Cepstral Coefficients Based Feature for Real Time Movement Imagery Classification

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Abstract—**This paper proposes a unique feature extraction method based on linear convolutive mixing model of the human brain for the real time application. Proposed method is very useful for electroencephalogram (EEG) signal based real time brain computer interface (BCI). The raw EEG signals are subjected to band pass filter to select the band of interest. The filtered EEG signals are subjected to the proposed feature extraction method. The proposed feature extraction method considers the Multivariate Gaussian Probability Density Function (MVGPDF) of Cepstral Coefficients (CC). The MVNGPDF is applied to generate the probabilistic features over cepstral coefficients. Further, the extracted feature is subjected to the conventional linear classifiers like Naive Bayes and linear discriminant analysis classifier to decide its belongings. The performance of the proposed feature extraction method is compared in terms of the classification accuracy and mutual information.**

Keywords: Electroencephalogram (EEG), Brain-computer interface (BCI), Cepstral Coefficient (CC), and Multivariate Gaussian Probability Density Function (MVGPDF)

I. INTRODUCTION

Brain Computer Interface (BCI) is the emerging research area and the sister technology of human-computer interaction (HCI). The BCI provides a direct neural interface between the human brain and a computer. The BCI system provides assistance to the human being with paralytic disability. The objective behind this type of research work is to control an assistive external device like an electric wheelchair [1]-[3], artificial limb [4] etc. using electric, magnetic or hemodynamic brain signals. The BCI framework consists of main five stages are Signal Acquisition, Preprocessing, Feature extraction and Classification followed by device control [1]-[6].

The performance of the BCI systems are evaluated by performance parameters like Mutual Information, Classification accuracy [6]-[7] etc. The maximum value of mutual information (MI) should be unity for two class problems. The maximum value of classification accuracy is 100 %. Achieving the maximum value of classification accuracy and the maximum value of MI under unsupervised learning paradigm is still open problem in the BCI researcher community. To resolve this issue, the authors propose a novel technique of feature extraction from the EEG signals while keeping in mind the time complexity.

The EEG signals are non-stationary signals. The five to hundred millisecond signals considered as quasi stationary signal [5]. Over a large period of time, the EEG signal behaves as non-stationary signal. EEG signal reflects the sequence of the brain activities. Based on this quasi-stationary behavior, a cepstral coefficient based feature extraction method has applied to extract the brain wave information from the EEG signals. Normally EEG signals are recorded with the sampling frequency less than 1 KHz, so that a linearity assumption can be applied in the EEG signal processing [8]-[10].

Multivariate Gaussian probability density functions of cepstral coefficients used as features in the proposed algorithm. Butterworth band pass filter has been used as a preprocessing technique. The cepstral coefficients with MVGPDF are used as feature extraction method [11]-[12]. The outcomes of the feature extraction are taken as final feature matrix. To analyze the performance of the feature extraction process, the extracted features are classified by two well-known linear classifiers Naive Bayes [13]-[16] and Discriminate Analysis [17]-[19]. The detection of movement related thought pattern in the human brain is done through the movement imagery classification methods and the final stage of the brain pattern identification is to control an external machine by the thought of the user [1]-[2]. This paper is organized into five sections. Section II describes the experimental paradigm of BCI competition dataset [20]- [22]. Section III describes the proposed methodology, and Section IV describes the result and discussions followed by the conclusion and future work.

II. EXPERIMENTAL PARADIGM

The BCI competition II dataset III was used for this analysis [20]-[22]. The EEG dataset has provided by the Department of Medical Informatics, Institute for Biomedical Engineering, University of Technology Graz. Data comprises right hand and left hand of MI tasks recorded from one healthy subject from 3 electrodes. The EEG

Dataset comprises 280 trials including training and testing data. The cue was presented from three second to nine second. At the same time, the feedback was presented to the subject. Within this period, it should be possible to distinguish the two types of trials. The sampling frequency of the data set was 128Hz.

The data set contains 3 EEG channels, 140 trials with 9 seconds each. Timing scheme of the paradigm displayed in Fig. 1.

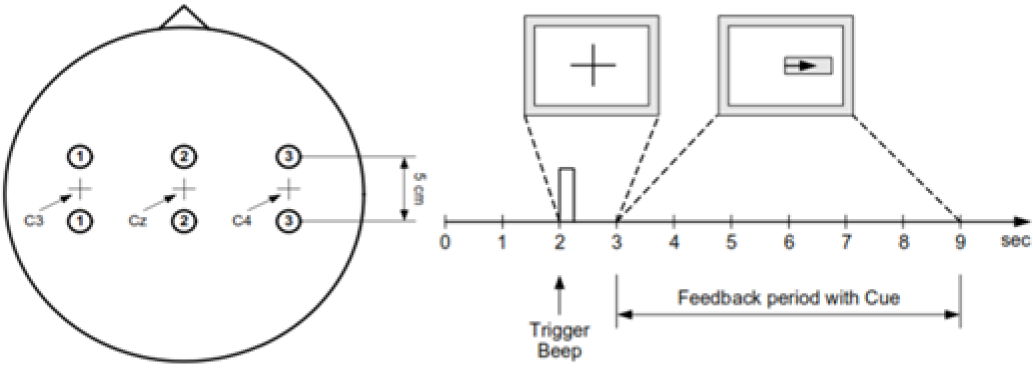

Fig. 1. Timing scheme of the paradigm

III. PROPOSED METHODOLOGY

The Proposed methodology of the EEG signal preprocessing is shown in Fig. 2. The recorded EEG signals (displays in block I), Butterworth band pass filter has been applied to extract motor band signal from the row EEG signal (displays in block II). The filtered signal is subjected to cepstral coefficient estimation method (displays in block III). The cepstral coefficients were further subjected to MVGPDF estimation (displays in block IV), the MVGPDF of the cepstral coefficients are taken as feature matrix, which are further subjected to two classifiers (displays in block VA and VB).

The raw EEG signal is represented as $E_C^i(n)$ where C ∈ [C3, C4] and i ∈ [left, right].

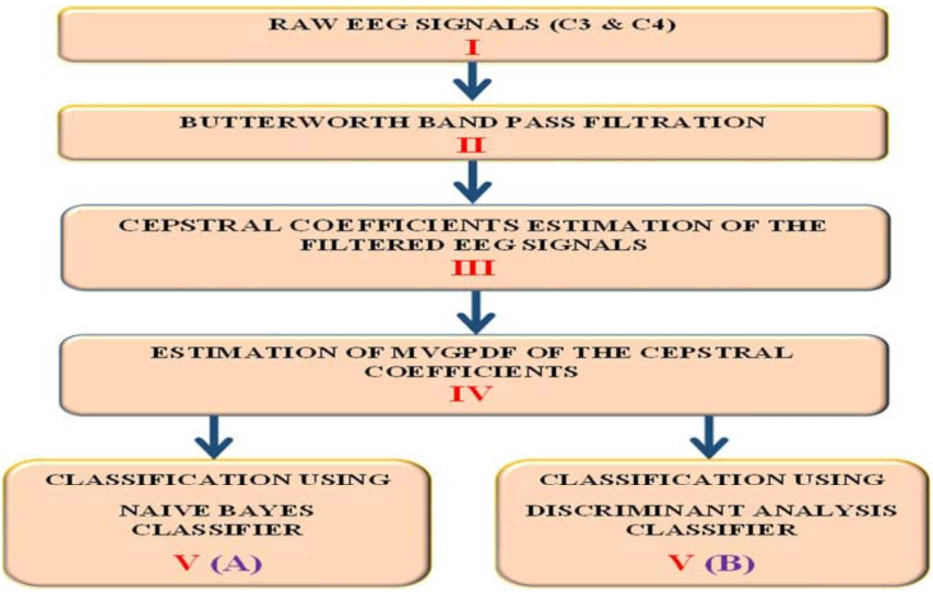

Fig. 2. Proposed Methodology

A. *Preprocessing using Band Pass Filter*

It is known to all that the EEG signals contain maximum information in the small frequency bands. These frequency bands are basically retrieved from the raw EEG signals. In order to retrieve the frequency band information one can use digital filter either finite response filter (FIR) or infinite response filter (IIR). The frequency band information's are also known as rhythmic information. Here band pass IIR filter was used for filtering the alpha and beta band signal i.e. 8-30 Hz frequency band. The Butterworth band pass filtered EEG signal X (n) can be expressed as

$$h(n) * E_C^i(n) = X_C^i(n) \tag{1}$$

where h(n) is the impulse response of order six and E is the raw EEG signal.

B. Feature Extraction

Feature is a unique characteristics of the signal. In order to distinguish, how one can select the hidden characteristics from the signals, is very fundamental problem, in pattern recognition approach. The way by which one can extract the hidden information from the signal is known as feature extraction. The BCI community have used features to distinguish movement imagery classification like power spectral density, autoregressive coefficients, wavelet coefficients, asymmetry coefficients, hjorth parameter etc [23]-[24]. The applied feature extraction method cannot achieve 100% classification accuracy as well as maximum value of mutual information unity. The action potentials of the excited neurons are recorded through the electrode placed over the scalp. Under the assumptions that human brain is a linear mixing system. The recorded EEG signal has to pass the inverse filtering approach to estimate the synchronized active potential for both movement imagery classification. The most important technique to do the inverse filtering is the cepstrum method. The estimated cepstral coefficients are further subjected to multivariate Gaussian density function to estimate probabilistic feature.

a. Cepstral Coefficients (CC)

The concept of cepstral coefficients basically used to calculate the original excitation function in speech production system [9]. It is very interesting concept to perform the inverse filtering from the recorded speech signal. Motivated by the cepstral analysis of speech signal, the authors think to apply similar analysis to get the synchronized active potential from each channel to retrieve the movement imagery information[8],[10]. The recorded EEG Signal has been divided into seven frames with 50% overlap using hamming window. Twenty numbers of filter bank channels and twelve number of cepstral coefficients (C) have been estimated from each frame. Fig.2 depicts the way to calculate the cepstral coefficient.

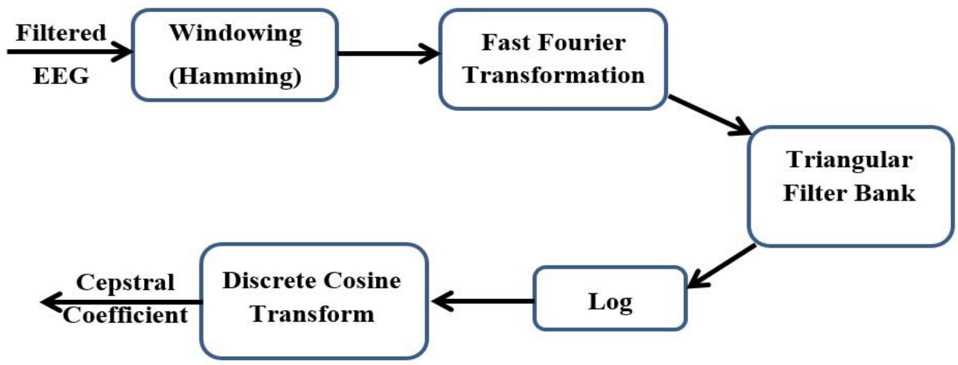

Fig. 3. Cepstral coefficient estimation method

$$X_C^i(n) \longrightarrow \boxed{\text{Cepstral Coefficient Estimation}} \longrightarrow [C_C^i]_r \quad , \tag{2}$$

where r is the number of cepstral coefficient.

b. Multivariate Gaussian Probability Density Function (MVGPDF)

Multivariate Gaussian probability density function is a generalization of the one-dimensional Gaussion probability density function in higher dimensions. A random vector is said to be k-variate Gaussion distributed if every linear combination of its k components has a univariate Gaussion distribution. Its significance derives from the central limit theorem. The multivariate Gaussion distribution is used to describe, any set of correlated real-valued random variables each of which clusters around a mean value [11]-[12].

$$\frac{1}{\sqrt{|\Sigma|(2\pi)^d}} e^{-\frac{1}{2}([C_C^i]_r-\mu)\Sigma^{-1}([C_C^i]_r-\mu)'} = f([C_C^i]_r,\mu,\Sigma)=[M_C^i]_r \quad , \tag{3}$$

where μ is the mean Σ is the covariance of Cepstral coefficients and M_C^i is the multivariate Gaussian pdf of size twelve by one, has taken as feature matrix and it was further processed for classification.

C. Feature Classification

a. Naive Bayes classifier (N B)

Naive Bayes classifiers are the family of simple probabilistic classifiers. Naive Bayes classifiers are based on the Bayes' theorem with strong (naive) independence assumptions between the features. The Naive Bayes classifiers are highly scalable classifier that requires a number of features to solve a learning problem [13]-[16].

b. Discriminate Analysis Classifier (DA)

Discriminant Analysis is a well-known linear classifier based on the Fisher criterion. The dimensionality reduction is the supreme property for characterizing the statistical data. Linear classifier projects multidimensional data into one dimension and classifier take decision for classification of its belonging as per some defined measure [17]-[19].

IV. Result and Discussion

In order to evaluate the performance of the proposed real time feature extraction method, authors consider two different type of classifier Naive Bayes and Discriminant Analysis classifier. Classification Accuracy and Mutual Information are taken as the parameter of evaluation. The performance of the proposed algorithm for training data set displayed in Fig. 4. Fig. 5 shows the performance of the proposed algorithm for testing data set. The outcome of the both classifier shows in the Fig. 4 and Fig.5. The maximum Classification Accuracy for training data has been achieved for DA classifier approximately about 91% and for NB classifier about 86% in same time instance displayed in Fig. 4.

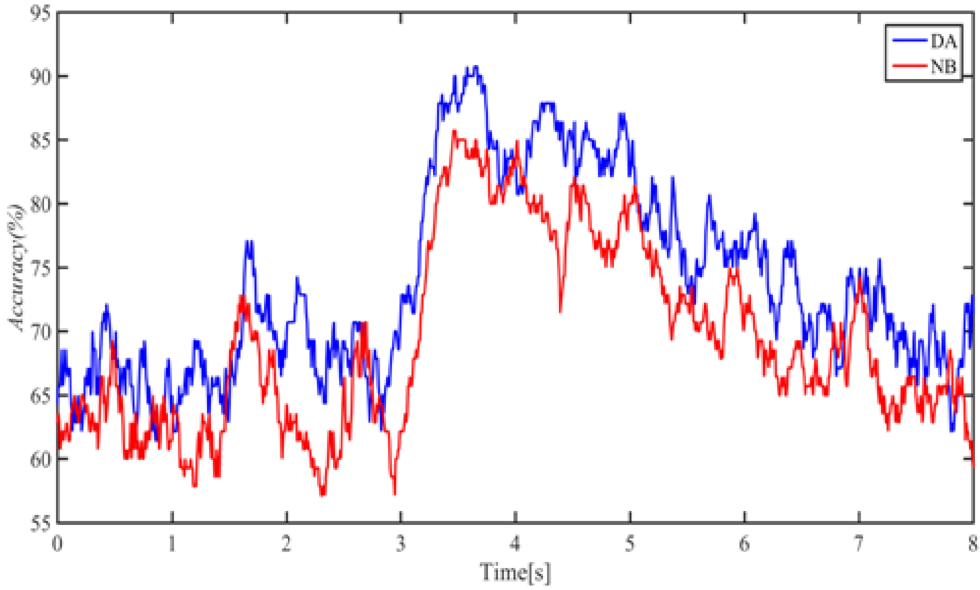

Fig. 4. Classification Accuracy plot for training data of BCI Competition dataset III using both Classifiers

The maximum Classification Accuracy for testing dataset has been achieved for DA classifier approximately about 80% and for NB classifier about 81% in the nearly same time instance displayed in Fig. 5.

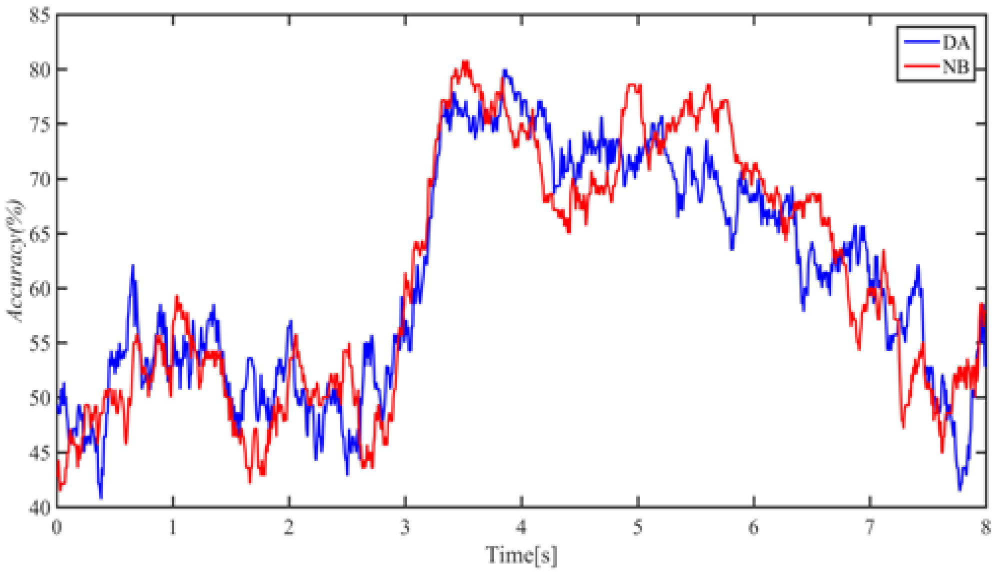

Fig. 5. Classification Accuracy plot for testing data of BCI Competition dataset III using both Classifiers

The highest Mutual Information for training data set has been achieved for DA classifier 0.78 and for NB classifier 0.51 in same time instance displayed in Fig. 6.

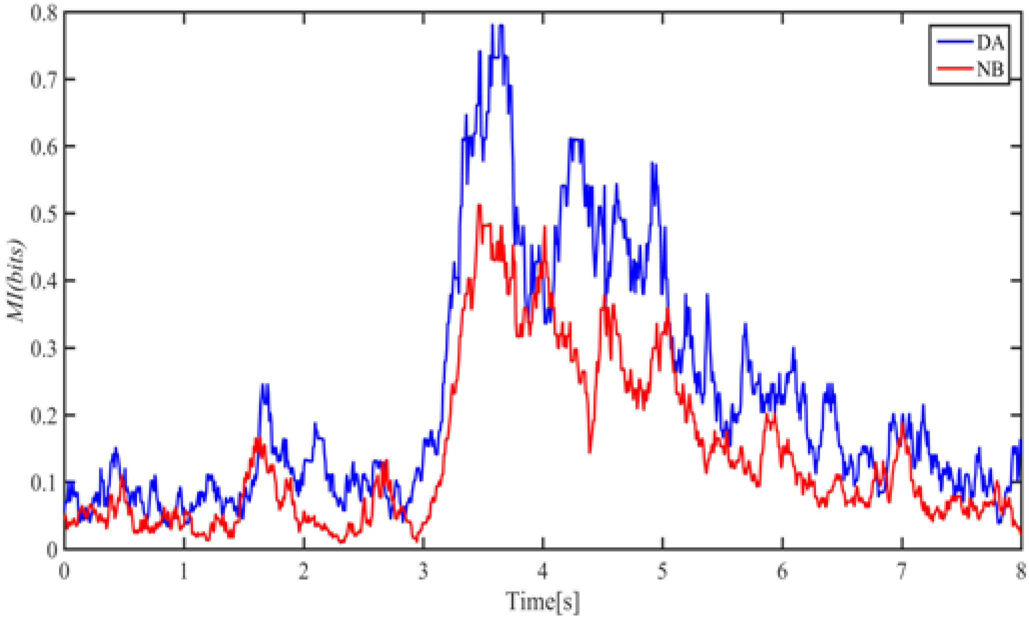

Fig. 6. Mutual Information plot for training data of BCI Competition dataset III using both Classifiers

The maximum Mutual Information for testing data set has been achieved for DA classifier 0.31 and for NB classifier 0.34 in same time instance displayed in Fig. 7.

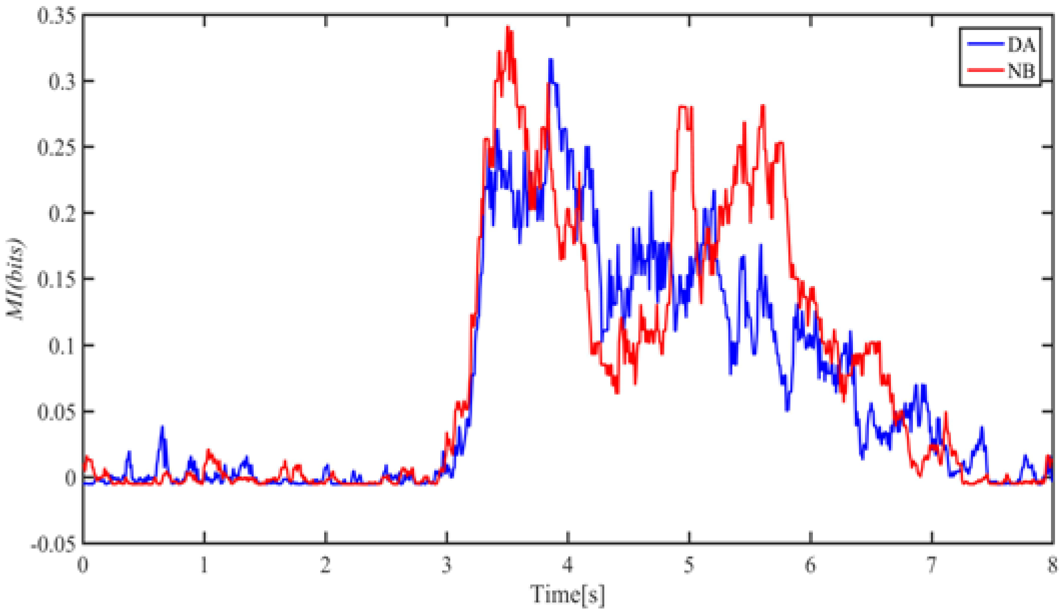

Fig. 7. Mutual Information plot for testing data of BCI Competition dataset III using both Classifiers

The variation of classification accuracy of proposed algorithm for training and testing data set with respect to time using NB Classifier displayed in Fig. 8. The classification accuracy training data set shows higher accuracy then the testing dataset.

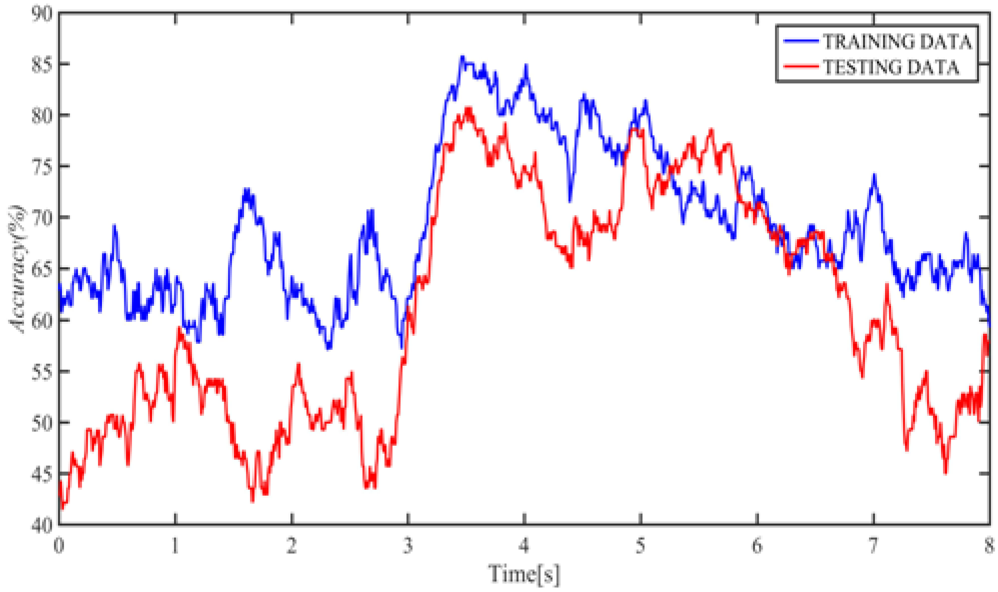

Fig. 8. Classification Accuracy plot for training and testing data of BCI Competition dataset III using Naive Bayes Classifier

The variation of classification accuracy of proposed algorithm for training and testing data set with respect to time using DA Classifier displayed in Fig. 9.

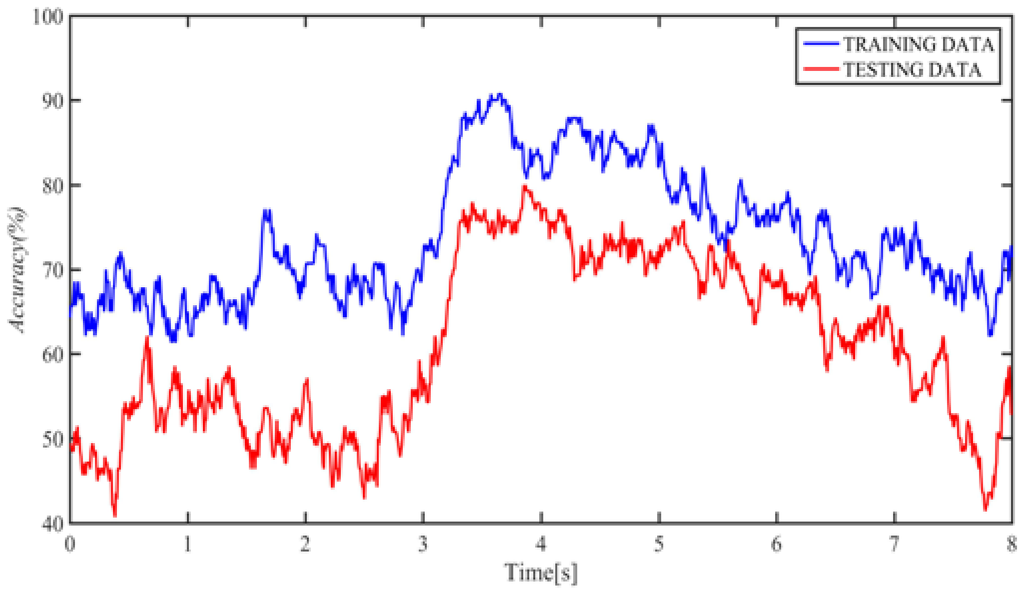

Fig. 9. Classification Accuracy plot for training and testing data of BCI Competition dataset III using Discriminant Analysis Classifier

The classification accuracy of proposed algorithm for training data set shows higher accuracy then the testing dataset. It is an open challenge for the researchers of BCI to achieve 100% classification accuracy in real time situations.

V. Conclusion and Future Work

The proposed algorithm is more effective in training dataset by using DA classifier in comparison with testing data set and NB Classifier. The highest classification accuracy and mutual information has been achieved in between 3 to 6 second. The classification accuracy and mutual information maintains the same trend for training and testing dataset that proves the repeatability and robust ness of the proposed algorithm. This feature extraction mechanism is unable to provide 100% classification accuracy, because the cepstral coefficients are calculated by tacking linearity assumption in the brain model. Human brain is a nonlinear system. The classification accuracy can be improved by tacking nonlinearity assumption. The future work of this research can be extended by nonlinear modeling. The proposed method can be applied to control robotic movement.

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