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Classification Techniques in Brain Computer Interface: A Review

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Abstract

Paper reviews the classification algorithm for the brain computer interface. The characteristics of the EEG signals are changes over time, updating the classifiers of the brain computer interface (BCI). It will eventually improve the performance of the system. The development of the new adaptive classifiers are not easy because of we cannot predict the intension of the user, in some cases it may be possible to predict the labels of the EEG segments using some information of the state. We briefly present commonly used algorithm and their description of properties. By literature review we presented them in terms of performance. The main point come into Scenario that there is no comprehensive review of signal processing algorithm for EEG signals. The aim of this review paper is to obtain the limitations and importance of the algorithm is to provide a guideline to the researchers in these fields. Techniques employed for the signal preprocessing, feature extraction and feature classification are discussed, but review focused on signals classification.

Keywords*: BCI, EEG.*

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1. Introduction

The Brain Computer Interface (BCI) 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 one system is used as the input of the other 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 [4] SSVEP-Motor 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 algorithms that have a great impact on the performance of the BCI system, particularly detection of transfer rate and accuracy. The paper conducts comprehensive review of algorithms for signal processing for BCI's system. It focuses on data preprocessing, feature extraction, and classification.

2. 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 [17]. 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 [8,18,19].

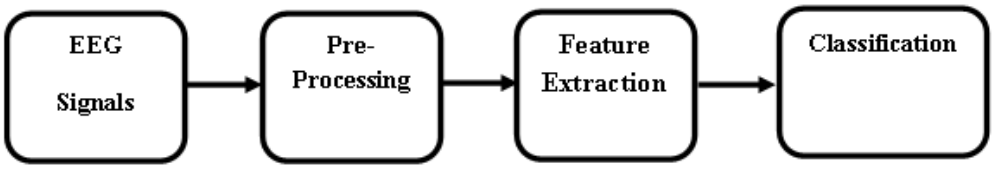

Fig: Signal Processing

A) Preprocessing

Signal preprocessing is also known as signal enhancement. To extract the feature we have to first pre-process the data. It is done after data acquisition. It usually enhances the signal and improve signal to noise ratio (SNR). A typical step in preprocessing is band pass filtering. Band pass filters are designed to remove high frequency noises and DC bias. In preprocessing, channel selection with respect to data decimation is determined 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.

i) *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.

ii) *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 [20]. 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 multivariables 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.

B) 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, Time-Frequency 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 [7,9]. 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) [18].

i) *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].

ii) *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].

iii) *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 [9, 21].

C) Classification

In order to control a BCI, the user needs to produce different brain signals patterns that will be identified by the system and translated into the commands. 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 translate 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.

3. 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.

A) 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:

- *Linear Discriminate Analysis*
  It uses hypotheses to separate the data representing the different classes [15]. 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 equal covariance matrix for both classes. The separating hyperplane is obtained by seeking the projection that maximizes the distance between the two classes' means and minimize the interclass variance [12,16]. Solve N-class problem (N>2) several hyperplanes are used. The strategy used in multiclass BCI is one versus rest strategy which consists in separating each class from all others. This technique has very low computational requirement which makes it suitable 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 [20]; 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 is known as linear SVM [20]. This classifiers always applied to the large number of synchronous 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*
  Fisher suggested transforming multivariate observations to univariate observations such that the univariate observations derived from each population is maximally separated. The separation of these univariate observations can be examined by their mean difference [13]. Fisher classification rule maximizes the variation between samples variability to within samples variability.

B) Neural Networks (NN)

NN is assembly of different artificial neurons which enables to produce nonlinear decision boundaries. The most useful NN for BCI is Multilayer Perceptron (MLP).

Multi Layer Perceptron (MLP)

MLP is composed of several layers, one input layer, one or several hidden layers and output layers. Each neurons of the each layer is connected with the 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 to the LDA and therefore is has been used in BCI application. As a kind of ANN model, Multilayer Perceptron (MLP) models have been widely utilized [20] which perform competitive prediction ability against other methods [20]. In back-propagation (BP) algorithm was developed and now has been widely used in training MLP feed-forward neural networks.

C) 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 to a feature vector the class it belonging to with highest probability. It used to compute posteriori probability that feature vector has of belonging to a given class. Using the MAP (Maximum A Posteriori) rule and these probabilities, the class of this feature vector can be estimated. Bayes quadratic consists in assuming a different normal distribution of data. This leads to quadratic decision boundaries, which explains the name of the classifier. Even though this classifier is not widely used for BCI, it has been applied with success to motor imagery and mental task classification [15].
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 observing 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 [15]. HMM is a probabilistic model that assigns probabilities to sequences of symbols. It is a generative model, meaning that the probability distribution is defined by taking a series of steps that incrementally produce the sequence of symbols by making random choices. Think of an HMM as a machine that generates sequences. Hidden Markov Models (HMMs, hereafter) are relatively simple to understand as a generative process, and they are extremely useful in many applications. Unfortunately the algorithmic details are notoriously hard to understand and tedious to work out.

D) Nearest Neighbor Classifiers
They work in assigning the feature vectors to a class according to its neighbor within the training set. These neighbors can be feature vectors from the training set as in the case of l-nearest neighbors (kNN).

E) Combinations of the Classifiers
Strategies used in BCI for combinations of different classifiers are as follows: Boosting, Voting, and 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 final class will be that of the majority, it is the most popular way of combining classifiers in BCI research. Voting with MLP and SVM are been attempted.
Stacking: It is very useful way to combing classifiers each of them classify the input feature vector. These are called level-0 classifiers [15]. The output of the each classifier is then given as input to the so-called Meta classifiers which helps to final decision. Stacking has been used in BCI research using HMM as level-0 classifiers 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.

4. 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. 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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