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Literature Review of Feature Extraction Methods for Classification of EEG Signals

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ABSTRACT

In this work, we have documented and compare various feature extraction methods for classification using EEG signal. This paper contains a comparative study of data reduction methods which enhances the classification accuracy. Deep study of decomposition of signals into the frequency sub bands by wavelet method (DWT) and a set of statistical features that were extracted from the EEG signals to represent the distribution of wavelet coefficients is explained. Data dimension methods like ICA, PCA and LDA are used for the reduction of dimension of data and signal vectors which can be converted to features vectors and after data reduction by suitable selection method are fed to the classifiers and the performance and accuracy of classifiers are compare in terms of accuracy to show the excellent classification process.

Keywords: BCI, Electroencplogram; DWT; PCA

I. INTRODUCTION

In last decades the BCI system is developed with the goal to provide direct communication between human brain and external world [1], [2]. The Brain computer interface system first proposed by Vidal in 1970 to express the phenomenon of brain electrical signal for Human computer interface. In 1988 Farwell and Donchin introduce the BCI which rely on evoked potential generated by brain. The Satter in 1992 presented an efficient technique for BCI which rely on visual evoked potential [1]. The main goal of BCI is to develop a system which allows partially or fully disabled person which used to control the external parameter processing the EEG signal [2]. The total disabled and paralyzed person requires non-muscular communication so that the control of external factor can be possible [1], [3]. Now a days the BCI system uses advance biosensor and signal acquisition technology for EEG or ECoG [5], [8]. The common brain computer interface system required acquisition of brain activity signals and processing of signal by classifier to classify and perform a particular task.

There are several challenges in the BCI system such as information transfer rate, error rate, autonomy and cognitive load [4]. The information transfer rate depends on how many sensors are used to acquire brain activity signal and bandwidth of channel from which this signals are given to system. The error rate described by classification error occurred by allocating task to external device. The load on brain to control the complex task is also challenge stated in hybrid BCI interface system [6] which depends on how much critical the system is (critical system means how many dimension the user has to control).

EEG is a unique technique which can be used to interface the human brain with outside environment via electrical signals generated from EEG device. These electrical activities develops inside the brain which is produced by

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the physical task or strong imagination to control desired object. It involves the spatial mapping of electrodes and special functions which are mapped to the various regions of our brain to get a particular or desired signal for the required application. There are various limitations in EEG data acquisition system the first one is the electrical activities that are recorded from the outer layer of brain called scalp which contains noise as the result of disturbances and electrical movement of electrodes so we have to remove the noise factor and the second is that it depends upon the number of electrodes that are used. If we apply larger number of electrode then also signal degradation occurs which decreases the BCI performance so the selection of optimum number of channel that suited for both accuracy and performance is needed.

Due to these parameters the cost of system, resolution is effected [1]. Most of the other EEG technique are bulky and requires heavy equipment but in this method there is less hardware cost significantly as compare to other technique. These sensors can be used in every field other than medical research where MRI, SPECT, MRS and other techniques. These technique requires large equipment and handling cost and are very costly and bulky. These methods has very high temporal resolution, on the order of milliseconds as compare to other techniques. It is commonly recorded at sampling rates between 250 and 2000 Hz in in medical research, but advanced EEG data gathering systems are capable of recording at sampling rates more than this sampling rate if desired we can record and unlike other technique which are non-invasive but on the other hand they provides better resolution [2].EEG techniques allows for advanced study of the responses to auditory stimuli. EEG has ability to resist magnetic field or high intensity greater than 1 tesla unlike the other technique which can cause serious issues with the data or it can degrade the data which further decrease the efficiency. This is extremely non-invasive, whereas (ECoG) is invasive technique which actually requires electrodes to be placed on the surface of the brain and in this way this technique is more superior to use and more flexible than the other methods. Therefore, the main point is to select the minimum no of channels so that the optimum accuracy can be easily obtain which can further balance both performance and control parameters. Due to its ease of use, cost and high temporal resolution this method is the most commonly used.

II. DEFINITIONS OF BCI, EEG AND BRAIN SIGNALS

2.1 Brain computer interface

Brain-Computer Interface (BCI) helps in establishing a communication channel between our brain and computer. With these techniques many strange activities like moving right or left hand or eye blinking can be easily interpreted with helps of EEG and ECOG techniques. The Major Types of BCI systemsare :

Motor Rehabilitation System – This type of system involves the human imagination based on physical task such as moving left or right hand and this can be easily interpreted through BCI system by using neuro rehabilitation concepts this is also called as motor imagery. This imaginative task produces a specific pattern of brain activity which can be further used for the communication purpose such as controlling objects, and for navigation in real time etc. In the past few years various research has been conducted to obtain a new and promising approach to build a MI based system this serves an important perspective to upgrade the motor rehabilitation in various applications.

Code-based BCI – This systems involves a pseudorandom sequences which is stimulated on the screen also called code based BCI, so in this way a system can be developed in which a robotic devices can be easily

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controlled so that by this type of system a code based system can be developed which is based on active EEG electrodes which are placed on the scalp of the user and is connected to a bio signal amplifier for the amplification of EEG signal the function of this amplifier is to amplify the EEG signals and send it to the BCI systems so that it enables the subjects to control the robotic devices as this system provides very high accuracy and promising for controlling the real time applications so in this type of systems a continuous control system is required to achieve high efficiency .

Steady State Visual Evoked Potential (SSVEP) – This stands for steady state evoked potential which is based on the intelligently use of static oscillating light sources or led As we know oscillating light sources oscillates at a particular frequency this principle is used in this technique .when a person see a specific light or led so all the attention of individual or subject focused at that time and this task or activity of person produces electrical signals or movements at the occipital lobe .This information can be used for the real time communication with outside world. The algorithm which is used here is based on the comparison of EEG frequency components and the light the user was focused at and identifies the movement the user wants to send into the system so according to this technique we can build a system in which we can use for flickering light in order to identify the motor imagery task and when there is no light it means that the system is at stationary position or at rest For example, when building a BCI design based on Steady State Visual Evoked Potential (SSVEP), we need the brain signals only from the electrodes C3 ,C4 and (O1 & O2) located in the visual region (Occipital Lobe) which contains the brain signals of our interest . Similarly for a BCI design based on feet or hand motor imagery movement, the relevant brain signals are present only in the motor or sensorimotor cortex region. Hence, the spatially filtered brain signals from the electrodes (C4 & C3) located on right and left motor cortex is sufficient for this particular BCI design.

2.2 The EEG

Electro encephalo graphy (EEG), records and measure electrical activity of the brain which is the main essence of this project. The human brain is the most important part of the whole body. It generates different kind of waves while performing the different task can be stated as different states. These waves helps in better understanding of the human activities, for example hand or leg movement, eye blink etc. Brain waves have fascinated many researchers.[14] There have been continuous improvement in the development of brain machine interface with help of EEG signals [3]. Electroencephalography (EEG) detects the neural activity of Brain and this can help in detecting the emotion states or imagination like moving left hand or right hand, sleeping state .Drowsiness, Visual imagination. The detection of neural activity which is disturbances occurs inside the brain also called as electrical movements of the brain can be used as a form of signal from which emotion can be easily detected and is very popular method because it does not requires any physical effort from the user. This model can be used to build a system in which a human emotion can be easily feed and depending upon the application it can be used in a real time situation as shown in above table with different brain waves each activity is associated with a particular frequency range [13]

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Brain wave	***Activity***	***Frequency Range***
Beta	*Alert/working*	*12-30Hz*
Alpha	*Relaxed/Reflecting*	*7.5-12Hz*
Theta	*Drowsy/Visual Imagery*	*4-7.5 Hz*
Delta	*Sleeping/Dreaming*	*Up to 4Hz*

Table. 1. The types of EEG waveforms

III. METHODS AND TECHNIQUES FOR BCI DESIGN

The main system approach to make the BCI system accurate is totally depends on training of the system and subject who used the system. The project is ongoing on brain training research is the most effective way of controlling of the brain signal which needed to control the device. This training involve the simple task such as targeting, selecting, navigating, signals for data acquisition system.

3.1 Subjects and Data Recording

All the EEG signals were recorded with same 128or 256 channel amplifier system and for the data acquisition various EEG devices are available for example miindwave,g..usbamp bio signal amplifier from Guger Technologies[4]. Bio signal amplifier data acquisition provides better analysis for EEG waveforms because data analysis and acquisition can be done online. There are various tool boxes that are Stim box, SSVEP, g.USB Amplifier and g.GAMMAAsys and for recording the EEG signal g.GAMMA cap is used. Electrodes are inserted at desired position via small holes and additional electrode position can be added by the user. For the proper positioning or how to mount the g.GAMMAcap we have to calculate the distance between the Nassion and Inion and the distance between the left and right preauricular points of the subject.[6]The position at the half of both distances is the vertex position Cz. The amount of difference in readings depends upon the cap size, head size and head shape. So data acquisition is an important step in feature extraction and classification of EEG signal because all the parameter extraction and classification is totally dependent on the type of data that is collected through brain sensor.[17-21]

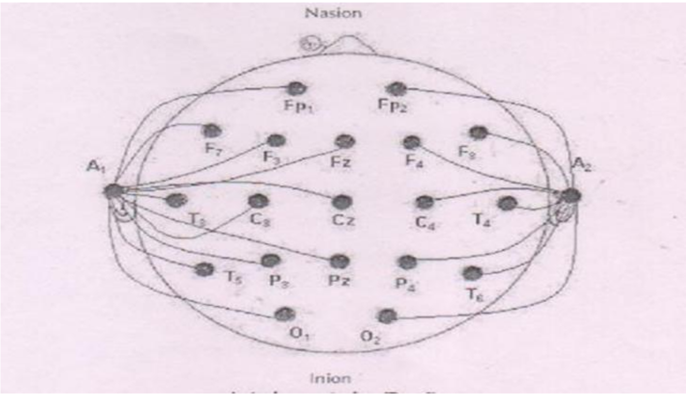

Fig 1. Placement of electrodes 10-20 system

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3.2 Analysis Using Discrete Wavelet Transform

Wavelet analysis technique defines an algorithm which involves the multistage window method. In this method the length of window has variable size this feature of wavelet is used in this technique. This method involves the use of large time interval where we need low frequency information and where we have to find high frequency information we need to set the length of window to be shorter so accordingly we can use this type of technique. Fourier transform cannot be applied to the transitory signals as plenty of signals in EEG contains non stationary components so this technique cannot be applied for EEG so wavelet transform must be used in wavelet transform variety of probing function are used and depending upon the comparison with the threshold function window length can be control and we can easily extract features from the signals. This concept leads to the equation for the continuous wavelet transform (CWT).

$$CWT_f(a,b) = \frac{1}{\sqrt{a}} \int_R \psi\left(\frac{t-b}{a}\right) f(t)\,dt. \tag{1}$$

One major advantage of wavelet technique is its flexibility to perform general analysis — that is, to analyze or can be apply to localize the window size and localization area of a larger signal is done. In the wavelet packet technique, signal is compressed and noise is removed by using the Fourier transform technique exactly same ideas can be developed to extract the feature of EEG signal the basic idea and technique will be the same as traditional method but the only difference is that we can easily analysis the complex problem in easy and flexible manner and here we have to deal with EEG signal as in wavelet analysis approximations method are used to spilt the details of signals as shown below and these details will be the required feature. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the EEG signal in time and frequency. The following statistical features can be used to represent the time–frequency distribution of the EEG signals such as mean of the absolute values of the coefficients, average power of the wavelet coefficients in each sub-band and he following statistical features were used to represent the time frequency distribution of EEG signals which are mean of the absolute of coefficients in each sub bands and Average power of wavelet coefficients in each sub band. These features represents the frequency distribution of signal. Standard deviation of the coefficients in each sub bands and ratio of absolute mean values of adjacent sub bands represents the amount of changes in frequency distribution so these features were calculated for the specific application and used for the classification of EEG signals.

3.3 Feature Extraction methods

3.3.1 Principle component analysis (PCA)

Principal component analysis (PCA) is a well-established method for feature extraction and dimensionality reduction. In PCA, we seek to represent the d-dimensional data in a lower dimensional space. This will reduce the degrees of freedom; reduce the space and time complexities. The objective is to represent data in a space that best expresses the variation in a sum-squared error sense. This technique is mostly useful for segmenting signals from multiple sources. It facilitates significantly if we know how many independent components exist ahead of time, as with standard clustering methods. The basic approach in principal components is theoretically rather

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simple. First, the d-dimensional mean vector μ and d × d covariance matrix are computed for the full data set. Next, the eigenvectors and eigenvalues are computed, and sorted according to decreasing eigenvalue. Call these eigenvectors e1 with eigenvalue λ1, e2 with eigenvalue λ2, and so on. Subsequently, the largest k such eigenvectors are chosen. In practice, this is done by looking at a spectrum of eigenvectors. Often there will be dimension implying an inherent dimensionality of the subspace governing the signal. The other dimensions are noise form a k × k matrix whose columns consist of the k eigenvectors.

$$x' = A\,(x - \mu) \qquad (2)$$

The central idea of PCA is to transforms data linearly into a low-dimensional subspace by obtaining the maximized variance of the data. The resulting vectors are an uncorrelated orthogonal basis set. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric. ICA is very closely related to the method called blind source separation (BSS) or blind signal separation. A "source" means here an original signal, i.e. independent component, like the speaker in a cocktail party problem. "Blind" means that we know very little, if anything, on the mixing matrix, and make little assumptions on the source signals. ICA is one method, perhaps the most widely used, for performing blind source separation. In many applications, it would be more realistic to assume that there is some noise in the measurements, which would mean adding a noise term in the model. For simplicity, we omit any noise terms, since the estimation of the noise-free model is difficult enough in itself, and seems to be sufficient for many applications

3.3.2 Independent component analysis (ICA)

ICA is a feature extraction method that transform multivariate random signal into a signal having components that are mutually independent. Independent components can be extracted from the mixed signals by using this method.[11] In this manner, independence denotes the information carried by one component cannot be inferred from the others. Statistically this means that joint probability of independent quantities is obtained as the product of the probability of each of them. Suppose there are c independent scalar source signals x (t) i for i=1,...,c where we can consider t to be a time index $1 \leq t \leq T$. For notational convenience we group the c values at an instant into a vector x(t) and assume, further, that the vector has zero mean. The ICA technique appears ideally suited for performing source separation in domains where, the sources are independent. Although the ICA model of the EEG ignores the known variable synchronization of separate EEG generators by common subcortical or corticocortical influences [5], it appears promising for identifying concurrent signal sources that are either situated too close together, or are too widely distributed to be separated by current localization techniques. Here, we report a first application of the ICA algorithm to analysis of 14-channel EEG and ERP recordings during sustained eyes-closed performance of an auditory detection task, and give evidence suggesting that the ICA algorithm may be useful for identifying psychophysiological state transitions. ICA appears to be a promising new analysis tool for human EEG and ERP research. It can isolate a wide range of artifacts to a few output channels while removing them from remaining channels. These may in turn represent the time course of activity in long lasting or transient independent 'brain sources' on which the algorithm converges reliably. By incorporating higher-order statistical information, ICA avoids the non-uniqueness associated with decor relating decompositions. The algorithm also appears to be useful for decomposing evoked response data into spatially distinct subcomponents, while measures of non-stationarity in the ICA source solution may be useful for observing brain state changes.[10]

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3.3.3. Linear discriminant analysis (LDA)

The aim of LDA is to create a new variable that is a combination of the original predictors. This is accomplished by maximizing the differences between the predefined groups, with respect to the new variable. The goal is to combine the predictor scores in such a way that, a single new composite variable, the discriminant score, is formed. This can be viewed as an excessive data dimension reduction technique that compresses the p-dimensional predictors into a one-dimensional line. [12]At the end of the process it is hoped that each class will have a normal distribution of discriminant scores but with the largest possible difference in mean scores for the classes. In reality, the degree of overlap between the discriminant score distributions can be used as a measure of the success of the technique. Discriminant scores are calculated by a discriminant function which has the form:

$$D = wZ + w Z + w Z ++ wpZp \ldots \qquad (3)$$

As a result a discriminant score is a weighted linear combination of the predictors. The weights are estimated to maximize the differences between class mean discriminant scores. Generally, those predictors which have large dissimilarities between class means will have larger weights, at the same time weights will be small when class means are similar [6].

Linear Discriminant Analysis (LDA) is a Bayes optimal classifier, provided the distribution of features in each of two classes is normal with the same covariance matrix [22]. LDA projects d-dimensional data into a line, reducing the dimensionality by mapping L distributions to (L-1) dimensional subspace. LDA maximizes the ratio of between class variance to the within-class variance in any particular data set, thus providing maximal separability. It doesn’t change the location of the original data sets but provides more class separability and draws a decision region between the given classes. The LDA finds a one-dimensional subspace in which the classes are usually well separated by a linear separating hyper plane.[22]

3.3.4 Classifiers

Support vector machine consists of a vector in which all the learning is acquired in the training set which is very useful to develop a new data. Support vector machine algorithm is declared as efficient and most reliable method for the parameter extraction and classification. The basic principle of SVM classifiers is that it segregate the data by an accurate hyperplane in which all the data points of one class is almost separated from another class. In this classification hyperplane stands for the largest displacement among the two or more classes. The main advantages of SVM classifiers is that it reduces the error rate of misclassifying signals in the desired training set. SVM is most preferred technique because it shows high performance and does not need any superior information or other method to be used. One more advantage of SVM is that binary class can also be implemented in this technique so in this classification method proper multiclass techniques are required to use the multiple classes for developing a classification based system. In this classification various method are used but the two methods are very important the first method involves by compressing and constructing various binary classifiers into a single unit and suppressing them into one module and other method is to build an optimization formula and consider all the data into that formulation these two methods are very useful for the feature extraction. According to the latest research no comparison is found which consists of both these methods so accordingly we can use multiclass. Another method used for the classification is neighbor based classification

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(KNN). It is a type of event based learning method which depends upon the radial distance of neighbor and according to the nearest neighbor classification of signals is done from the extracted feature. According to the literature survey Linear SVM shows best accuracy as compared to other classifiers for EEG signal.

IV. METHODOLOGY

Data acquisition is done using bio-signal amplifier data acquisition system followed by signal processing in which the noise and redundant data can be easily removed by using band pass filtering and wavelet packet technique (wavelet packet).The extracted features from various technique such as Principal component analysis and independent component analysis (ICA) of the EEG data were used to obtain feature vectors from the Gaussian method from the weighted concept from each feature vector. These feature vectors were the inputs to the classifiers. Two dimensional mapping technique is used for activity based selection of features which are located in the primary and sensory motor regions of the brain. The output feature vectors thus obtained are given as input to two classifiers, viz. linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA).These two methods are then compared and found that the LDA gives normal accuracy and QDA gives better accuracy than other methods and depending upon this research an efficient feature extraction method can also be used in addition with proposed method for the comparison of results. The ideal methodology is shown below**.**

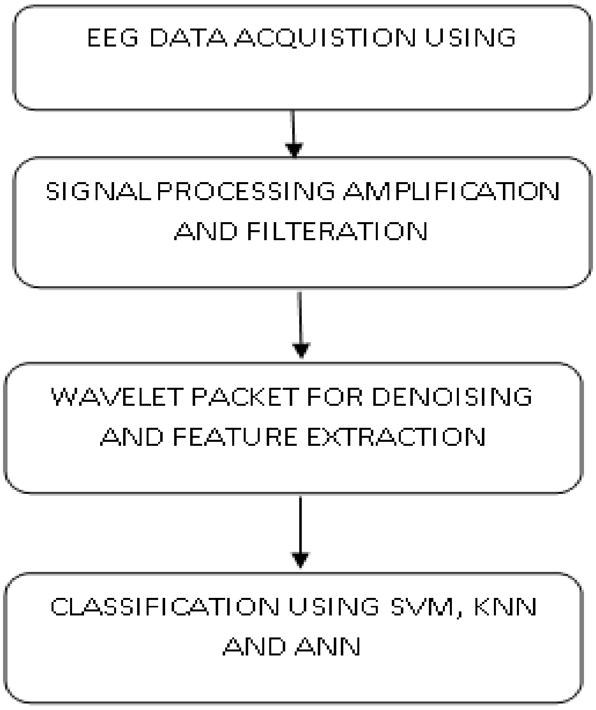

Fig 2. Design flow for feature extraction and classification

V. DISCUSSIONS

Although the previous works have shown good performance on the EEG signal classification, there still remain some problems to be solved. First, the number of available EEG patterns for the classifier training is not much more, which shows us that the generalization ability of a feature extraction methods dominates the accuracy of

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online EEG classification. A feature transformation mechanism that can minimize the error rate, it can be anticipated that the size of between-class overlap region can be significantly reduced and the classification performance can be significantly improved. In order to achieve this, the PCA, ICA and LDA algorithms are used. Based on the results of the present study and experience in the EEG signal classification problem, we would like to emphasize the following. The high classification accuracy of the SVM classifier gives insights into the features used for defining the EEG signals. The conclusion drawn in the applications demonstrated that the DWT coefficients are the features, which will represent the EEG signals, and by the usage of these features a good distinction between classes can be obtained.

Support Vector Machines (SVMs) are based on preprocessing the data to represent patterns in a high dimension — typically much higher than the original feature space. With an appropriate nonlinear mapping to a sufficiently high dimension, data from two categories can always be separated by a hyperplane. As a result, while the original features bring sufficient information for good classification, mapping to a higher dimensional feature space make available better discriminatory evidence that are absent in the original feature space. The problem of training an SVM is to select the nonlinear functions that map the input to a higher dimensional space.

VI. CONCLUSION

In the field of BCI system designing the main aim is to revolutionizing the human computer interaction future with exponentially increasing the outcomes in many number of fields. In this literature review the discussion of novel system like ECoG and EEG based BCI and the methodology with some limitation is done, also the methodology is not restricted to the flow of modules of only one BCI application it is explore with the nowadays system criteria. There are some system which discussed are based on the evoked potential such as SSVEP based and VCP based which has some difficulties in user training and lack of gaze control issues. As compare to other module the signal acquisition and signal processing are relatively simple to implement with the help of classifier which are widely used. There are some desires from the user and BCI system such as long term training of the user for estimated EEG signal, system should have the improve signal processing unit to handle low quality signal and development of accurate EEG signal block such that it can allow the simulation based analysis.

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