ORIGINAL ARTICLE

The Improvement of a Brain Computer Interface Based on EEG Signals

Maryam Khakpour* (ID)

Department of Computer Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

Abstract

Purpose: Brain Computer Interface (BCI) has provided a novel way of communication that can significantly revolutionize life of people suffering from disabilities. Motor Imagery (MI) EEG BCI is one of the most promising solutions to address. The main phases of such systems include signal acquisition, pre-processing, feature extraction, classification and the intended interface. The challenging obstacles in such systems are to detect and extract efficient features that present reliability and robustness alongside promising classification accuracy. In this paper it is endeavored to present a robust method for a two-class MI BCI that results in high accuracy.

Materials and Methods: For this purpose, the dataset 2b from BCI competition 2008, consisting of three channels (C3, C and Cz), was utilized. Firstly, the signals were bandpass filtered. Secondly, Common Spatial Pattern (CSP) was employed and then a number of features, including non-linear chaotic features were extracted from channels C3 and C4. After feature selection phase the number of features were reduced to 38 and 47. Finally, these features were fed into two classifiers, namely Support Vector Machine classifier (SVM) and Bagging to evaluate the performance of the system.

Results: Classification accuracy and Cohen's Kappa coefficient of the proposed method for two MI EEG channels are 96.40% and 0.92, respectively.

Conclusion: These results indicate the high accuracy and stability of our method in comparison with similar studies. Therefore, it can be a promising approach in two-class MI BCI systems.

Keywords: Brain Computer Interface; Electroencephalography Signal; Motor Imagery; Common Spatial Pattern; Non-Linear and Chaotic Features; Support Vector Machine.

1. Introduction

The term Brain Computer Interface (BCI) is referred to the direct communication among humans' brain and external devices. This phenomenon has been a significant interdisciplinary topic in recent years owing to its function in aid of rehabilitating the disabled by making a new communication channel in the absence of external stimuli. In fact, this technology empowers the subject to perform different tasks without any physical movements. Electroencephalography (EEG) signals have gained in popularity among BCI technologies for being noninvasive, inexpensive and portable. In this method, the located electrodes on the scalp measure electrical activity in the brain. Particularly, Motor Imagery BCIs based on EEG signals (MI-EEG BCIs) process and interpret the signals of imagined tasks into commands to control various peripherals, wheelchairs or prostheses for stroke patients or paralyzed people [1–3].

This procedure is established through some primary steps, i.e., signal acquisition, pre-processing, feature extraction, and classification. Attaining a higher and more accurate performance by efficient feature extraction and classification has always been a critical issue in BCI applications. A large number of researches have been done over these phases to resolve the issue [4]. Several algorithms have been proposed and led to some advances in the process. However, there are still improvements need to be done to achieve the optimum, especially for extracting the most important and beneficial features from the EEG signals. One of the most promising and widely used approaches in feature extraction stage is Common Spatial Pattern (CSP). EEG signals are instinctively non-linear while CSP maps them onto a linear structure, which makes MI-EEG features prone to differentiate [2-5].

Furthermore, diverse feature extraction methods for two class MI BCIs have been applied in different studies. BCI competition IV dataset 2b is one of the frequently used datasets in this matter. For instance, using this dataset, a SCP-based method was presented by Ang *et al.* [6]. Their proposed method, Filter Bank Common Spatial Pattern (FBCSP), consists of band-pass filtering and spatial filtering employing the CSP algorithm. To ameliorate MI-BCI performance, Gaur *et al.* [7] presented a method based on Empirical Mode

Decomposition (EMD) in their study. After decomposition of EEG signals using EMD, Hjorth and band power features were extracted and lastly, a Linear Discriminant Analysis (LDA) was used for classification of left and right hand MIs. Rezaei Tabar *et al.* [8] aimed to enhance classification performance of MI-EEG signals using a deep learning approach. In their study, the extracted features of Convolutional Neural Networks were classified by means of a deep Stacked Auto Encoder (SAE) network. In another study, Kim *et al.* [9] have mentioned the importance of extraction adaptive and robust features due to time, frequency and spatial characteristics of EEG signals. Their proposed method extracted the most effective features using Weighted Difference of Power Spectral Density. Eventually, Support Vector Machine (SVM) was used to show the classification accuracy. In the study of Bagh *et al.* [10] Hilbert Transform (HT) was applied on μ (8-12 Hz) and β (13-30 Hz) band signals to calculate Event-Related Patterns. The prediction of left and right hand movements was done by two machine learning classifiers, SVM and Logistic Regression (LR).

In this paper, our main focus is on feature extraction stage. Attempts have been made to adopt a stable and robust approach which also serves reasonable accuracy. In order to meet this target, spatial filter is implemented and then non-linear chaotic features are taken into consideration. This method has driven promising accuracy and consistency after classification.

2. Materials and Methods

The procedure of the proposed method includes three main steps. Firstly, a pre-processing approach is implemented to purify EEG signals. In the second and most important step, several features are extracted following applying CSP algorithm. The number of features is reduced after feature selection. Finally, the extracted features are analyzed through two classifiers, Support Vector Machine (SVM) and an ensemble method, i.e., bagging. The results are presented through statistical measures to evaluate the accuracy, consistency and robustness of the proposed algorithm. Eventually, results of this paper is compared to other studies over the same dataset.

2.1. Dataset

In this study, dataset 2b from BCI competition IV was employed. The EEG signal acquisition was made from 9 right-handed subjects. Each subject took part in 5 sessions. This dataset included 2 classes of Motor Imagery, i.e., left hand (class1) and right hand (class2). Each session was formed of 6 runs. Each run had 2 classes of MI and 10 trials per class, which led to 120 trials per session. The first two sessions were recorded without feedback, whereas the last three sessions did not have feedback. All participants were sitting on an armchair in front of a flat screen monitor which was 1 meter away from them (Figure 1).
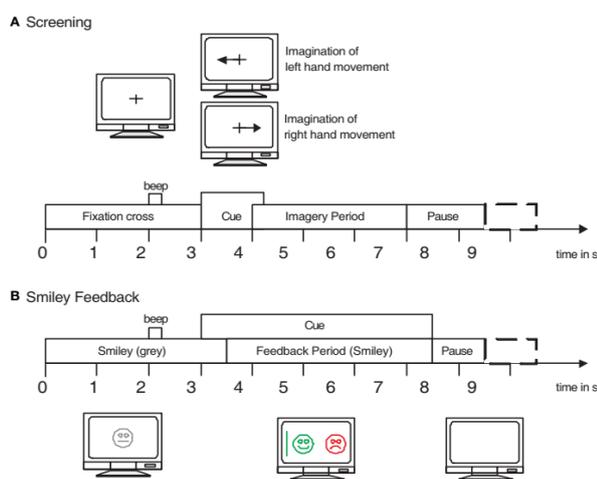

Figure 1. Timing and feedback system of the dataset

At the beginning of each trial a fixation cross was shown on the screen. Afterwards a cue, pointing to left or right, appeared for 1.25 seconds, which informed the subject to imagine the matching hand movement for 4 seconds. After each trial there was a short break. As mentioned earlier, four runs of three of these sessions were performed with smiley feedback. For each trial, at first there was a gray smiley in the center of the screen. At second 3, following a short warning beep, the subject was necessitated imagining the corresponding hand movement. The change of smiley from gray to green indicated the correct direction whilst red indicated the incorrect direction. The data was captured with a sampling frequency of 250 Hz from three bipolar channels of C3, Cz, and C4. A bandpass-filter between 0.5 Hz and 100 Hz was also applied [11].

2.2. Pre-Processing

In order to remove noise, artifacts and unwanted signals from raw EEG signals, a pre-processing method is initially needed. Furthermore, MI BCIs for detecting left and right hand movements focus on frequency bands of 8–12 Hz and 16–24 Hz of C3 and C4 channels to extract features. Therefore, a Finite Impulse Response (FIR) bandpass filter between 7 to 30 Hz is employed over our chosen dataset. It is also worth noting that in this study the focus is on channels C3 (for the right hand movements) and C4 (for the left hand movements), due to their electrode position, where the signal acquisition of motor cortex areas of the brain occurs. Movement related activities are lateralized and their activities are projected onto the left and right parts of the brain. Thereby, channel Cz, which is located in the central part of the brain, is excluded to decrease the dimensionality [12–14].

2.3. Feature Extraction

The second step that helps to reduce the dimensionality and enhance the classification performance is feature extraction. It is highly important to choose the features which can extract the most relevant and efficient information from our EEG signals whilst ignore the irrelevant and redundant information [12]. For this purpose, the first procedure in our study is applying Common Spatial Pattern (CSP) to decompose the signals.

2.3.1. Common Spatial Patterns

Owing to spatial properties of left and right MI, this algorithm has been one of the most powerful, efficient, and greatly used methods in MI BCIs and contributed to high classification performance and improvements of BCI systems. Spatially filtering EEG signals, it maximizes the variance of one class and simultaneously minimizes the variance of the other class, thus they are distinguishable to a certain extent [3-15]. Figure 2 indicates EEG signals of imagined movements of left and right hand which has been spatially filtered using CSP method. The first and second spatial filters maximize the variance of left hand signals, but they minimize the variance of right hand signals. The third and the fourth spatial filters maximize the variance of

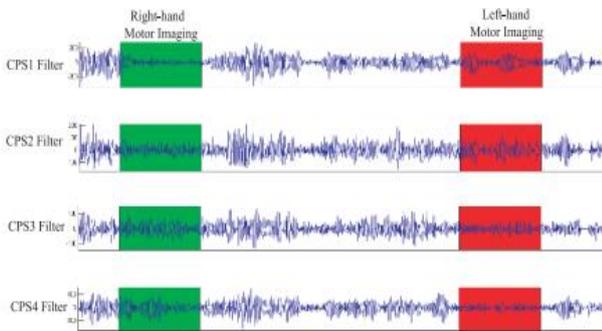right hand signals while they minimize the variance of left hand signals [16].

Figure 2. EEG signal filtered using CSP algorithm

2.3.2. Extraction of Features

At this point, we extract features from our spatially filtered signals. For this purpose a set of non-linear chaotic features and other efficient features are chosen. The following is a concise description of some of these features.

- Fractal Dimension: Fractal Dimension is a set of corresponding features that estimates the chaotic properties of our EEG signal and represents how meanderings or irregular the signal is. These fractal features include Box Dimension, Katz, Higuchi, Petrosian, and Sevcik Dimension [12-17].

- Hjorth Parameters: These parameters represent characteristics of the signal from three aspects; Activity, Mobility and Complexity. If y is the signal, y^' is the derivative of the signal. N and μ also indicate the number of samples and the mean of the signal in the window, respectively [17-18].

$$Activity(y) = \frac{\sum_{i=1}^{N}(y(i) - \mu)^2}{N} \qquad (1)$$

$$Mobility = \sqrt{\frac{VAR(y')}{VAR(y)}} \qquad (2)$$

$$Complexity = \frac{Mobility(y')}{Mobility(y)} \qquad (3)$$

- Hurst Exponent: Non-linearity and robustness in assessing the parameters of EEG signals make this feature suitable for such discriminating task of left and right hand motor imagery [19-20].

- Correlation Dimension: Another non-linear parameter is a measure of complexity and able to represent information about the nature of the system, thereby it helps to understand the system [20-21].

Figure 3 shows the name and number of all features extracted from each channel. Overall, 79 features were extracted from each channel.
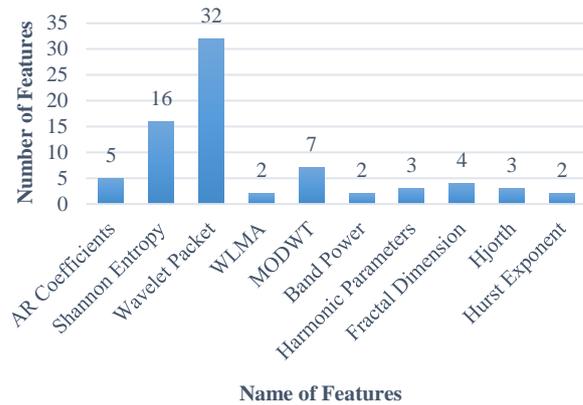

Figure 3. Name and number of extracted features

2.5. Feature Selection

Feature selection has played an important role in enhancing the performance of classification. Applying an appropriate technique at this step can lead to faster and more accurate computation, meanwhile, overcoming the curse of dimensionality, by reducing redundant and inefficient features. In this paper Student's t-test and Bonferroni correction have been implemented. Student's t-test makes an assessment to ensure that the extracted features carry a substantial difference between the two classes. The Bonferroni correction method has been employed to adjust p-values in order to counter the multiple comparisons problem. As a result, the number of features for channels C3 and C4 were reduced to 38 and 47 features, respectively [18, 22–24].

2.6. Classification

Last step of our MI-EEG signal processing is to train and test the system using a classifier. In this paper two machine learning classifiers have been implemented to assess the performance of the system.

2.6.1. Support Vector Machine

One of the successfully operated and commonly used classifiers in two class BCIs is Support Vector Machine (SVM). It is a discriminative classifier selecting a hyperplane to identify classes. This machine learning based classifier has shown efficient performance regardless of number of the classes and high dimensionality of training data. In addition, its structural simplicity, generalization properties, fast training and testing, and good empirical results in MI BCIs have made SVM, one of the most popular classification algorithms in designing BCI applications [3–25].

2.6.2. Bagging

Bagging stands for bootstrap aggregation. It is an Ensemble method, which combines several classifiers or multiple learning methods in different ways to attain a better performance and higher stability. Moreover, they reduce misclassification error. Although Ensembles methods have been successful to improve the performance of BCI systems, some of them are time consuming for real-time BCIs. Among these ensemble methods, bagging is less complex, faster and effective in solving over-fitting problem. For aggregation of the outputs in base learners, it uses voting for classification [26-27].

2.7. Evaluation of the Classification Performance

In such BCI applications the system requires training. This training needs to be done using labeled data from the existing dataset. The employed dataset has been already divided to train and test set. Until now, test data remained unseen and all the process was performed on train set. In addition to calculating the frequent measures of assessing performance of classification, i.e., accuracy, specificity and sensitivity, in this paper, the Cohen's kappa coefficient has also been presented.

Cohen's Kappa coefficient (K) is statistical measure that evaluates efficiency and robustness of a method. It measures how well the performance of an algorithm was in comparison to how well its performance would have been simply by chance. There are six ranges for values of K with different interpretations. The one that

relates this study is the last range of K values more than 0.80 which declares perfect agreement and robustness of a method [28-29].

These measures are formulated as follows:

$$Sensivity = \frac{TP}{TP+FN} \qquad (4)$$

$$Specificity = \frac{TN}{TN+FP} \qquad (5)$$

$$Accuracy = \frac{TN+TP}{TN+TP+FP+FN} \qquad (6)$$

$$K = \frac{2(TN \times TP - FP \times FN)}{(TN+FN)(FN+TP)+(FP+TP)(TN+FP)} \qquad (7)$$

Where TP is true positive, TN is true negative, FP is false positive and FN is false negative.

3. Results

In this section, firstly performance of the proposed method has been expressed in terms of Accuracy (Acc.), Sensitivity (Sen.), Specificity (Spe.), and Cohen's Kappa coefficient (K) for both classifiers and secondly the method has been compared to some of other works on the same dataset.

In this study, we strived to generate an approach that serves stability as well as high accuracy. Our purpose was to ameliorate the classification of an MI-BCI system based on EEG signals by paying special attention to the use of non-linear chaotic features rather than previously adopted linear methods. It is also remarkable to mention that the features were extracted only from two EEG channels (C3 and C4), which reduce the dimension and consequently computation.

After training the classifiers, it is time to apprise how successfully our method could perform over the feature-extracted test portion of the dataset. Table 1 indicates four statistical measures calculated to evaluate the classification performance using two well-known classifiers, i.e., SVM and bagging.

Table 1. Classification performance

Classification Performance			
Classifiers	Acc (%)	Sen (%)	Spe (%)	K
SVM	96.4	96.6	96.1	0.92
Bagging	96.5	96.6	96.4	0.92

As it is evident from the results, our proposed method could achieve the aim of distinguishing left and right hand motor imaginary task with a promising accuracy. Thus, the combination of spatial filtering and the selected set of features could function effectively. Evaluation of the method with two classifiers shows the generalization of the method. Additionally, the calculated Kappa values prove the robustness of it.

Several studies have implemented the same dataset (BCI competition IV dataset 2b) to design and advance a BCI system. The classification result of some of these methods is illustrated in Table 2. Various methods including optimizations over feature extraction, classification or both using linear, spatial or deep learning algorithms have been employed. However, we can observe that the proposed method outperformed the other ones compared to other reported results on this dataset in terms of accuracy and kappa value.

Table 2. Comparison between similar studies

Method	Accuracy (%)	Kappa
Malan *et al.* [2]	80.7	0.61
Luo *et al.* [30]	-	0.71
Sun *et al.* [31]	81.7	0.65
Tang *et al.* [32]	82.6	-
Luo *et al.* [33]	85.0	0.70
Dai *et al.* [34]	-	0.56
The proposed method	**96.4**	**0.92**

4. Conclusion

The main idea of this study was to advance classification performance of a two-class motor imagery BCI based on EEG signals. For this purpose, we discussed and proposed a feature extraction approach based on the integration of CSP with non-linear features. In comparison with other studies in the literature on the same dataset, the classification performance of this study has shown a more promising result. Furthermore, Kappa coefficient value states the reliability and robustness of the proposed method. Another advantage of using non-linear features is to decrease computational time. Extracting non-linear features compared to traditional linear features can be more effective in discriminating left and right hand movement of MI-BCIs, though more research is required on this issue.

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