Partial Directed Coherence for the Classification of Motor Imagery-Based Brain-Computer Interface

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Abstract. In recent years, the research community around the globe has contributed significantly to improve the brain-computer interface based assistive technologies. Electroencephalographic brain-computer interface enables the person to communicate with the outside world by creating an advanced communication protocol between the brain and the computer. Motor imagery-based BCIs aim to predict the specific patterns elicited by imagining some planned movements. Standard BCI systems incorporate the use of spatial features from the motor cortex. However, several researchers claim to have the intercommunication of different brain regions during the motor task. Thus, a unique approach like brain connectivity is essential to extract the intercommunication of brain regions through several electrode channels during a MI task. In this work, brain effective connectivity has been estimated using partial directed coherence, and it has been used as the feature extraction method. An extensive 2-class motor imagery dataset from Physionet database incorporating 91 subjects has been used for the validation purposes. Our proposed work reached the average classification accuracy of 97.45% using an SVM classifier. The findings of this study revealed the significance of brain connectivity features over the conventional features extracted from a single brain region.

Keywords: Brain-Computer Interface · Motor Imagery · Electroencephalogram · Feature Extraction · Classification · Partial directed coherence · Brain connectivity

1 Introduction

For people with neurological disorders, it would be really appreciable to have an independent system which can communicate via a non-muscular pathway to the outside world. Brain-Computer Interface (BCI) is a modern innovation in the field of engineering that offers an effective solution for assisting disabled people [1]. Electroencephalographic brain-computer interfaces provide an advanced communication pathway between brain and computer using non-invasive methods to aid differently-abled people to interact with devices such as neuroprosthetics, spelling application and wheelchairs. Electroencephalography (EEG) is a standard neuroimaging method of measuring the electrical

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current of brain cells using non-invasive metallic electrode sensors [2]. Several classical BCI paradigms, including evoked potentials such as steady-state evoked potentials (SSVEPs), event-related potentials (ERPs) such as P300 and motor imagery-based event-related synchronization/ desynchronization are used extensively in BCI research.

Motor imagery-based brain-computer interfaces intend to detect specific EEG patterns while the person performs the imagination of some planned movement such as wrist or feet movement [3]. Motor imagery-based BCI's makes it easier to boost the living standards of such physically disabled individuals. The motor cortex is triggered during a trial and creates modifications to its state [4]. Centered on this principle, researchers monitor electrical brain activity by placing a metallic electrode on the scalp for signal analysis of user intentions. Moreover, it is necessary to record brain signals without any artifacts to achieve significant outcomes.

The standard BCI signal processing systems comprises three key stages including pre-processing, feature extraction and classification. In pre-processing, raw EEG signals are cleaned to remove unwanted components such as eye blinks. It also provides an improvement in signal to noise ratio. In feature extraction, specific characteristics that encode special commands evoked in the brain are extracted from the signal; whereas classification allows the BCI system to discriminate different mental tasks.

To date, neuroimaging research investigating the neurological substrates behind motor imagery tasks have primarily focused on spatial features of the brain from individual channels which may not provide sufficient information. Since MI tasks involve the activation of multiple brain regions, awareness of brain connectivity tends to become a key element of neuroscience to understand the intercommunication of different regions. In this study, partial directed coherence (PDC) has been used in the estimation of brain effective connectivity. The extracted features have been used with support vector machines (SVM) for 2 class motor imagery prediction. Electroencephalographic MI dataset from Physionet database has been used in the proposed work.

2 Dataset Description

EEG motor imagery dataset from Physionet database [5] has been used for the validation of the proposed work. The database incorporates 109 subjects who performed the real and imagined movement of the left and right hand. However, for this study, we have only used the imagination dataset. The dataset has been recorded using the BCI2000 instrumentation system. The dataset is available online at [6], and it does not require any further authorization to be used in this study.

EEG data has been recorded as per 10–10 international system using 64 electrode channels with the sampling rate of 160 Hz. Out of 109 subjects, 91 subjects have been used in this work whereas 18 subjects including subject 29, 30, 34, 37, 41, 51, 64, 72, 73, 74, 76, 88, 89, 92, 100, 102, 104 and 106 have been excluded owing to incorrect data recording.

From 91 subjects, three sessions of motor imagery tasks have been recorded where each session comprises seven to eight random trials for two-class MI. Each left and the right trial has been recorded for 4 s, followed by the rest time of 4 s (see Fig. 1).

The overall description of the dataset is presented in Table 1.

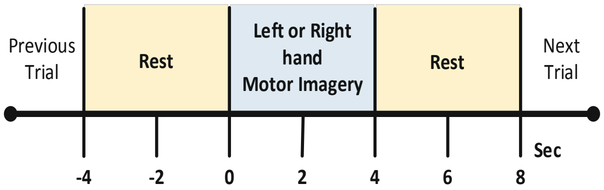

Fig. 1. Trial diagram of motor imagery dataset.

Table 1. Dataset description

Dataset	Physionet Database	EEG Motor Imagery Dataset
Sampling Rate	160 Hz	
Channels	64	
Subjects	91	
Trials	45 (Each Subject)	
	4095 (Total Trials)	
Classes	2 Classes	2 Classes

3 Methodology

The methodology used in this analysis to infer findings on connectivity across different brain regions for motor imagery tasks is depicted in Fig. 2.

Different pre-processing techniques including DC offset correction (i.e., high pass filter at 0.1 Hz), electrical interference removal (notch filter at 60 Hz) and bandpass filtration has been applied to clean EEG data. The raw EEG data was bandpass filtered between 7 Hz and 30 Hz to eliminate all the frequency components other than mu and beta as the studies [7–9] revealed the occurrence of MI patterns in the stated frequency range.

In addition, the EEG data from 91 subjects was pre-processed to select 14 out of 64 electrode channels from all major regions of the brain (i.e., left, right and central). Among these 14 channels, six (i.e., T7, P7, C3, P3, FC3 and CP3) are located in the left region, six (i.e., T8, P8, C4, P4, FC4 and CP4) are present in the right region, whereas only two (i.e., Cz and Fz) are located in the central region. These 14 channels are suggested by several researchers [10–13] for the implementation of motor imagery BCI system using a limited number of channels.

Moreover, the data was pre-processed in order to acquire the component of the signal in which the participant performed the activity of motor imagery through the elimination of the undesirable section of the signal. So, during an 8-s trial, 4-s rest state data was discarded, whereas the remaining 4s MI data was saved for further processing (see Fig. 1).

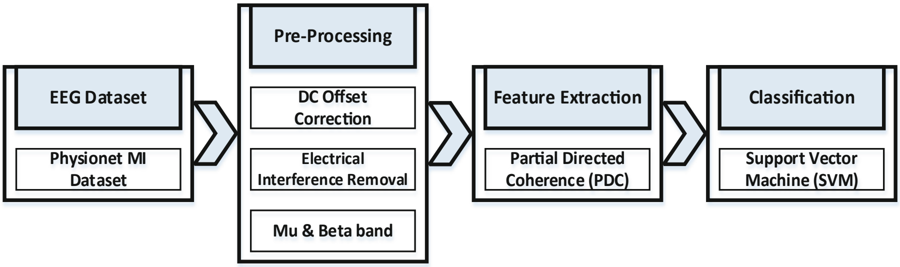

Fig. 2. Block diagram for the proposed methodology.

Eventually, brain connectivity has been determined using partial directed coherence (PDC), and the estimated connectivity has been used as a key feature in this work. Moreover, the support vector machine (SVM) has been used to classify two-class motor imagery tasks using computed features.

3.1 Feature Extraction

Partial directed coherence has been evaluated for the estimation of brain effective connectivity for the prediction of two-class MI. The connectivity estimation has been used as the feature extraction technique in the proposed study.

Effective connectivity can be expressed as a direct or indirect effect of a neural system on another at the synaptic or cortical level [14]. It can be estimated through various methods, including bivariate and multivariate connectivity estimators as well. Position of the electrode at different distances provides imprecise results while using bivariate connectivity estimator. However, multivariate estimation provides the solution to this problem by using Granger causality (GC).

Baccala and Sameshima [15] presented a multivariate based analysis method called the Partial Directed Coherence (PDC). It is a commonly used method to estimate the directional influence among different pair of channels using Multivariate Autoregressive Model (MVAR) through Granger causality. PDC has the capability to measure the active direct directional coupling among the multi-channel data.

The 1st step in Connectivity estimation is to adjust the multi-channel EEG data by performing the trial separation. The overall data comprising 14 selected channels from 91 subjects is divided into several trials, and the connectivity analysis is carried out for each trial separately.

Next step involves the estimation of Multivariate Autoregressive Model (MVAR) model coefficient, which has been conducted using Eq. 1.

$$A(t) = \sum\nolimits_{r=1}^{p} C(r)A(t-r) + E(t) \tag{1}$$

Here A(t) illustrates the 14-channels time-series EEG data, p is the model order which has been estimated using the ARFIT toolbox with the Schwarz's BIC optimizer, E(t) is the prediction error whereas C(r) is the covariance matrix representing the MVAR coefficients.

$$C = \begin{bmatrix} c_{11}(1)\ c_{12}(1) \ldots c_{1x}(1) \\ \vdots \quad\quad \vdots \quad\quad \vdots \\ c_{x1}(1)\ c_{x1}(1) \ldots c_{xx}(1) \end{bmatrix} \tag{2}$$

$$\vdots$$

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In Eq. 2, C is a matrix containing the MVAR values, where p is the model order and x is the number of electrode channels. This "x x x" matrix C is calculated for each value of z ranging from 1 to z. These parameters express the influence of one channel over the other; for example, $c_{12}(1)$ shows the influence of channel 2 over channel 1 at order 1.

After the calculation of the MVAR matrix, the next step is to estimate the partial directed coherence by defining the sampling frequency (i.e., 160 Hz) and the number of frequency bins (i.e., 64). The number of bin defines the number of portions in which the total frequency range (i.e., 7 – 30 Hz) will be divided for the connectivity analysis, which means that the PDC estimation process will be repeated for 64 times for each bin of the frequency.

After obtaining the MVAR coefficients matrix and assigning the above-mentioned parameters, $\overline{C}$ matrix is calculated by subtracting the matrix C from identity matrix I.. (See Eq. 3)

$$\overline{C}(r) = \begin{matrix} 1, r = 0 \\ -C(r), r > 0 \end{matrix} \tag{3}$$

Time to frequency transform (see Eq. 4) has been performed to convert the time series MVAR matrix $\overline{C}$ into the frequency domain $C(f)$.

$$C(f) = \sum\nolimits_{r=0}^{p} \overline{C}(r)e^{-j2\pi fr} \tag{4}$$

Finally, the frequency domain matrix $C(f)$ is normalized (see Eq. 5) to get the desired output called the partial directed coherence (PDC).

$$PDC_{ij}(f) = \frac{c_{ij}(f)}{\sqrt{\sum_{k=1}^{x} |c_{kj}(f)^2|^2}} \tag{5}$$

In above Eq. 5, the number of analyzed channels (except the current channel j) are denoted by x, while PDC_{ij} represents the PDC correlation indicators from A_j to A_i at specific frequency f.

The estimated PDC for each trial was in the form of a 3d matrix. So, matrix reshaping has been carried out to convert the 3d matrix to a 2d matrix for further signal processing (i.e., classification process). The PDC estimation resulted in a 14 × 14 × 64 matrix. Where 14 × 14 represents the interconnectivity of 14 electrode channels, and 64 represents the number of frequency bins.

3.2 Classification

Brain connectivity features in terms of partial directed coherence (PDC) extracted in the previous stage has been used as input to the Classification algorithms. Therefore, support vector machine (SVM) has been used with PDC for the 2-class MI prediction.

SVM is the machine learning (ML) based supervised learning technique widely used for the purpose of regression and classification. The SVM seeks to identify the hyperplane in an N-dimensional space that explicitly classifies data variables. Hyperplanes are decision boundaries that help classify the training points. The selection of hyperplane depends on the margin (i.e., the distance between the closed data point) and the hyperplane with maximum margin is selected. Such simple SVMs are called linear SVM. In

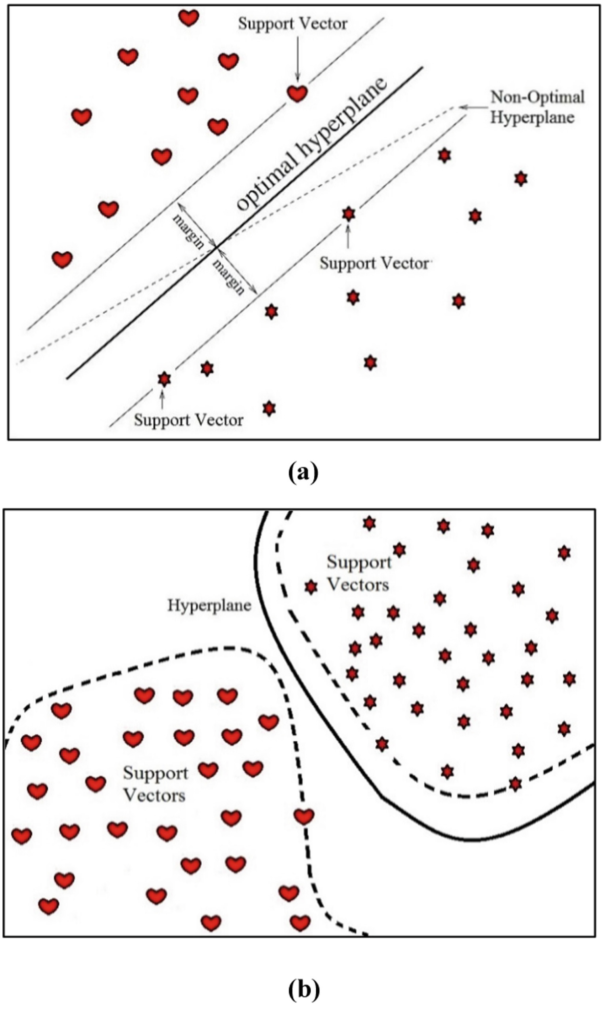

Fig. 3. Illustration of SVM. a) Linear SVM. b) Non-Linear SVM.

contrast, when the training data is not linearly separable, Kernel function helps to create a non-linear SVM in which the data can be mapped into another space with much higher dimensionality. There are several kernel functions, but Gaussian is the most common kernel function used in BCI research. Figure 3 provides an illustration of the linear and non-linear SVMs.

The imagination of the left-hand and right-hand movement is labelled as 0 and 1, respectively. However, Gaussian kernel function with rigorously tuned kernel scale of 0.9399 has been used with 10-fold cross-validation for two-class motor imagery classification.

4 Results and Discussions

This section portrays the performance of the proposed methodology based on motor imagery-based EEG data. In this work, 2-class MI has been classified using brain connectivity-based feature extraction technique with support vector machine (SVM).

To evaluate the classification performance of 91 subjects, confusion matrix has been computed as shown in Fig. 4. From the confusion matrix, we can see that the true prediction value (i.e., true positive rate or TPR) of class-0 is less than the true prediction value (i.e., true negative rate or TNR) of class-1. Left-hand (i.e., class-0) achieved the true prediction of 95.98%, whereas the right-hand (i.e., class-1) obtained the true prediction of 97.96%. However, the false prediction index (i.e., false-positive rate or FPR) of the left-hand class is less than the false prediction rate (i.e., false-negative rate or FNR) of right-hand class, where FPR and FNR are as low as 2.04% and 3.02%, respectively.

Furthermore, in order to evaluate the performance of each subject, Fig. 5 illustrates the comparison of classification accuracies (CA) against all 91 subjects. From Fig. 4, there is a clear trend of the classification accuracy above 95%; however, only two subjects (S24 and S91) have marked the CA less than 95%. The results also identify the maximum classification accuracy (i.e., 98.45%) which has been achieved by subject 67 and the minimum CA (i.e., 78.15%) which has been obtained by subject 91. However, the proposed BCI system achieved the average classification performance of 97.45% against 91 subjects of MI data.

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In addition, we have compared our proposed work with several most recent studies which have used similar MI-based EEG data (i.e., Physionet MI data). Table 2 presents the comparison of MI-based classification studies, where the proposed method (i.e., brain effective connectivity estimation) has outperformed all other techniques with significantly improved performance.

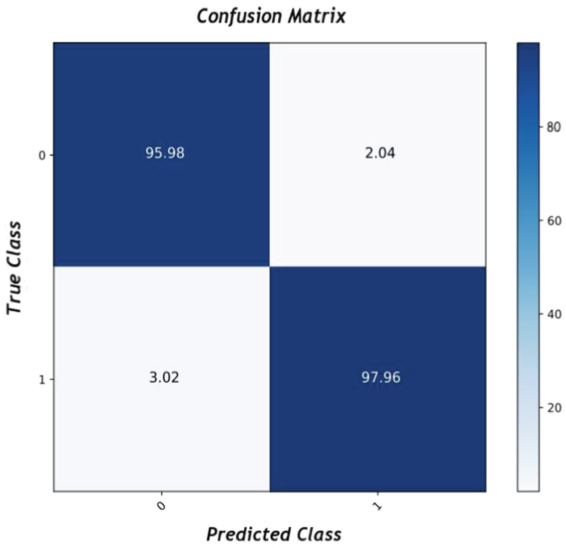

Fig. 4. Confusion matrix

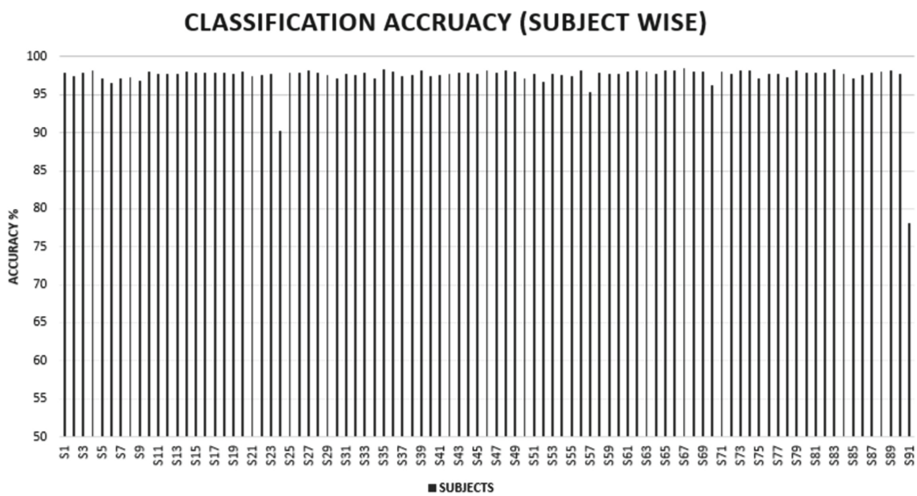

Fig. 5. Comparison of classification accuracy among 91 subjects

Table 2. Performance comparison

Work	Classification Accuracy
Xiaying et al. [16]	82.43%
Dalin et al. [17]	81.64%
Hesam et al. [18]	93.03%
Michael et al. [19]	76.21%
Chen et al. [20]	82.88%
Yimin et al. [21]	96.00%
This work	97.45%

5 Conclusion

In this study, we proposed a BCI system in which we have estimated brain connectivity using partial directed coherence (PDC) for motor imagery prediction. Two-class MI data from Physionet database incorporating 91 healthy subjects, where each subject performed the imagination of left and right-hand movement over several trials, has been used for the validation of the proposed work. Among 64 electrode channels, 14 channels covering all major regions of the brain were used in the proposed technique. The brain connectivity estimation was carried out to obtain 196 pairs of estimated PDC referring to 14x14x64 connectivity matrix for every single trial of each class. The 3-dimensional matrix was transformed into a 2-dimensional matrix by performing the matrix reshaping in order to feed the extracted features for the purpose of classification. SVM was used for the prediction of 2-class MI, and it achieved the average classification accuracy of 97.45%, which outperformed several recent studies using the same dataset for MI classification. The findings of this study reveal the importance of analyzing the interconnection of multiple brain regions using brain connectivity estimation.

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Authors' Contributions. Muhammad Ahsan Awais: Conceptualization, methodology, and original draft preparation.

Mohd Zuki Yusoff: Supervision, review, and editing.

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