An Insight on Various Classification Techniques Employed in Processing of EEG Brain Signals

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ABSTRACT- Brain Computer interface relies heavily on the way the signals received from the brain are processed. There are numerous method that have been put to use for classification. In this work we present a review on the popularly used classification techniques. This work intends to present the salient features of the technique employed along with its limitation such that it helps the researchers as a guideline

Keywords: BCI, EEG, SSVEP-NIRS Hybrid BCI, EEG-EMG Hybrid BCI , EEG-EOG Hybrid BCI

INTRODUCTION

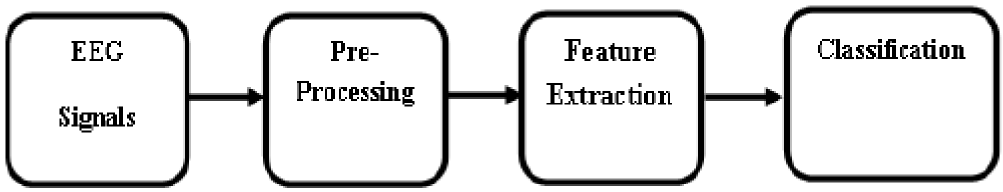
BCI (Brain-Computer Interface) plays the role of a mediator between the human brain and the computer. It provides an opportunity to the users to control the external devices by sending the signal from the brain to them. These BCI interfaces are extremely helpful to people suffering from motor disabilities or paralysis to communicate their thoughts to the world. BCI works by transforming the brain activity into digital form and serving it as a command to for the computer to act. Success of BCI depends upon the method used to extract the features and its classification.

The Brain Computer Interface (BCI) has is enables the communication pathway between the external stimuli's that will operate on the real-time application. The ultimate goal of the BCI is to create an effective interface which is helpful to the person with several disabilities [8]. The brain activity patterns used in Electroencephalography BCI are P300 [3], SSVEP [4] and MI. The BCI may be categorized into synchronous and asynchronous. In the recent work has validated the new approach to BCI i.e. Hybrid Brain Computer Interface. Hybrid BCI composed of two or more brain system. This BCI detects these two signals in sequential or simultaneous manner. With the use of two brain signals hybrid BCI can achieve the specific goals rather than conventional BCI. In simultaneously Hybrid BCI signals may be proceed parallel. In sequential hybrid BCI's, the output of previous system is used as the input to the next system [11]. One problem encountered in designing a BCI system is that the inputs to the system, i.e. the electroencephalogram (EEG) signals, are non-stationary. Among the factors that may cause non-stationarities in the EEG signals are the changes in the user's mental states; the way the user performs the same mental task and changes in electrodes' impedance. Due to the non-stationarities of the EEG signals, the statistical characteristics of the features used in a BCI system change over time subsequently, this may affect the performance of the system. Thus, it is of great interest to design a BCI classifier that is able to adapt to the changes in the characteristics of the EEG features [8]. In recent several studies have shown that many cases, hybrid brain computer interface may yield better performance than BCI. The types and combinations of the signals are discussed in the, setare Amiri et al. [4] SSVEPMotor Imagery Hybrid BCI, P300-SSVEP Hybrid BCI[1,10] , P300-Motor Imagery Hybrid BCI [6] , SSVEP-NIRS Hybrid BCI, EEG-EMG Hybrid BCI , EEG-EOG Hybrid BCI. With enhancement of the hybrid brain computer interface the need of signal processing is main issues in this content, but one important thing is to seem that there is not give special attention towards the signal processing. The main aim of the Hybrid brain computer interface is to improve Information transfer rate (ITR) in terms of the SSVEP and accuracy in terms of the P300 [13]. Various signal processing method and techniques are presented. The algorithm has a very good impact on the performance of the BCI system, particularly detection of transfer rate and accuracy. This paper conducts comprehensive review of algorithms for signal processing for BCI's system. It focuses on data preprocessing, feature extraction, classification.

This paper can be organized as follows: section II depicts as a signal processing and their components like preprocessing, feature extraction and signal processing, and also survey of classification algorithms. Section III introduces methods for combination of one or more algorithm for effective use, under section IV conclusion are included.

II SIGNAL PROCESSING

The BCI System included the multiple stages, including data acquisition, data preprocessing, feature extraction and feature classification and command translation [2]. The aim of the data preprocessing is to eliminate the nuisance signals,



feature extraction and classification uses the characteristics of the EEG signals to identify the subject intent to control external device [16]. The paper specifically give attention towards the review of algorithm used for EEG signals based BCI. It focuses on the preprocessing, feature extraction and signal processing. The objective of our review is to find most suitable algorithm for feature classification [8],[17],[18].

III PREPROCESSING

Signal preprocessing is also known as signal enhancement. To extract the feature we have to first preprocess the data. It is done after data acquisition. It usually intensifies the signal and upgrade signal to noise ratio (SNR). General step in preprocessing is band pass filtering. Band pass filters are designed to remove high frequency noises and DC bias. In preprocessing, channel selection of channel is done with respect to data decimation and is committed in a way to enhance the classification performance. Segments of data are collected and moving average filter is applied for best performance Artifacts are unwanted signals present in BCI. Artifacts have various origins, which include the utility frequency like noise, body and eye movements, or blinks. We can handle artifacts by three main approaches: avoidance, rejection and removal. By artifact avoidance the user should not execute any movement which may result in EEG artifacts. This can reduce artifacts, but obviously we cannot stop eye movements and blinks, so sometimes these artifacts may occur. There are two types of signal processing methods can be used in the EEG signal generation according to filtering types for preprocessing. Those are frequency filtering and spatial filtering. Frequency filtering: The signals are filtered according to the characteristics of the frequencies related signals. We have two types frequency filtering can be use for the preprocessing of the signals. They are Band pass filter and Notch filter. In Band pass filter frequency range is designed according to the frequency harmonics or to the simulation frequencies. Band pass filter is relatively simple to implement but the drawback is that it may be very stringent for explaining the time-varying signals. Usually notch filter is used for removing the power line interference. Spatial Filtering: In spatial filtering there is combination of signals from different channels to magnify the EEG responses. This can be done with the reduction of the interference of the noise. Signals from multiple channels are less affected by noise. The most affected signals are either unipolar or bipolar systems. This technique also can be used for the feature extraction techniques. Spatial filtering is classified techniques those are explained below. Maximum contrast combinations (MCC) is most frequently used method for spatial filtering. Principle component analysis (PCA) is use for the decomposition of signals into components of SSVEP signals and brain activity we need to use PCA. The dimension of the original data can be reduced by the help of PCA. A common spatial pattern method based on the(ACSP) method is based on the analytical representation of signals. Based on CSP method ACSP reflects amplitude as well as phase information of EEG [19]. Component average filter (CAR) is the average values of all the electrodes are subtracted from the channel of interest to make EEG recording nearly reference free. Canonical correlation analysis (CCA)is the relation between two multivariable data sets are computed by CCA after linear combinations of linear data. Other methods are KCCA, Multiway CCA and p-CCA. KCCA is used for the high dimension data sets. Multiway CCA uses optimal reference signals while p-CCA uses the phase information in reference signals.

IV FEATURE EXTRACTION

The goal of feature extraction is to select suitable data that subsequent classification or detection of Feature attempted to design BCI as amplitude value of EEG signals, band power, power spectral density, value auto regression and adaptive time frequency features and inverse model features. The EEG Signals have attenuated the area of research in BCI due to its advantages like portability and ease of use. Features are extracted from those signals using several methods: Time analysis, frequency analysis, TimeFrequency analysis Time-Frequency Space analysis. The extracted features are classified according to the classification algorithm employed on it during classification process. The EEG signals are based on time domain and signal energy distribution is varied. In order to extract features the signals are analyzed to give a description of the energy as a function of time or frequency. EEG signals are non-stationary due to this its spectrum changes with time; such a signal approximated with piecewise stationary, a sequence of independent stationary signals segment. Most of the brain activity patterns used to drive BCI as related to particular time variations of EEG, possible in specific frequency bonds. The time course of EEG signals should be taken into account during feature extraction [14], [7], and [9].

Different method are used for feature extraction from EEG signals like Adaptive Auto Regressive parameters (AAR), Fast Fourier Transformations (FFT), Principal Component Analysis (PCA), Independent Component Analysis (ICA), Genetic Algorithms (GA), Wavelet Transformations (WT), Wavelet Packet Decomposition (WPD) [17], [7]. Independent Component Analysis- Independent Component Analysis (ICA) is used as a feature extraction method. ICA forms the components that are independent to each other. From the components essential features were extracted using ICA. One of the more important applications of ICA is Blind Source Separation (BSS). This helps to selecting the independent signals and noise separation from brain signals. Blind Source Separation (BSS) of acoustic signals are referred to as Cocktail party problem means separation of a number of independent components from a set of un-controlling records [7], [9]. Principal Component Analysis- Principal Component Analysis (PCA) is a feature extraction method as well as pre-processing technique. It is a powerful tool for analyzing and for reducing the dimension of data without loss of information [7]. By using PCA the information present at all the time series multi channel is extracted as principal components. By eliminating the artifacts and by forming the principal components PCA reduces the dimensions of signals [9]. Wavelet Transform- Wavelet Transformation is also used for feature extraction and was formulated by Morlet and Grossman in 1984. In Scott et.al proposed a method to perform the feature extraction with the B-Spline parameters. This function can act as low pass filter as well as high pass filter and with these filtering characteristics it stood as B-spline clients. By using multi resolution analysis filter coefficients can be obtained [7], [9], [20].

V CLASSIFICATION

In order to control a BCI, the user needs to produce different brain signals patterns that will be founded by the system and converted into the commands. Most present BCI, this recognition depends on a classification algorithm i.e. an algorithm that mainly focuses at automatically evaluate class of data as illustrated by a feature vector [14]. The very important point is that none has specifically work toward the classification algorithm and their properties. Pattern reorganization and emphasizes are main steps of the classification. The main aim of brain computer interface is to convert brain activity into a command for computer. To archive the aim signals transfer either regression and classification algorithm can be used. These algorithm, used to identify “pattern” of brain activity. The performance of BCI depends on both feature and classification employed. There are various classification methods which are used to design a BCI system like Linear discriminant analysis (LDA), Fisher's linear Discriminant analysis (FLDA), Stepwise linear discriminant analysis (SWLDA), Bayesian linear discriminant analysis (BLDA), Support vector machine (SVM), Gaussian

Support vector machine (Gaussian SVM), Maximum Likelihood (ML). In this we surveys about LDA, FLDA, SWDA, BLDA and linear SVM which are mostly used in P300 based BCI.

VI SURVEY OF CLASSIFICATION ALGORITHM USED IN BCI

This sections surveys classification algorithm used to design BCI System; they are divided into five types: linear classifiers, neural networks, non-linear Bayesian classifiers, nearest neighbors' classifiers and combinations of classifiers. Linear Classifiers: they are discriminate algorithm used linear function to distinguish classes. They are most probably algorithm for BCI.

Two main types of linear classifiers are as follows:

1. Linear Discriminate Analysis (LDA)

2. Support vector machine (SVM) Linear Discriminate Analysis:-

It uses hypotheses to separate the data representing the dissimilar classes [14]. For two class problem, the class of feature vector depends upon side of the hyperplane the vector is. It assumes normal distribution of data with similar covariance matrix for these two classes. The separating hyperplane is get by seeking the projection that maximizes distance between two classes' means and minimize the interclass variance [12], [15]. To Solve N-class problem (N>2) we use several hyperplanes. The strategy used in multiclass BCI is one versus rest strategy which consists in dividing each class from all others. This approach has very low computational condition which makes it acceptable for online BCI system. Therefore these classifiers are simple to use and generally provides good result. It can be use with P300, SSVEP and MI [19]; a drawback of the LDA is linearity that can provide poor results on complexity nonlinear EEG data.

Support vector machine:- SVM also uses the discriminate hyperplane to identify the classes, regarding to the SVM hyperplane it maximizes the margins i.e. increase the distances from nearest training sets, such SVM enables the classifiers using linear decision boundaries and it is also known as linear SVM [19]. This classifiers always applied to the large number of synchrouns BCI problems. The advantages of SVM are maximizes the margin gaps and, the regularization term the SVM have good generalization property that have been insensitive to overtraining and curse of dimensionality.

Fisher's Linear Discriminant Analysis :- Method suggested that transforming multivariate examination to univariate examination such that the univariate examination is derived from each population is maximally divided. The dividation of these univariate observations can be observed by their mean difference [15], [13]. Fisher classification rule increases the difference between samples variability to within samples variability.

Neural Networks: - NN is assembly of different artificial neurons which allow to producing nonlinear decision boundaries. The most useful NN for BCI is Multilayer Perceptron (MLP). MultiLayer Perceptron (MLP): MLP is composed of several layers, one input layer, one or several hidden layers and output layers. Each neurons of every layer is connected with output of the previous one. Added to the fact they can classify number of classes, this makes NN makes very flexible classifiers that are used for the BCI problems, binary or multiclass, synchronous or asynchronous BCI. MLP are universal approximation makes these classifies sensitive to overtraining, especially for noisy and non-stationary data. MLP without hidden layer are called as perceptron, perceptron is equivalent ot the LDA and therefore is has been used in BCI application. As a type of ANN model, MLP model have been widely utilized and which is perform competitive prediction ability against other methods [19], [20]. Back-propagation (BP) algorithm has been developed and widely used in training MLP feed-forward neural networks [20].

Non-linear Bayesian Classifiers: - this section introduces two Bayesians classifiers used in BCI

Bayesians quadratic and hidden markov model (HMM).

These classifiers produce non-linear decision boundaries. Theses classifiers are not more popular than linear classifiers. Bayes quadratic: - it aims to assigning a feature vector to the class which it belonging to with highest probability. It used to compute posteriori probability that feature vector has been belonging to a given class. Using the Maximum a Posteriori (MAP) rule and these expectation, class of this feature vector can be calculated. Bayes quadratic present in assuming a different kind of normal distribution of data. This goes to quadratic decision boundaries, which defines the name of the classifier. After all this classifier isn't widely used for Brain computer interface (BCI), it has been used with success to MI (Motor Imagery) and mental task classification [14].

Hidden Markov Model: - it is generally used in the field of speech recognition. It can provide an automation that can be provide the probability of noticing a given sequence of feature vector. Each state of the automation can modelize the probability of observing given feature vectors. HMM is suitable algorithm for classification of time series, HMM have been used to classification of temporal sequence of BCI feature. [14] HMM basically probabilistic models that assigns probabilities to sequence of symbols. It is a generative model means that probability distribution is done by taking a series of steps that produces inclemently sequence of symbol created a random choice. Consider HMM as a machine that generates sequences. HMM are relatively easy to understand as a generative process, and they are highly useful in many applications. Unhappily the algorithmic details are wanted hard to understand and boring to work out.

VII COMBINATIONS OF THE CLASSIFIERS

Strategies used in BCI for combinations of different classifiers are as follows: Boosting Voting Stacking Boosting: in this method classifiers are arranging in cascade and every classifier focuses on the error committed by the previous one. It can build one powerful classifier among the several weak. According to the research it should be going to mislabels, it was not successfully. Voting: in voting several classifier are used and feature vector class are assigning to them. The majority will be treating as final class; it is general way of combining two or more classifier in BCI. Voting with MLP and SVM are been attempted [14]. Stacking: it is very useful way to combing classifiers each of them classify the input feature vector. These are called level-0 classifiers [14]. The output of the each classifier is then given as input to the so-called Meta classifiers which helps to final decision. Stacking is used in BCI research as level-0 classifiers of HMM and SVM as meta-classifiers. The main objective of the such techniques are combining a similar classifiers is very useful to outperform one of its own way.

CONCLUSION

In brain computer interface (BCI) signal processing is most important. The signal processing includes preprocessing; feature extraction and feature classification, but no one give any special attention toward theses process. This paper mostly concentrated on the classification. Classification algorithms are one of the most important factors to decide the accuracy and ITR of BCI system. All EEG signals are non-linear and non-stationary in nature. Non-linear and adaptive classifiers are effective for EEG based BCI system. Most of the recent research focuses on combinations of different classifiers in different organization. Recently ANN classification algorithms prove be effective classifiers due to its ability to modify itself during online session.

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