau^T e(t+\tau) = \widehat{W}^T \binom{e(t)}{e(t+\tau)} \quad (7)$$

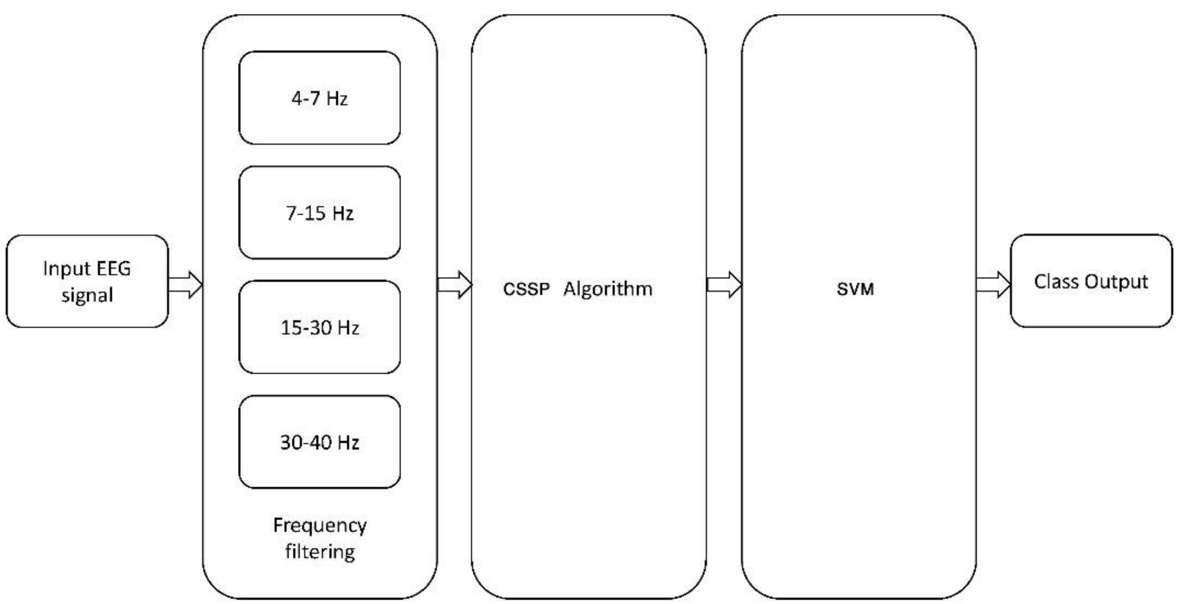

Fig. 5.General structure of CSSP method.

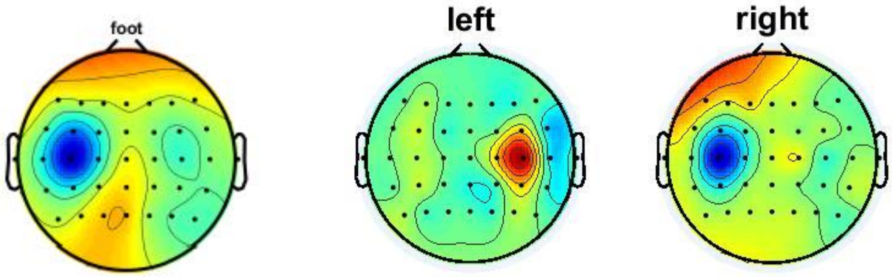

Fig. 6. EEG Topography for foot, left, and right hand using CSSP method.

where E_τ is a τ -time delayed signal matrix of E, and

$$\widehat{W}^T = [W^T . W_\tau^T] \quad (8)$$

is a CSSP matrix. then we can apply this method easily in the same way to the CSP algorithm.

2.2.1. Feature Extraction

The purpose of feature extraction is to extract features that have different values in different groups that cause the data of two or more groups to be separated. The 8 to 30 Hz frequency band we are looking for is not the optimal frequency band for all subjects. Therefore, frequency optimization should also be done. In addition to spatial optimization, the CSSP algorithm also performs frequency optimization. CSSP looks like the FIR filter. We apply the FIR filter. It means that we apply a frequency filter and frequency optimization occurs.

In the next step, CSSP is applied to the data to extract the features, and then SVM is used to classify the data. SVM is a supervised machine learning algorithm that is mostly used in classification problems. If the categories are linearly separable, maximum-sized hyperplanes are obtained that can be used to separate them. In cases where the data is not linearly separable, the data is mapped to a larger space to be linearly separated in this space. SVM algorithms use mathematical functions as kernels. The kernel's job is to convert the data as needed. SVM algorithms use different kernels.

In this study, we used CSSP to solve the CSP problem, which in addition to spatial optimization, does frequency optimization. Figure 5 shows the general structure of CSSP method and Figure 6 shows EEG Topography for foot, left, and right hand using CSSP method.

Although this filter is similar to the FIR filter, it is not an optimal FIR filter. If it was to be optimal, it must have b0, b1, b2, b3 coefficients so that we can pass the desired frequency content. Because the dimensions are so high, it is computationally time-consuming and complex. For solving this problem, it is necessary to use CSSSP as CSSP.

2.2.2. Data Used

The data used is standard data recorded by Brunner et al. and is provided by bbci.de. In

Table 1. ***Classification accuracies (%) for motor imagery by several methods. D: degree feature CC: clustering coefficient***

Method	Accuracy (%)
D	70
CC	66
D+CSP	73
CC+CSP	68
CSP	75
Our method using CSSP	93.6

this database, 9 people have undergone EEG registration. Signal recording was performed in four visual classes including left-hand movement, right-hand movement, both feet, and language. EEG data with a sampling frequency of 1000 Hz was collected from 22 areas of the scalp using Ag / AgCl electrodes. The low cut-off frequency was 0.1 Hz and the high was 250 Hz. The impedance for EEG electrodes is less than 20 kW [24].

3. RESULTS

This study includes data loading, preprocessing, feature extraction, feature selection, and classification. This BCI includes the application of CSP-based space filters, the CSSP filter. Because some of the trials of this database have been identified by experts in the field of EEG as trials containing artifacts. In addition, the labels of some trials are stored as NaN. We have removed these trials from our processing. To select the feature, we used the SFS feature algorithm or sequential direct search. SFS reduces an initial n-dimensional feature space to a m-dimensional feature subspace where m < n. The motivation behind feature selection algorithms is to automatically select a subset of features that is most relevant to the problem. The goal of feature selection is two-fold: We want to improve the computational efficiency and reduce the generalization error of the model by removing irrelevant features or noise. A wrapper approach such as sequential feature selection is especially useful if embedded feature selection. Finally, this algorithm achieved high accuracy by selecting six features together. In total, while the accuracy in the CSP method was 87.5%, in the CSSP method it reached 93.6 %.

4. FUTURE APPLICATIONS

The method used in this study is comprehensive in different fields, when we are going to buy from the stock market, we have to decide which one to buy. When we are going to walk, stand, raise our hands, it all comes down to a decision. What is the better way than for a person with mobility to send the necessary message to his or her brain when moving, such as his or her artificial robotic legs, to walk. The method used in this study can be used in various studies on diseases such as MS, Parkinson's, and Alzheimer's

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