Classification of EEG Signals Based on Imaginary Movement of Right and Left Hand Wrist

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***Abstract*— In this paper we present EEG signal classification used to design Brain–Computer Interface (BCI) system based on imagination of movements of the left and the right hand wrist. A comparative study of two different classifiers has been reported for four different movement of each of the wrist. SVM classifier indicates the average classification accuracy of 94% for the same movement (right Vs left) of wrists and 91% for different movements of both the wrists. An Eigenbrain technique is used for feature extraction and classifies the extracted features by using two different classifiers for achieving best accuracy. The feature reduction here has been performed using Principal Component Analysis (PCA).**

Keywords—Brain-computer interface; Linear discriminant analysis; Support-vector machine; Principal component analysis.

I. INTRODUCTION

Brain computer interfaces are the new and most interesting era of research of the current century with immense potentials to improve human lifestyle. A brain–computer interface (BCI) uses brain signals to drive external devices without participation of the spinal and peripheral motor system [9]. The brain activities for BCI can be measured using EEG (Electroencephalography). EEG based BCI is preferable because of its non-invasive nature, and its superior temporal resolution that reflect brain dynamic changes. It also has the capability to bring the disabled people back to the mainstream of life providing assistive rehabilitation. With proper research and implementation of advances BCI can contribute to the wide spectrum of areas viz. robotics, mass communication, automobiles, military purposes, healthcare, games and entertainment, etc. In order to control a BCI, the user must produce different brain activity patterns that will be identified by the system and translated into commands. In most existing BCI, this identification relies on a classification algorithm, i.e., an algorithm that aims at automatically estimating the class of data as represented by a feature vector [1]. Imagination of movements uses mental tasks for BCI application. Most of BCIs are based on classification of imagination of different parts of the body; these are left and right hand, left and right leg etc. [8]. We present the classification accuracy of four different movements (extension, flexion, pronation and supination) between the left and right wrist. Eigenbrain is best suited for feature extraction for BCI application. Eigenbrains represent eigenvectors of the covariance matrix. Eigenvectors of covariance matrix called Eigenbrains that can be used to represent the brain's electrical activity have been employed for feature extraction. The useful feature is found in last three channels of the EEG.

Extracted features are applied as input of the classifier to classify imaginary left and right wrist movement for BCI application. The classifier then uses the extracted feature vectors to train itself. After training, the classifier becomes able to classify inputs. The accuracy of classifier is one of the main pitfalls of the development of the BCI systems which directly affect the decisions made as the BCI output. This accuracy is affected by the quality of the EEG signal and the processing algorithms. The given block diagram describes the procedure followed for classification of EEG signal for wrist movement.

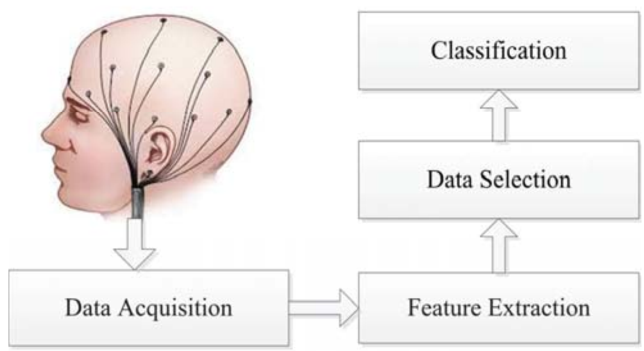

Fig. 1. Block diagram of different stages of EEG classification.

II. MATERIAL AND METHODS

EEG recording was done on a Biosemi^{TM} Active Two system using the 64 channel montage based on international 10-20 system. The Biosemi Active two hardwares have an antialiasing filter has a fifth-order sine response with a -3 dB point at 1/5th below the selected sampling rate. The sampling rate was 256 samples /s. The system with a preamplifier stage can correct for high impedances (in the range of 100 KΩ) on the electrodes. So impedance measurements are not necessary. As per recommendation of the Active Two system, the offset voltage (between the A/D box and the body) during electrode placement should be within 50 μV for effective electrode contact and care was taken to make sure that all the electrodes lie within these limits. Eight additional monopolar electrodes (labelled EX) are provided in the Biosemi™ Active Two system for measuring potentials from other parts of the body. These electrodes are used for reference. In our experiment reference was from the right ear. All electrodes had the same ground. To eliminate the possibility that there was electromyography (EMG) from the limbs related to the movement imagery task, EMG was bipolarly recorded during imaginary movements within two pairs of EX electrodes placed 2 cm. apart on the flexer carpi and extensor carpi muscles. Trials that had any significant activity (e.g. more than 1 standard deviation above rest levels) were to be discarded. Electro-oculograms (EOGs) were recorded from the orbicularis oculi, outer cantus of the right eye and the middle of the lower loop of the orbicularis oculi. While this was done to eliminate EOG artefacts in another study [11], the EOG electrodes would have detected significant facial EMG if present. Based on these criteria, however, no trials needed to be discarded in this study. Although residual EMG in the gamma band may have remained despite these measures, we feel that the EMG contamination is not class-related and the contamination, if any, would be uncorrelated.

III. THEORY AND CALCULATION

Feature Extraction

All 64 channels of EEG signals are considered for feature extraction. Feature is extracted using Eigenbrain technique. More useful information found in last three channels of EEG. So, three Eigenbrains (i.e., Eigenvectors of covariance matrix) corresponding to largest (in magnitude) eigenvalues are selected. These three eigenvectors are multiplied with original EEG signal to know the characteristics of all 64 channels of EEG, which forms a very large feature vector which is hard to analyse altogether.

To overcome this difficulty feature reduction is done to select the most important and independent features. It is mainly done by principal component analysis (PCA). Reducing the number of features and selecting the most important features reduces the complexity of the analysis procedures, hence increasing the rate to computation with better accuracy.

Eigenbrains

In eigenbrains technique, we assess the strength of the interaction between variables in the given terms time varying signal at channel.

Let $C_i(t)$ be the time varying signal at channel i and $C_j(t)$ be the signal at channel j and

$$C_{ij}(t) = C_i(t) - C_j(t)$$

Let $E = e_{ij}$ be the covariance matrix of interaction strengths associated with the channel.

$$e_{ij} = \begin{cases} 1 & if\ i = j \\ \dfrac{1}{0.001 + f(C_{ij})} & otherwise \end{cases} \tag{1}$$

Where $f(C_{ij})$ is the mean absolute value or root mean square value of C_{ij}.

$$f(C_{ij}) = \frac{1}{T}\sum_{t=0}^{T-1}\left|C_{ij}(t)\right| \tag{2}$$

Here the different classifiers are being used and results were tested for all the three subjects, these results were obtained by considering the feature extraction of the data. Each of four imagined wrist movements was individually tested to discriminate for left and right wrist movements.

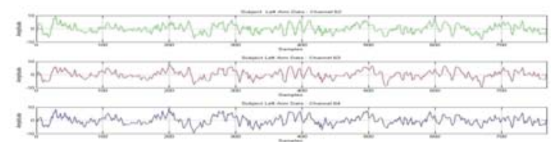

Fig. 2. EEG signal amplitude for last three channels.

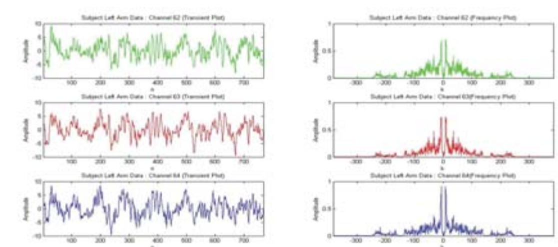

Fig. 3. Energy spectrum of EEG signal for last three channels.

IV. RESULTS AND DISCUSSIONS

We tested the result on three subjects' datasets, there are 8 sets of data for each subject: four sets of data are for Right hand wrist and four sets of data are for Left hand wrist of four different kind of movements (extension (E) /flexion (F), and pronation (palm down P)/ supination (palm up S)). The sampling frequency is 256 samples / sec.

Basically the EEG data set used in this work is a three dimensional data [channel, trial, sample], [64×60×768]. Fig. 2 shows the EEG signals for last three channels (channel-62, channel-63, and channel-64) for 768 samples. Fig. 3 shows the real-part of power density spectrum of these three channels. All features have been implemented in MATLAB (R 2013a).

We are taking three features per trial, hence, the data obtained after feature reduction was a matrix of [60 ×3] are applied to the input of the classifier and results were tested using linear and non-linear classifiers. The data sets were divided into five groups of a matrix of [12×3], a combination of four groups constituted to training set and the fifth was used for test set (not used in training). The classifier is trained using 4 of the 5 groups and is test on the remaining data. This procedure is repeated for all the five possible combinations and results are averaged. Using this heuristic, we were able to test each group of data independently.

Each of four imagined wrist movements was individually tested to discriminate for left and right wrist movement. There is sixteen combinations are possible as listed in Table I. performance of the classifier, i.e., accuracy is obtained by confusion matrix. Accuracy is calculated for all five groups of combination of data and results are averaged for same movement (Mov1 vs Mov1) and different movement (Mov1 vs Mov2) of right versus left hand wrist.

Similarly the same procedure is repeated for another two subjects also for the same movement and different movements. In this paper these results are not displayed to avoid repeatability.

In order to evaluate the accuracy in terms of similar type of movement and different type of movement the diagonal and off-diagonal elements were averaged and these results are reproduced. The diagonal elements of the Table IV shows the classification accuracies for same type of movement in the right and left wrist and off-diagonal elements shows the classification accuracies for different type of movements. Same procedure is also repeated for non-linear classifier.

TABLE I. COMBINATIONS FOR DISCRIMINATION OF RIGHT VS LEFT

R vs L	**Mov1**	**Mov2**	**Mov3**	**Mov4**
Mov1	R1, L1	R1, L2	R1, L3	R1, L4
Mov2	R2, L1	R2, L2	R2, L3	R2, L4
Mov3	R3, L1	R3, L2	R3, L3	R3, L4
Mov3	R4, L1	R4, L2	R4, L3	R4, L4

TABLE II. MOV1 R1 VS MOV1L1 FOR SVM CLASSIFIER

Group of Training data	**Test data**	**Classification Accuracy (%)**
G_1 G_2 G_3 G_4	G_5	87
G_1 G_2 G_3 G_5	G_4	91
G_1 G_2 G_4 G_5	G_3	100
G_1 G_3 G_4 G_5	G_2	100
G_2 G_3 G_4 G_5	G_1	50
Average Result		**85**

TABLE III. MOV1 R1 VS MOV2 L2 FOR SVM CLASSIFIER

Group of Training data	**Test data**	**Classification Accuracy (%)**
G_1 G_2 G_3 G_4	G_5	87
G_1 G_2 G_3 G_5	G_4	100
G_1 G_2 G_4 G_5	G_3	100
G_1 G_3 G_4 G_5	G_2	100
G_2 G_3 G_4 G_5	G_1	83
Average Result		**94**

TABLE IV. CLASSIFICATION ACCURACY OF SUBJECT1 FOR SVM CLASSIFIER

L / R	**Mov1**	**Mov2**	**Mov3**	**Mov4**
Mov1	85	94	71	71
Mov2	70	78	67	60
Mov3	78	94	72	72
Mov4	94	79	97	91

CONCLUSION

The results obtained in different combinations of movements are satisfactory. The main goal of this report was to identify the signal analysis algorithms capable for detecting brain activity produced by motor imagination. For the most subjects the reliable classification accuracy achieved around 78-95 % for the same movement and 76-95% for different movement is obtained using different type of classifiers. From the result we conclude that Eigenbrain technique is successful in providing discrimination between left and right imaginary wrist movements.

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