EEG SIGNAL PROCESSING TECHNIQUES FOR MENTAL TASK CLASSIFICATION

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***Abstract*— Electroencephalography (EEG) based Brain Computer Interface for mental task detection has gained lot of interests from researchers in last decade. The main components of EEG based BCI are EEG signal acquisition, EEG signal preprocessing, feature extraction from EEG signal and classification of EEG signal (mental tasks). This paper reviews and discusses the components of EEG based BCI system: EEG signal acquisition techniques, preprocessing methods, different feature extraction methods and different classification techniques used for mental task classification**

***Index Terms*— Brain Computer-Interface, EEG Signal Processing, EEG signal Classification, Feature Extraction.**

I. INTRODUCTION

BCI is a system which connects the brain activities of the user to the computer. BCI allows controlling various devices with the help of brain signal, without using any muscular activities [1][2]. In recent years mental tasks have been studied by many researchers and their study shows that BCI is useful for physically challenged individual. Such individuals who have lost all their voluntary actions can only rely on their cognitive actions to interact with others BCI is useful for them [3].

The electroencephalogram (EEG) signals provide rich information about the electrical activity of human brain. EEG signal is captured from scalp of human.EEG is the recording of electrical signal produced along the scalp i.e. it is the process of measuring electrical fluctuation along the scalp, that fluctuation is caused by mental activity [4]. EEG signal undergo changes in amplitude as well as in frequency while different mental tasks are performed [5]. EEG based BCI is useful for classification of mental tasks [6]. In which EEG signal related to different mental activities are captured and mental activities are classified.

Many researchers have used EEG based BCI for mental tasks classification. Their research is useful for controlling electronic devices. A. Fattouh et.al [7] and E. Rechy-ramirez et.al [8] used EEG based BCI to control wheelchair. H. Shedeed et.al [9] proposed system for controlling robotic arm using EEG signals
Main parts of EEG based BCI are signal acquisition, preprocessing, feature extraction and classification. Features which are extracted from EEG signal helps classifier to classify mental tasks. If improper features are

extracted then they cannot help classifier to classify the mental tasks properly, which makes BCI inappropriate. Therefore feature extraction and classifier plays important role in EEG based BCI system.

This paper reviews the EEG signal processing techniques required for mental task detection, from EEG data acquisition to classification methods of EEG signal. The rest of paper is organized as follows. Section II reviews EEG signal Acquisition methods. Section III discusses about noise removal techniques from EEG signal Discusses about various methods to extract Features from EEG signal. Section IV reviews classification techniques and section V conclusion.

II. Signal Acquisition

The 1st part of BCI is brain signal acquisition. Various neuroimaging techniques are available they are classified as structural neuroimaging, functional neuroimaging and electro-physiological neuroimaging. X-ray, angiography, CT scan, ultrasound, MRI comes under structural neuroimaging. PET, SPECT and fMRI falls under functional neuroimaging. EEG and MEG categorized under electro-physiological neuroimaging [10]. Out of these techniques available for brain signal acquisition EEG is less expensive, can acquire brain signal non-invasively, more precise, relative ease of use and excellent time resolution that's why it is mostly used .

EEG signal can be acquired non-invasively by placing electrodes on the scalp. A standard naming and electrode positioning design called 10-20 International system is available. In this design, "10" and "20" means that the distance between the contiguous electrodes placed on the skull is either 10% or 20% of the front-to-back or right-to-left total distance of the skull. Fig 1 shows that standard 10-20 electrode system [11]. Each electrode position represents a lobe and number identifies hemisphere location. 'F' means frontal, 'C' means central, T' means temporal and 'P' means parietal lobe of brain. Fig 2 represents the Brain lobes [11].

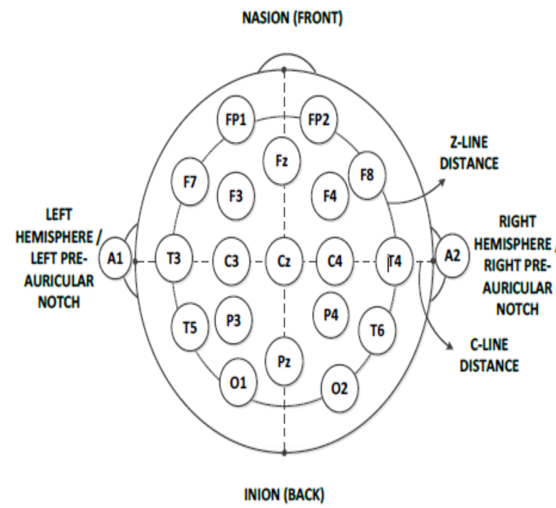

Fig 2: 10-20 international system

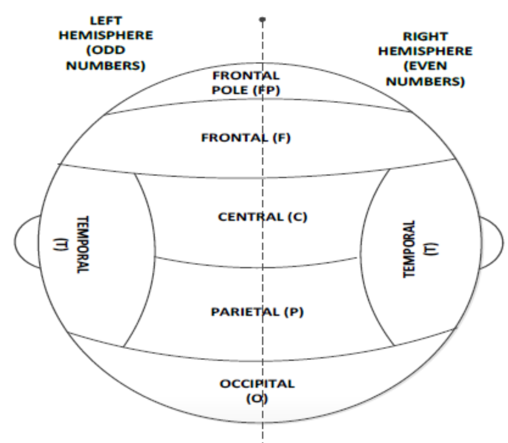

Fig 3: Brain Lobes

Now mental EEG signal related to particular mental tasks are acquired by using 10-20 system. In which user thinks about that activity and generated EEG signal represent particular mental activity. Anderson has acquired EEG signal for 5 mental tasks using 10-20 system [12]. Then acquired EEG signal is applied to preprocessing for removal of noise from EEG signal. Mental task related signal can be any signals which are obtained by any mental activity.

III. EEG SIGNAL PREPROCESSING AND FEATURE EXTRACTION

While recording EEG signal for mental task it is get contaminated by noise. Artifacts in EEG (electroencephalogram) records are caused by various factors, like line interference, EOG (electro-oculogram) and ECG (electrocardiogram). These noise sources increase the difficulty in analyzing the EEG [13]. To extract information from EEG signal, it must be filtered i.e. noise must be removed from it. Artefact removal can be removed using ICA, CAR, SL, PCA, CSP and Adaptive Filtering.

After preprocessing signal becomes noise-free, but we cannot discriminate between different mental tasks by just looking/ visually inspecting EEG signal. To discriminate between different EEG signal feature extraction technique is needed. Extracted features from EEG signal will help classifier to classify mental tasks. A variety of different feature extraction methods exist like Adaptive Auto Regressive parameters (AAR), Fast Fourier Transformations (FFT), PSE, Wavelet Transformations (WT), ICA [14]

A. Fourier Transform (FT)

Fourier Transform converts time domain signal into frequency domain. Discrete Fourier Transform converts discrete time domain signal into discrete Fourier domain signal [15]. EEG signal is time domain signal. In order to recognize the features EEG signal is analyzed using FT and then energy of that signal is calculated, this process is also called as PSD (Power spectral density). EEG signal is non-stationary signal and FT works better for stationary signal. But short time period EEG signal (approx. 1 sec) can be considered as stationary signal. Such signals can be obtained by applying short time window over EEG signal and then FFT is applied on that signal. This is known as Short Time Fourier Transform (STFT). Equation for STFT is

$$Xstft[m,n] = \sum_{K=0}^{L-1} x(K) * w(K-m)\, e^{-j2\pi nK/L}$$

(1)

Where x[k] denotes a signal and w[k] denotes an L-point window function. After that power is calculated from each STFT signal which represents a feature of EEG signal. A. Suleiman [16] proposed FT technique for feature extraction from EEG signal. In which he divided EEG signal into 1 sec duration. The STFT is applied to one second EEG signal. Al EEG signal doesn’t contain any useful information above 30hz,the result normalized from 1 to 30 Hz. In this way 1 sec signal is transformed into 30 values applied them to classifier to detect and classify mental tasks (Baseline, Mental arithmetic and mouse click). Paralyzed individual can control electronic device by eye blinking. S. Valipour [17] used PSD technique to extract features from eye pone and eye closed EEG signal. In which he extracted PSD from theta(0-4hz) band to beta (13-30hz) band. And stated that alpha band dominates for eye blink.

B. Wavelet Transform(WT)

As the EEG signal is non-stationary, the most suitable way for feature extraction from the raw data is the use of the time-frequency domain methods like wavelet transform (WT) [18]. Wavelet transform provides accurate time information at high frequency and accurate frequency information at low frequency, this property is important in biomedical applications [19]. For discrete data Discrete Wavelet Transform (DWT) is widely used. DWT uses low pass filter and high pass filter. EEG signal is passed through these filters. Low pass filter gives approximation coefficients and high pass filter gives detail coefficients. These coefficients represent the features of EEG signal which is related to particular mental activity. R. Yohanas [20] has used DWT method for feature extraction from EEG signal to recognize the emotions happy and sad. He used DWT coefficients, PSD , and Wavelet Sub-Band Energy and Entropy as feature . He used SVM and ELM for classification of emotions and he got 84% and 89% accuracies for classifier respectively. He stated that Symlets order 6 was chosen as the best wavelet function as it generally showed better performance than other wavelet functions. This may indicate that the waveform of Symlets order 6 is similar to the transient activities in the EEG signals that correspond to sad or happy emotions. H. Dingyin [21] used WPD as a feature extraction method for motor imaginary EEG signal. He used coefficients mean of WPD and wavelet packet entropy as a features. FDA used to measure separability and k-NN for classification. He got 90% accuracy. Stated that db4 is an appropriate for EEG signal analysis. N. Hazarika[22] also used wavelet transform for classification of normal and SCH, OCD. He used wavelet coefficients as features. He got 66% and 71% classifier accuracy. S. Imran [23] proposed use of Wavelet transform for classification motor and imaginary EEG signal. Features extracted are energy, entropy, variance and maximum of wavelet coefficients. He used PCA to reduce dimensionality of extracted features. Stated that large no of wavelet families are there and amongst them db family shows good performance in EEG signal analysis. D. Upadhyay [24] used DWT for feature extraction from EEG signal of five mental tasks. Min, Max, Mean and Std. of wavelet coefficients are used as features. In [25] dwt is used for feature extraction.

C. Power Spectral Entropy (PSE)

In order to extract features which can best reflect the different mental tasks, a new EEG feature with power spectral entropy (PSE) is proposed in this paper [26]. PSE measures the spectral complication of an uncertain system through information entropy. In PSE first entropy of signal is calculated and then Fast Fourier Transform (FFT) is applied which converts the time-series of signals into the power spectrum referred to as information entropy of power spectrum as power spectral entropy. A. Zhang [26] proposed feature extraction using PSE for classification of imaginary right and left hand movement. In this paper DFT of EEG signal is obtained then, PSD is calculated and it is normalized and finally entropy of normalized signal is calculated to obtain PSE. Values of PSE are used as features of EEG signal of imagined mental tasks and applied to classifier. 90% accuracy is obtained.

D. Independent Component Analysis (ICA)

ICA is a signal processing technique in which observed random data are transformed into components that are statistically independent of each other. ICA is a statistical method whose goal is to find a linear representation of non-Gaussian data so that the components are statistically independent. ICA is used for feature extraction from mental task EEG signal to classify imaginary tasks [27]. If EEG signals are linear mixture of several sources, independent sources obtained by ICA. It is assumed that at time instant *t* the observed n-dimensional data vector *x(t)* is given by

$$x(t) = \sum_{i=1}^{n} a_i s_i = AS(t)$$

(2)

Where *x(t)* is EEG signal, *si* are the source signals and the *ai* form the mixing matrix A which is nothing but statistically independent spatial map. The estimated source signal obtained by solution of ICA equation.

$$F(t) = Dx(t)$$

(3)

Where, D is demixing matrix. Coefficients of *Fi(t)* represents features of EEG signal and they can be used for classification of mental tasks. J. Navarro[28] used ICA technique for feature extraction from EEG signal (imagined five wrist movements), classifier accuracy obtained ranging from 70%-90%. J. sita [29] used ICA technique for mapping of motor area of brain.

E. Auto Regressive (AR)

Autoregressive (AR) AR modeling is one of the prominent parametric methods. It indicates that linear mixture of the past EEG samples plus an independent component (white noise) brings existing EEG sample [30]. Several features expressed the reason for reputation of AR modeling of EEG: i) Short-term EEG spectrum can be distinguished by AR process with sensible accuracy; ii) AR model is totally applied in time series analysis context; iii) Parameters of AR model are estimated by simple algorithms. AR models are suitable choice to analyze EEG for biomedical engineers [31]. Various auto regressive methods are employed in feature extraction of EEG signals and are Bilinear AAR, Adaptive AR parameters (AAR), multivariate AAR (MVAAR).

$$Xt = a1x1 + a2x2 + \cdots + apxp + noise \quad (4)$$

xi represents EEG signal *a= (1, 2,….,p)* is the ith AR Coefficient. Burg's method is used to estimate AR coefficient. Main challenge in AR model is to select proper model order [32]. M. Polak [32] used AR model and FFT for feature extraction from an EEG signal, and stated that AR shows good performance that FFT. V. Maiorescu [33] used AR model with MLPNN to classify EEG signal. In [34] EEG signals are modeled using single-channel and multi-channel autoregressive (AR) techniques. The coefficients of these models are used to classify EEG data into one of two classes corresponding to the mental task the subjects are performing. A neural network is trained to perform the classification. When applying a trained network to test data, the authors find that the multivariate AR representation performs slightly better, resulting in an average classification accuracy of about 91%.

F. Principal 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.

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IV. Classification

After feature extraction the signals are classified into various classes using various classifiers. Different types of classifiers include linear classifiers, Artificial Neural Networks (ANN) based classifiers, nonlinear Bayesian classifiers and, nearest neighbor classifiers. Of these classifiers linear classifiers and non linear Bayesian classifiers are mostly used in BCI design. [35]

A. Linear Classifiers

As name suggests Linear classifier uses the linear functions to classify signals into corresponding classes. Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM) are the types of linear classifiers

1) LDA The main task of LDA is to use hyper plane to separate or to discriminate data which represents different classes.LDA creates a boundary between two classes. It is mainly used to classify two class problems. To separate N class problem, N hyper plane are required. To create multiple hyper plane one verses rest strategy is used. (LDA) is a traditional dimension reduction method which finds projective directions to maximize separability between classes. However, when the number of labeled data points is small, the performance of LDA is degraded severely [36].

Author [37] worked on detection of Epileptic seizer detection using EMD and LDA and the sensitivity and specificity obtained with this method were 69.4% and 69.2% respectively . In this [38] author used K-NN classifier with LDA to perform a pair-wise classification of the 10 combinations of mental tasks. Two different discriminate functions such as linear and quadratic were used in LDA classifier and their effects on the classification performance are presented. The experimental results show that the proposed method gives promising pair-wise classification accuracy from 78.80% to 100%.

2) SVM: SVM also uses a hyper plane to separate the data. It discriminates data sets with clear gap that is as wide as possible to classify them into their relevant category. The hyper plane maximizes the margin that is the distance between the hyper plane and the nearest points from each class that are called as support vectors. The objective of this method is to provide good generalization by maximizing the performance of machine while minimizing the complexity of learned model. Author [39] used SVM classifier for classification of online EEG data of two mental tasks and he observed accuracy of 87%. In [40] this author has used SVM to recognize the mental tasks (thinking left, thinking right, math and carol). SVM is used to classify EEG signal in [41][42][43].

B. ANN

ANNs are non linear classifiers composed of large number of interconnected elements called neurons [44]. Each neuron in ANN simulates the biological neuron and is capable of performing simple computational tasks. The most frequently used neural network is the Multi Layer Perceptron Neural Network (MLPNN) in which, the network is arranged into three layers viz., input layer, hidden layer and output layer[45]. The advantage of MLPNN is that its fast operation, ease of implementation and requiring small training sets. The no. of inputs denotes the no. of features selected and, no. of outputs denotes the no. of classes formed. The complexity of an ANN is estimated by the no. of neurons in the hidden layer of it. The large the no. of neurons in hidden layer the more the complexity, less no. of neurons in hidden layer causes classification errors. No specific criterion was defined for making this decision in hidden layer. In this author used ANN to classify 5 mental tasks, mean classifying accuracy obtained was 90.75% and for classifying two tasks mean classifying accuracy obtained 99.87% [46]. Author used ANN to classify epileptic seizer detection [47]. Other type of neural network is PNN, which is also used for classification of mental tasks [48]

C. Nearest Neighbor Classifier

NNCs assign a feature vector to a class based on its nearest neighbors. They consist in assigning a feature vector to a class according to its nearest neighbor(s). This neighbor can be a feature vector from the training set as in the case of k Nearest Neighbors (kNN) classifiers. The aim of this technique is to assign to an unseen point the dominant class among its k nearest neighbors within the training set. For BCI, these nearest neighbors are usually obtained using a metric distance. With a sufficiently high value of k and enough training samples, kNN can approximate any function which enables it to produce nonlinear decision boundaries. In this paper different ANN methods are compared [49] [50]. Helpful Hints

V. Conclusion

In this paper we have surveyed the different methods for mental task classification. We have survey six feature extraction methods FT, WT, PSE, ICA, AR and PCA. We also surveyed the Linear, Nonlinear, and Nearest neighbor Classifiers Brain Computer Interface goes through many phases: signal acquisition, Brain Signal Acquisition, Brain Signal Preprocessing, Feature Extraction, Classification, and the intended application. Lots more options are there to choose from feature Extraction methods and Classification methods with a major focus on EEG based BCI for mental task detection

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