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Research article

Motor Tasks Classification Using Phase Locking Value in a BCI Based EEG Paradigm

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Abstract: Brain-computer interface (BCI) is developing very quickly with applications extending to medical and non-medical fields. Electroencephalography (EEG) is used in BCI to detect and analyze brain signals. An approach based on phase synchronization was tested on two datasets (one with EEG signals recorded from 15 healthy subjects and one with EEG signals recorded from 9 subjects with disabilities). Phase locking value was tested as feature extraction method from EEG signals. k-nearest neighbor (KNN) and support vector machine (SVM) classifiers were applied for discrimination between tasks (right hand motor imagery, left hand motor imagery and feet motor imagery). Classification rates above 81% obtained with kNN and 92% achieved with SVM indicate that phase synchronization based method can be exploited in developing BCI systems for controlling and assisting people with upper and lower limb disabilities.

Keywords: brain computer interface; phase synchronization; upper and lower limb disabilities

1. Introduction

Brain-computer interface (BCI) is defined as a device that enables communication between the brain and external devices. Non-invasive BCI technologies are often used to collect brain signals because they are cost-effective, low-risk, and portable. Electroencephalography (EEG) is the most commonly used BCI method because it can acquire brain signals with high temporal resolution by placing non-invasive electrodes on the scalp [1].

The main structure of a BCI based on EEG signals is: signal acquisition, signal pre-processing, feature extraction, classification and device control [2].

Most of the EEG-based BCI systems rely on the following paradigms: event related desynchronization / event related synchronization (ERD/ERS) associated with motor imagery (MI), event-related potentials like P300, steady-state visual evoked potentials (SSVEP) and slow cortical potentials (SCP) [3-7].

Motor imagery (MI) is a BCI paradigm where users are asked to imagine performing certain movements without actually moving any body parts [8].

Mu rhythm is an oscillation of the EEG signal in the frequency band of 8-12 Hz and is localized in the central, Rolandic region. EEG recordings on healthy subjects have shown that the Mu rhythm occurs at just a few milliseconds before movement, and the amplitude of the desynchronization effect is reflected in the neural network involved in task performance. This is supported by the fact that more complex tasks train more cells and the desynchronization is larger.

ERD reflects the activation of cortical tissues and ERS reflects the inhibition [9].

The EEG signals are defined by their amplitude and by their phase characteristics.

The supporting literature indicate that motor imagery can lead to accuracy rates above 70% in certain brain computer interface users with functional disabilities. This suggests that MI is an effective approach in BCI systems. Specifically, motor imagery is considered particularly suitable and practical for applications such as motor function rehabilitation in stroke patients, where it can aid in recovery by promoting motor control [10-14].

The Common Spatial Pattern (CSP) and Power Spectral Density (PSD) [2] techniques have been utilized to extract distinctive amplitude features from EEG signals. Phase is considered to be more relevant than amplitude for discriminating motor imagery tasks in EEG signals [15]. Phase synchronization indicates if the phase difference is close to a constant within a specified time interval. For this reason it is necessary that the EEG signal to be filtered in a narrow frequency band [16].

An offline analysis was tested for extracting and classifying features contained in EEG signals using phase locking value index based on phase synchronization. PLV was applied in a BCI paradigm based on sensorimotor rhythms (Mu rhythm) in order to conclude that phase synchronization can be used to determine changes that appear during right hand motor imagery, left hand motor imagery and feet motor imagery.

Section I belongs to introduction, in Section II are described the datasets used and in Section III are presented the methods used for processing and classifying the EEG features. The results of this research are presented in Section IV.

2. Datasets

A. Dataset I

EEGs were recorded from 15 healthy volunteers (10 women and 5 men aged 19 - 60) using g.tec system in the biomedical signal processing laboratory of the Faculty of Medical Bioengineering. The g.tec system [17], g.GAMMAsys, was composed from the following components: 8 active electrodes were mounted on g.GAMMACAP and connected via g.GAMMAbox to amplifier, g.MOBIlab+ module and BCI 2000 platform [18]. Channels CP3, CP4, P3, C3, PZ, C4, P4, and CZ were selected for the electrode placement. Electrodes were applied to the volunteer's scalp in accordance with the International Reference System 10–20. On the right ear, the reference electrode was positioned. The volunteers were advised not to move, not to speak and not to blink during the experiment. The volunteers were placed in front of a PC monitor that displayed right arrows, left arrows and bottom arrows random. Volunteers were instructed to imagine the movement of the hand or both feet indicated by the arrow. Volunteers were advised to try to relax once the screen was white. Every arrow showed up for 30 times. Two seconds separated each visual stimulus and 256 Hz was the sampling frequency employed. The EEG recordings were made in different days.

B. Dataset II

Dataset II - *BNCI 2015-004 Motor Imagery* contains EEG signals recorded on 2 separate days from 9 participants (2 men and 7 women aged 38 - 42) with motor disabilities. Before taking part in this research, participants had no prior experience with BCI. They carried out five different mental tasks (MT) in accordance with a cue-guided experimental paradigm: mental word association (WORD), mental subtraction (SUB), spatial navigation (NAV), imagining of the right hand movement (HAND), and imagination of the movement of both feet (FEET) [10].

3. Methods

Phase locking value (PLV) is used for measuring synchronization in the time domain and for analyzing EEG signals during motor imagery [19]. PLV characterizes the stability of the phase difference between the phases $\varphi_x(t)$ and $\varphi_y(t)$ for signals $s_x(t)$ and $s_y(t)$,

$$PLV = \left|\langle e^{j\Delta\varphi(t)} \rangle\right| \quad (1)$$

where $\Delta\varphi(t) = \varphi_y(t) - \varphi_x(t)$ and $<>$ is the mediation operator.

In order to calculate PLV index, it is necessary to know the instantaneous phases $\varphi_x(t)$ and $\varphi_y(t)$ of the signals $s_x(t)$ and $s_y(t)$. The Hilbert transform is given by [19]:

$$\tilde{s}(t) = \frac{1}{\pi} p.v. \int_{-\infty}^{+\infty} \frac{s(\tau)}{t-\tau} d\,\tau \quad (2)$$

where $p.v.$ represents the principal Cauchy value.

A Support Vector Machine (SVM) uses a discriminant hyperplane to select classes. SVM is utilized in BCI systems to select features from EEG signals and classify them into different classes. Due to its high accuracy, the SVM algorithm is well suited for use in BCI applications where accurate classification is required [8].

The k Nearest Neighbours (kNN) classifier is a method of classes classification that uses k nearest classes in the training set. kNN is one of the simplest learning algorithms, as an object is classified based on the majority vote of its neighbors, often being classified into the category that most of its k neighbors belong to. The algorithm search for data in the training set that is similar or close to the record to be classified [20].

Classification rate is a very important metrics in BCI systems and determines how frequently the BCI makes a right selection or what proportion of all selections are correct [2].

$$Classification\ rate = \frac{correctly\ classified\ test\ trials}{total\ test\ trials} x100 \quad (3)$$

4. Feature Extraction

EEG signals from the database I are loaded into MATLAB. To eliminate phase distortions, these signals were filtered using a finite impulse response bandpass filter of order 50. The filtering was focused on the frequency band of 8 to 12 Hz, which corresponds to the Mu rhythm. Segments related to right hand motor imagery, left hand motor imagery and feet motor imagery were extracted from the EEG signals. The Hilbert transform was applied to compute the instantaneous phase for each channel and PLV was calculated (Eq. 1) for the pairs of EEG channels illustrated in Fig. 1. Electrodes Cz and Pz from the supplementary motor area were used to form the pairs of EEG channels (Fig. 1). Three feature matrices were formed: right hand movement imagery matrix (RH), left hand movement imagery (LH) and feet movement imagery (FEET). The binary classification was tested for the following: RH_LH, RH_FEET and LH_FEET. The multiclass classification was made for: RH, LH and FEET.

The average classification rates were reported using the cross-validation method applied to kNN and SVM classifiers and to each subject. A 5x5 cross validation approach was tested.

Figure 1 depicts the flow chart of the tested method and the classification models used.

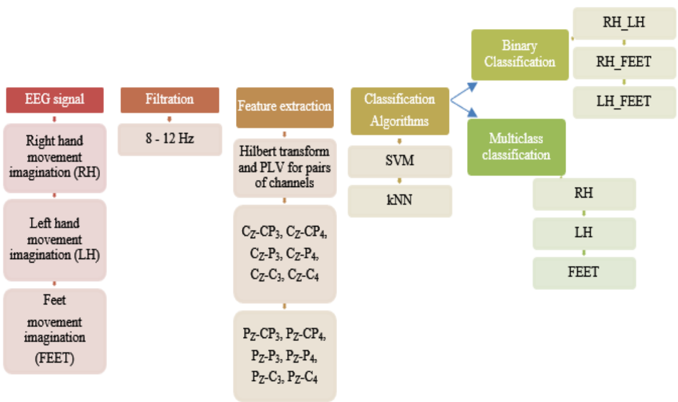

Figure 1. Flow chart of the proposed method – Dataset I

4. Results

The offline approach using PLV was tested for the extraction and classification of features contained in EEG signals. First the method was applied for Dataset I and after that for Dataset II taking into consideration only imagining of the right hand movement and imagination of the movement of both feet.

Figure 2 displays the classification rates (%) attained with kNN classifier for binary classification RH_LH, RH_FEET and LH_FEET – Dataset I. The classification rates were above 95% for all the cases and the highest median was achieved for LH_FEET.

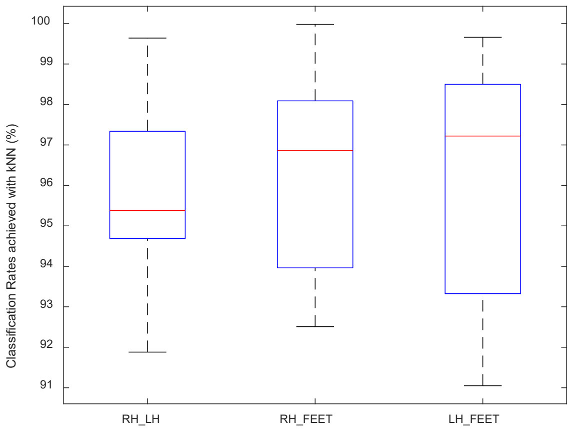

Figure 2. The classification rates (%) obtained with kNN for RH_LH, RH_FEET and LH_FEET – Dataset I

In Figure 3 are shown the classification rates (%) obtained with SVM for RH_LH, RH_FEET and LH_FEET – Dataset I. The median of the classification accuracy was above 96% for all cases.

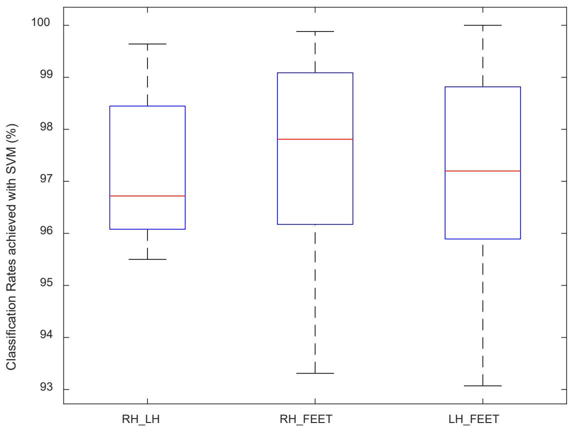

Figure 3. The classification rates (%) realized with SVM for RH_LH, RH_FEET and LH_FEET – Dataset I

Figure 4 shows the experimental results gained with classifiers kNN and SVM using a multiclass classification – Dataset I. The classification rates obtained were above 94% with SVM and above 98% with kNN.

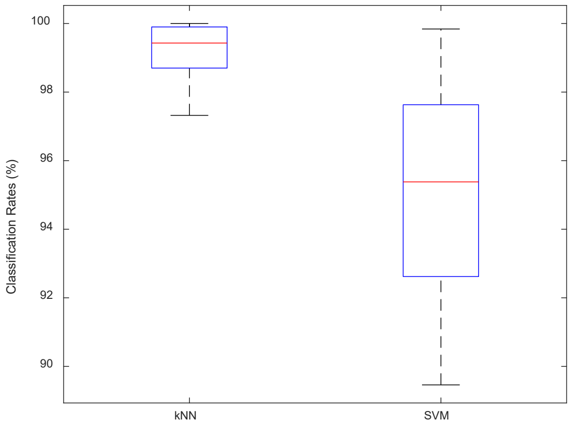

Figure 4. Results of multiclass classification rates (%) for classifiers kNN and SVM – Dataset I

In Figure 5 are depicted the classification rates realized with kNN and SVM for RH_FEET – Dataset II. The results were higher with kNN classifier (> 94%) than with SVM classifier.

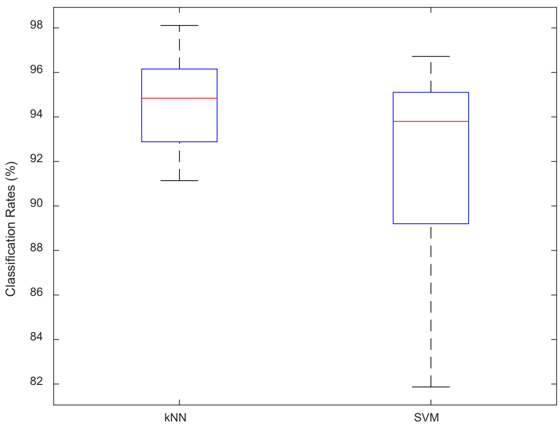

Figure 5. The classification rates (%) obtained with kNN and SVM for RH_FEET – Dataset II

Table 3 displays the maximum, mean and median classification rate (%) for Dataset I using classifiers kNN and SVM for binary and multiclass classification. A maximum classification rate was achieved with SVM classifier. With kNN the best results were obtained for RH_FEET and with SVM the highest values were attained with multiclass classification.

Table 1. The maximum, average and median classification rate using binary and multiclass classification for kNN and SVM – Dataset I

Dataset I						
Classifier	**kNN**			**SVM**		
Binary classification	**Max (%)**	**Mean (%)**	**Median (%)**	**Max (%)**	**Mean (%)**	**Median (%)**
RH_LH	99.64	95.9	95.38	99.64	97.20	96.72
RH_FEET	99.98	96.3	96.86	99.88	97.54	97.81
LH_FEET	99.66	96.18	97.22	100	97.21	97.2
Multiclass Classification	99.84	95.18	95.46	100	99.08	99.59

The results realized for RH_FEET – Dataset II are presented in Table 4 The highest values of max, mean and median classification rates were obtained with kNN classifier.

Table 2. The maximum, average and median classification rate using binary and multiclass classification for kNN and SVM – Dataset II

Dataset II						
Classifier	**kNN**			**SVM**		
Binary classification	**Max (%)**	**Mean (%)**	**Median (%)**	**Max (%)**	**Mean (%)**	**Median (%)**
RH_FEET	98.11	94.64	94.84	96.72	91.47	93.80

Dairi and his colleagues [22] reported a 98.5% accuracy using a quadratic time-frequency distribution and deep belief network-driven isolation forest scheme to classify the EEG signals.

6. Conclusions

Phase locking value based on phase synchronization was tested on two datasets: a dataset composed of EEG signals from 15 healthy volunteers and a dataset formed from EEG signals from 9 participants with motor disabilities.

SVM and kNN classifiers were applied in order to classify motor imagery tasks. Binary classification and multiclass classification were tested.

For Dataset I the highest median classification rate (97.22%) was obtained for LH_FEET and kNN classifier. When SVM classifier was used the highest median classification rate of 97.81% was achieved for RH_FEET. The best results of multiclass classification were realized with SVM classifier.

For Dataset II only the case RH_FEET could be tested. The highest classification rates were attained with kNN classifier (94.84%).

The subjects from Dataset I and Dataset II did not receive BCI training before participating at the experiments. The PLV can be used as a tool for further rehabilitation since all the subjects from Dataset II have motor disabilities.

The approach was tested on two different datasets in order to ensure the accuracy of the feature extraction method and of the classification methods.

The research based on classification rates obtained showed that the proposed method is able to classify two classes (right hand and left hand, right hand and feet, left hand and feet) and multiple classes (right hand, left hand and feet) with a median classification rate above 90%.

Future research implies testing the proposed method on other databases with subjects with motor disabilities.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. The University of Medicine and Pharmacy "Grigore T. Popa" from Iasi Ethics Committee has approved this study (no. 191 – 25.05.2022) and all participants have signed an informed consent form prior to taking part in the research.

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