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Review paper on Feature Extraction Methods for EEG Signal Analysis

Akshaya R. Mane[1], Prof. S. D. Biradar[2] and Prof. R. K. Shastri[3]
[1 2 3](Department Of Electronics and Telecommunication Engineering,VPCOE/ Savitribi Phule University, India)

Abstract :- The main aim of Brain Computer interface is to effectively classify Electroencephalogram (EEG). EEG signals are used to extract correct information from brain and classify with different mental tasks. This paper compares different feature extraction methods such as wavelet transform, Independent component analysis, Principal component analysis, Autoregressive model and Empirical mode decomposition. Feature represents distinguishing property and significant measurement which are obtained from section of a different methodology pattern. It is necessary that extracted features should not lose the important information from the signal. EEG signal analysis is used in many health applications because it has ability to identify brain stimulation effectively which is nowadays widely used in brain computer interfaces. The review on these methods mainly focuses on feature extraction techniques used in EEG signal analysis

Keywords- autoregressive model (AR), Electroencephalogram (EEG), independent component analysis (ICA), principal component analysis (PCA), wavelet transform (WT)

I. INTRODUCTION

Brain is very complex part of our body. It consists of approximately 100 billion nerve cells. These cells are called as neurons. Signals are generated by the neurons in different parts of brain when they are excited [1]. Physiological control process and external stimuli helps in passing signal to other parts of body. Hence EEG signals provide rich information about electrical activity of brain. Nowadays for clinical and research purpose EEG signal are mostly used to detect activity of various action within the brain .As EEG signal generates large amount of data which is difficult to analyze by observation. They are having low amplitude because of skull's composition. In modern biomedical applications EEG signal is investigated as function of human- computer communication. Computers help in recognition of abnormalities in brain from EEG signal.EEG signal occurs in frequency ranges of delta (0.5-4 Hz) theta (4-8 Hz), alpha (8-13 Hz) and beta (>13 Hz) [2].To record electrical signals, electrodes are arranged on the surface of scalp using 10-20 system. International Federation of societies and clinical neurophysiology has recommended this system. As name indicates that distance between the adjacent electrodes are either 10% or 20% from total front-back or left-right portion of skull. Placement of electrodes according to this system is shown in Fig1,

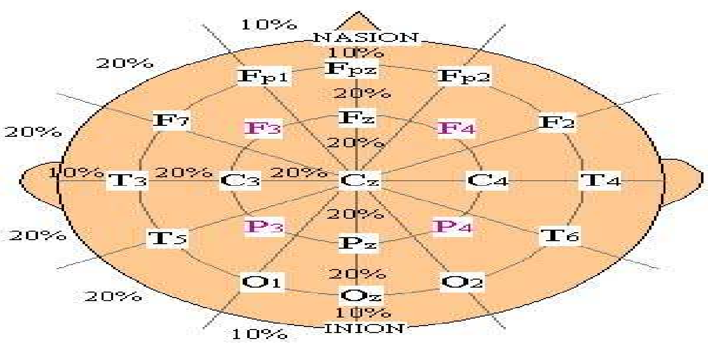

Fig.1.10-20 system placement of electrodes [3]

It uses letters and numbers for placement of electrodes. The electrode site is labeled with a letter which corresponds to the area of the brain, and a number which indicates the right hemisphere - even, or the left hemisphere – odd. Nasion and Inion are the anatomical landmarks. Nasion is point in between nose and forehead. Inion is lowest point from backside of brain. The EEG signal represents voltage difference between two electrodes, one or more electrodes can be used as reference electrodes to measure the output voltage. As EEG reflects thousands of simulations ongoing brain activity Event related potential (ERP) provide continuous measure of processing between stimulus and response, making it possible to determine which stages are being affected by specific experimental manipulation. Small size of ERPs cans measures large EEG data [4].

Brain Computer Interface (BCI)- BCI is now developing technique for communication of brain thoughts with the other outside environment. It is classified in the category of invasive and noninvasive BCI. It has flexibility to capture EEG signal.EEG signal is known as basic building block for BCI system. Success of BCI depends upon proper selection of feature extraction methodology [5].Basic BCI system is shown in below Fig.2

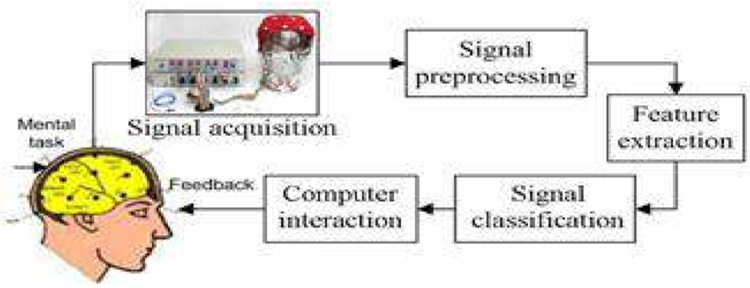

Fig.2.Basic BCI system [18]

BCI mainly consists of some basic stages such as preprocessing, feature extraction and some classification techniques. Preprocessing consists of acquisition of raw EEG data, elimination of artifacts and enhancement of signal. As most important characteristic of EEG data is to obtain features from vector. Last stage is the signal classification in which different algorithms and classifiers are used to obtain accuracy to the defined system. There are two types of BCI systems such as Invasive and Noninvasive BCI. Invasive systems used to provide a reliable manner for connecting neurons in brain and devices that are based on proper surgical techniques however, the relative increase in signal quality as compared with scalp-based sensors has been disputed. For everyday applications in healthy populations, any potential benefit based on increased signal quality must be balanced against the potential risks associated with both the surgery and the long-term implantation of these devices. Noninvasive EEG-based BCIs, which measure the electrical activity of the brain using electrodes placed along the scalp skin used to provide a feasible method for communication of the human brain with external devices [6].

II. METHODOLOGY

The different methodologies for EEG signal analysis are present. Some of them are-

2.1. Wavelet transform

P.Jahankhani and K.Revett have proposed [7] wavelet transforms (WT) to analyze various transient events in biomedical field. They have described that WT is suitable for nonstationary signals and has advantage over spectral analysis. For time frequency representation of a signal wavelet is an effective method. The important feature of WT is that it provides accurate frequency information at the low frequencies and accurate time information at the high frequencies. This property is important in biomedical applications. Because most signals in the biomedical field always contain high frequency components with short time period and low frequency components with long time period. The WT provides multiresolution analysis of nonstationary signals. It is shown in Fig.3

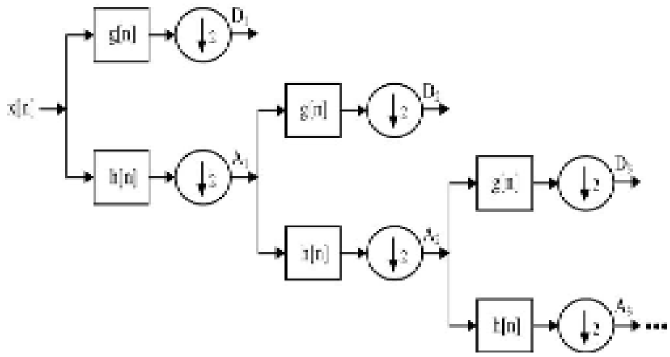

Fig.3.Wavelet decomposition process [8]

Where g[n] is high-pass filter and h[n] is low-pass filter. WT is most suitable for location of transient events. It has advantage over spectral analysis [9].Here EEG signal is decomposed into D1-D4 levels. Wavelet overcomes the limitations of short time fourier transform (STFT). In serious patients detection of disorder in the brain using conventional method is very inconvenient. Frequency content in the EEG signal provides useful information as compared to time domain [10]. The mother function $\psi(n)$ is convolved with the signal x(n). Its function is given by formula,

$$w_{\psi}x(b,a) = \sum_{n'}^{N-1} x(n')\psi * (n' - b/a) \tag{2.1}$$

where a is called as scale coefficient and b is called shift coefficient [11]. Formation of mother wavelet is important because when it is fixed then it is easy to understand signal at possible coefficients a and b [12]. Decomposition levels of EEG signal are selected based upon dominant frequency components which are present in the signal. This decomposition of EEG signal leads to formation of coefficients called as wavelet coefficient [13]. From different families of wavelet Daubechies family of order 2 (db2) is mostly used due to its smoothing function. Down sample output of high pass filter provides detail wavelet coefficient and low pass filter provides approximation wavelet coefficient [14]. The discrete wavelet transform is a signal processing tool that has many engineering and scientific applications for various tasks. It develops quantifying spikes, sharp waves and spike-waves. In DWT signal analyses different frequency bands using filters. It is mainly used in detection of epileptic seizures [15]. Wavelet provides features such as maximum, minimum, mean and standard deviation coefficient of each sub-band [16] [17]. WT is used in the detection of mental tasks such as resting, multiplication, figure rotation and letter composition etc.

2.2 Independent Component Analysis

W.Zhou and J.Gotman have proposed [18] independent component analysis (ICA) in determination of source signal localization of independent components using single dipole model. They have described that this is very important for removing artifacts from eye movement. ICA method is based upon the linear transformation of the recorded EEG signal hence used in the study of brain signals.ICA is statistical and computational technique for revealing hidden factors that underlie sets of random variables. It is formulated as,

x1(t)=a11s1+a12s2 (2.2)

x2(t)=a21s1+a22s2 (2.3)

where a11,a12,a21 and a22 are parameters and signals are given by s1(t) and s2(t) using the recorded signals x1(t) and x2(t).It is capable of producing subcomponents of multivariate signal. Data analyzed by ICA could originate from many different kind of application fields including the digital images or databases.ICA can reveal information on brain activity by giving access to its independent components. The main goal of applying ICA is to find linear representation of nongaussian data so that components are linearly or statistically independent. ICA defines generative model for observed multivariate data which is typically given as large database of samples. For the decomposition of ongoing EEG signal ICA is used. Any statistical model for EEG without sensor noise can be expressed in Eq.2.4 ,

x=As (2.4)

where $X = [x_1, x_2, \dots, x_I]^T$, $S = [s_1, s_2, \dots, s_I]^T$. A is called mixing matrix and it is related to ICA components. This is generative mode where data is generated by process of mixing components of signals. An important property of the general nonlinear mixing model consists of so called post-nonlinear mixtures [19]. When ICA is applied to EEG signal it can turns into event related and nonevent related sources. Assumptions for ICA separations are the distribution of values in each source signal are nongaussian and source signals are independent of each other. An important application of ICA is Blind Source Separation. Because in this process there is separation of mixed measured signals into an independent sources [20] [21]. The use of ICA for blind source separation application of EEG signal is reasonable because of (1) EEG data recorded at multiple scalp sensors are linear sums of temporally independent components which are arises from spatially fixed or overlapping brain areas and the propagation time delays are negligible; (2) the eye artifacts and EEG are independent since they have a completely different generating mechanism [22] .This helps in identifying the independent signals and also noise separation from brain signal. ICA decomposition is well suited when it gives better stability and reliability. To find stability it requires ICASSO software because its stability index reflects isolation and compactness of cluster [23]. For clustering features extracted are spectral, topographical, similarity over trial and temporal features[24].ICA, applied to data of sufficient length and quality typically provides many components on account for an appreciable amount of variance in the original signal and whose scalp projection looks like that of a single equivalent dipole located in the model brain cavity[25] [26].

2.3 Autoregressive Modeling

A.Zabidi and W.Mansor have proposed [27] Autoregressive model (AR) as feature extraction technique for classification of writing task from EEG signal. Imagined writing task provides useful information that is used to improve the writing disorders. They have used AR model with Multi Layer Perceptron (MLP) for discrimination of alphabets. AR model is used in application of classifying imagined letters from EEG signal. It is also used in the detection of mental tasks using neural network and provides 91% accuracy. The EEG signal undergoes changes in the amplitude as well as frequency while different mental tasks are performed. Hence these features can be captured and extracted using modeling techniques, such as autoregressive models. AR model has been widely used for EEG analysis. It shows the linear combination of ICA and past EEG which brings the present EEG samples. The basic idea of autoregressive (AR) model is the assumption that the real EEG can be can be approximated by so called AR process. With this assumption the order and parameters of approximation AR model are chosen in a way to fit the measured EEG as closely as possible. For every particular AR model, it provides alternative way for EEG spectral properties. The observed data denoted by x(n) is output of a linear system characterized by a transfer function , H(z). Then, x(n) meets an AR model with order p of the formula,

$$x(n) = -\sum_{i=1}^{p} ap(i)x(n-i) + v(n) \qquad (2.5)$$

ap(i) are the AR parameters, x(n) the observations and v(n) is the excitation white noise[28][29].

For every AR process the power spectrum can be estimated analytically. It is calculated as,

$$p\,(f) = e_t^2 / \left| 1 + \sum_{i=1}^{p} ap(i)x(n-i) \right| \tag{2.6}$$

This model can be applicable to stationary signals. This assumption rarely holds for EEG concept of local stationary was proposed within small intervals of time ,the EEG signal departs only slightly from stationary. AR model defines error in the prediction of x(n) is based upon the EEG data. AR coefficient, model order and power spectrum features are obtained which helps in improving accuracy of classifier. As number of AR order increases the performance of classifier increases linearly. The selection of the accurate order plays the most important role in AR modeling of time series [30].Various AR methods are available such as Bilinear AAR, Adaptive AR parameters, multivariate AAR. In adaptive autoregressive model Kalman filter is mostly used to evaluate AR parameters [31]. It can achieve classification accuracy of 83% in case of multivariate AAR model. AR is able to present an expression of a frequency domain signal characteristics [32]. AR model has problem to estimate the models parameters when the measured EEG signal has limited length. For modeling EEGs by using an AR model needs accurate values for prediction order and its coefficient values. High prediction order cannot split the true peaks in the frequency spectrum and low prediction order causes to combining near peaks in frequency domain [33].

2.4 Principal Component Analysis

E.Braack, et al. have proposed [34] transcranial magnetic stimulation (TMS) technique with EEG signal. For this work they have used principal component analysis (PCA) for suppressing the first two artifacts in EEG data. PCA helps in reducing TMS induced artifacts and hence reveals TMS evoked potential also. PCA is statistical procedure that uses orthogonal transformation to convert set of observations of possibly correlated variables into set of values of linearly uncorrelated variables called principal component analysis.PCA is well established multivariate data technique which finds the direction of data. It is considered as second order statistical method.PCA method decomposes covariance matrix Φ of mean zero with N*p observed data matrix. As Φ=LP^T where L=principal component score matrix and P=(P1,..Pp) is leading matrix of PCA. Principal components can improve signal similarity to improve good accuracy for signal classification [35].In some ICA algorithms PCA is used as preprocessing technique [36].This method is also used for the segmenting signal from multiple source signals and reduces dimensions in space with low complexity [37].Highest number of eigenvalue of eigenvector represents principal component analysis because it can gives significant relationship between data dimension [38].

2.5 Empirical Mode Decomposition

Huang, et al. (1998) has introduced the concept of Empirical Mode Decomposition and application of Hilbert transform, which is called Hilbert-Huang Transform, to extract time-frequency information data from a nonlinear and nonstationary signal. R. Oweis and W. Abdulhay has proposed [39] EMD method for recognition of seizure and Nonseizure detection. From this intrinsic mode functions are extracted to obtain amplitude and frequency components. M.Chen and D.Mandic have developed [40] EMD method for qualitative assessment of EMD process. They have used delay vector variance technique for analysis of first IMF signal nature which resembles to the original EEG signal. Empirical mode decomposition (EMD) method is considered as emerging technique in different signal processing fields such as biomedical signal analysis [41]. EMD is process of extracting amplitude and frequency modulated oscillatory patterns from time series data. These patterns are called as Intrinsic Mode Function (IMF) [42] [43].The principle of this method consist of decomposition of EEG signal into limited number of IMF.As EMD was proposed as fundamental part of Hilbert Huang Transform (HHT). It is carried out in two stages: Using EMD algorithm we can obtain IMF. Instantaneous frequency spectrum of initial sequence is obtained by applying HHT to the result of above stage.

Sifting process is used until final constant residue is obtained [46] [47].As the number of IMF increases, the corresponding data becomes smoother [48]. Successive IMF has lower frequency than previous one hence EMD acts as filter [49]. EMD is used in an application of seizure and Nonseizure detection. It provides features like instantaneous frequency, energy and amplitude using LS-SVM classifier it provides better accuracy, specificity and sensitivity. The EMD algorithm is however very sensitive to noise in the recorded signal. This can increases complications due to mode mixing. Mean frequencies of different IMFs are used for discriminating the signals.

TABLE I

COMPARISON OF FEATURE EXTRACTION METHODS

1	WT	1. Wavelet is capable method to analyze signal with discontinuities through the varying window size. 2 .It can extract energy and analyze signal in both time and frequency domain. 3.It is mainly suited for transient changes in signal.	1. Heisenberg Uncertainty reduces its performance. 2.It require appropriate selection of mother wavelet
2	ICA	1.ICA is computationally efficient and it shows high performance for large sizeddata. 2.It can decomposes signal into temporal independent and fixed components	1. ICA requires more computational area for decomposition. 2. ICA is based on linearity of signal.
3	AR	1.AR requires short time period to record EEG data. 2.It gives better frequency resolution. 3.AR reduces spectral loss problems and provides better accuracy for spectral analysis.	1. Complications arise in developing model properties for EEG signal. 2. Incorrect selection of model order will give poor spectrum estimation.
4	PCA	1.Useful technique for reducing dimensionality of data without important loss of information.	1.PCA assumes data is continuous and linear. 2. For more complications PCA fails to process on data.
5	EMD	1.It is powerful technique to decompose EEG signal into set of IMFs. 2.EMD is adaptive and data driven process. 3.It provides multiresolution analysis	The EMD algorithm is very sensitive to noise in the recorded signal. This can increases complications due to mode mixing.

III. CONCLUSION

In this paper five different methods are discussed for EEG signal analysis. Each method is having some advantages and limitations. Frequency domain methods does not provide high-quality performance for some EEG signals where as time-frequency methods does not provide detailed information about EEG data as much as frequency domain methods. Hence according to different mental task related applications accurate method should to be chosen for better results.

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