Performance Analysis of Epileptic EEG Expert System Using Scaled Conjugate Back Propagation Based ANN Classifier

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Abstract— **Epilepsy is a neurological disorder with prevalence of about 1-2% of the world's population. Epilepsy is a neurological condition in which is due to chronic abnormal bursts of electrical discharge in the brain. Monitoring brain activity through the electroencephalogram (EEG) has become an important tool in the diagnosis of epilepsy. The EEG recordings of patients suffering from epilepsy show two categories of abnormal activity: inter-ictal, abnormal signals recorded between epileptic seizures; and ictal, the activity recorded during an epileptic seizure. The term EEG refers that the brain activity emits the signal from head and being drawn. It is produced by bombardment of neurons within the brain. EEG signal provides valuable information of the brain function and neurobiological disorders as it provides a visual display of the recorded waveform and allows computer aided signal processing techniques to characterize them. This gives a prime motivation to apply the advanced digital signal processing techniques for analysis of EEG signals. The main objective of our research is to analyze the acquired EEG signals using signal processing tools such as wavelet transform and classify them into di erent classes. The features from the EEG are extracted using statistical analysis of parameters obtained by wavelet transform and Auto-Regressive model. Total 300 EEG data subjects were analyzed. These data were grouped in three classes' i.e, Normal patient class, Epileptic patient class and epileptic patient during non-seizure zone respectively. In order to achieve this we have applied a backpropgation based neural network classifier. After feature extraction secondary goal is to improve the accuracy of classification. 100 subjects from each set were analysed for feature extraction and classification and data were divided in training, testing and validation of proposed algorithm.**

Index Terms— EEG, Epilepsy, Wavelet transform; Feature Extraction, Neural network, Backpropogation Neural Network.

I. INTRODUCTION

Generally, the detection of epilepsy can be achieved by visual scanning of EEG recordings for inter-ictal and ictal activities by an experienced neurophysiologist. However, visual review of the vast amount of EEG data has serious drawbacks. Visual inspection is very time consuming and inefficient, especially in the case of long-term recordings. In addition, disagreement among the neurophysiologists on the same recording is possible due to the subjective nature of the analysis and due to the variety of inter-ictal spikes morphology.

Moreover, the EEG patterns that characterize an epileptic seizure are similar to waves that are part of the background noise and to artifacts (especially in extra cranial recordings) such as eye blinks and other eye movements, muscle activity, electrocardiogram, electrode "pop" and electrical interference. For these reasons, methods for the automated detection of inter-ictal spikes and epileptic seizures can serve as valuable clinical tools for the scrutiny of EEG data in a more objective and computationally efficient manner.[1]

1.1 Wavelet Transform- The discrete wavelet transform (DWT) is quite an effective tool for Time-Frequency analysis of signals. Wavelet transform can be defined as a spectral estimation technique in which any general function can be expressed as a sum of an infinite series of wavelets. In DWT the time-scale representation of the signal can be achieved using digital filtering techniques. The approach for the multi-resolution decomposition of a signal x(n) is shown in Fig. 1.1. The DWT is computed by successive low pass and high pass filtering of the signal x (n). Each step consists of two digital filters and two down samplers by 2. The high pass filter g[] is the discrete mother wavelet and the low pass filter h[.] is its mirror version. At each level the down sampled outputs of the high pass filter produce the detail coefficients and that of low pass filter gives the approximation coefficients. The approximation coefficients are further decomposed and the procedure is continued as shown in figure.1.1.

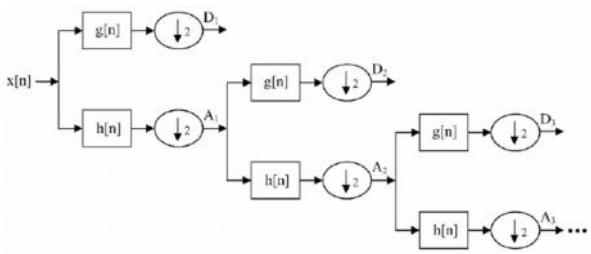

Figure 1.1. Computation process of DWT

The standard equation of Discrete Wavelet Transform is given as-

$$w_{m,n} = \left\langle x(t), \cdot_{m,n} \right\rangle = a_0^{m/2} \int f(t) \cdot (a_0^m(t) - nb_0) dt \tag{1.1}$$

Where sub wavelets is given by-

$$\cdot_{m,n}(t) = a_0^{m/2} \cdot (a_0^m(t) - nb_0) \qquad m, n \in Z \tag{1.2}$$

The DWT decomposition can be described as

$$a\,k \quad l \;= x\,k \;* \varphi k,l\,(n)$$

$$d\,k \quad l \;= x\,k \;* \psi k,l\,(n)$$

where *a*(*k*)(*l*) and *d(k)*(*l*) are the approximation coefficients and the detail coefficients at resolution k, respectively.
The wavelet transform gives us multi-resolution description of a signal. It addresses the problems of non-stationary signals and hence is particularly suited for feature extraction of EEG signals [2]. At high frequencies it provides a good time resolution and for low frequencies it provides better frequency resolution, this is because the transform is computed using a mother wavelet and different basis functions which are generated from the mother wavelet through scaling and translation operations. Hence it has a varying window size which is broad at low frequencies and narrow at high frequencies, thus providing optimal resolution at all frequencies.

1.2.Auto-Regressive Process-

The power spectral density (PSD) of the EEG signals is computed by using Burg Autoregressive (AR) Model in the present work. This method is based on minimization of forward and backward prediction errors while constraining the AR parameters to satisfy the Levinson-Durbin recursion process. Autoregressive coefficients provide us the important features in terms of the power spectral density (PSD). The Burg method estimates the reflection coefficients a_k. Since, this method describes the input signals by using the all pole model. So the selection of model order is critical because the very low model order produces smooth spectrum and too large model order effect in stability. Any stochastic process can be modeled by using AR process.[10,11,12]
Assume our samples, x (0), x (1), …, x(L-1) are drawn from an Mth-order AR model with a zero-mean IID sequence, w(n) as input is given as-

$$H(z) = \frac{1}{1 - a_1 z^{-1} - a_2 z^{-2} - \ldots - a_M z^{-M}} \tag{1.3}$$

A corresponding difference equation is given as-

$$x(n) = a_1 x(n-1) + a_2 x(n-2) + \ldots + a_M x(n-M) + w(n) \tag{1.4}$$

The Magnitude Spectrum is of the form

$$R(e^{j\mu}) = \frac{\pm_w^2}{\left|1 - a_1 z^{-1} - a_2 z^{-2} - \ldots - a_M z^{-M}\right|^2} \tag{1.5}$$

$$R_{AR}(e^{j\mu}) = \frac{\pm_w^2}{\left|1 - c_1 z^{-1} - c_2 z^{-2} - \ldots - c_p z^{-p}\right|^2} = \frac{\pm_w^2}{\left|\mathbf{f}^t \mathbf{s}\right|^2} \tag{1.6}$$

Where f represents the model parameters and s is referred to as a frequency scanning vector or steering vector. We must estimate the noise power, the model order AND the filter coefficients. This would be easy except we know that an AR model of order p > M will produce a smaller error than p = M.

1.3 Data base- The raw EEG signal is obtained from university of Bonn which consists of total 5 sets (classes) of data (SET A, SET B, SET C, SET D, and SET E) corresponding to five different pathological and normal cases. Three data sets are selected from 5 data sets in this work. These three types of data represent three classes of EEG signals (SET A

contains recordings from healthy volunteers with open eyes, SET D contains recording of epilepsy patients in the epileptogenic zone during the seizure free interval, and SET E contains the recordings of epilepsy patients during epileptic seizures)
All recordings were measured using Standard Electrode placement scheme also called as International 10-20 system. Each data set contains the 100 single channel recordings. The length of each single channel recording was of 26.3 sec.The 128 channel amplifier had been used for each channel [3]. The data were sampled at a rate of 173.61 samples per second using the 12 bit ADC. So the total samples present in single channel recording are nearly equal to 4097 samples (173.61×23.6). The band pass filter was fixed at 0.53-40 Hz (12dB/octave) [4].

II. METHODOLOGIES

DWT successfully analyses the multi-resolution signal at different frequency bands, by decomposing the signal into approximation and detail information. The method for frequency band separation for epilepsy detection is implemented in MATLAB 2013a. The flowchart of the proposed methodology for detection of epileptic data from normal data is shown in figure Epilepsy Detection using EEG requires feature extraction from the acquired signal in specific frequency range of delta, theta, alpha, beta, and gamma. Though some researchers have mentioned the use of DWT decomposition to obtain these bands, the method given is inadequate to achieve these. First this study explicitly describes the method of up-sampling and recombining of several decomposed sub bands to achieve the required frequencies. Data is first pre-processed by removing dc component from the signal thereby achieving different levels of decomposition for Daubechies order-2 wavelet with a sampling frequency of 173.6 Hz on each signal of 4096 samples.
The overall process can be explained using following flowchart-

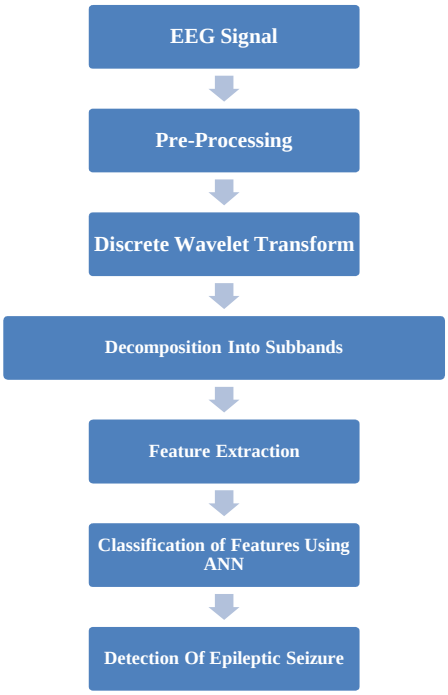

Fig2.1Steps of Detection Of Epilepsy Using EEG

2.1 Feature Extraction using Wavelet Transform– From the data available at [9] a rectangular window of length 256 discrete data was selected to form a single EEG segment. For analysis of signals using Wavelet transform selection of the appropriate wavelet and number of decomposition level is of utmost importance. The wavelet coefficients were computed using daubechies wavelet of order 2 because its smoothing features are more suitable to detect changes in EEG signal. In the present study, the EEG signals were decomposed into details D1-D5 and one approximation A5. After calculating coefficients we can calculate various features using statistical analysis of coefficients. [4]
The feature extraction is shown in fig 2.2-

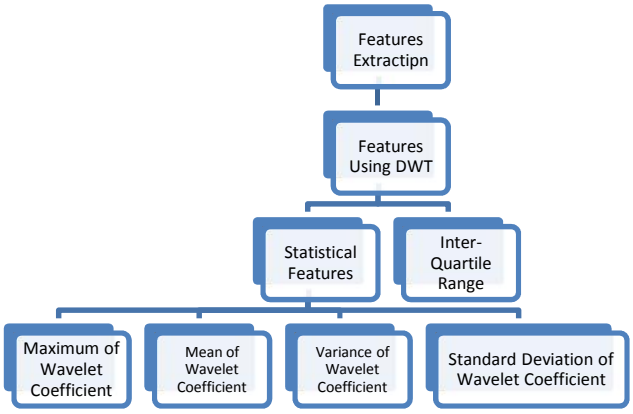

Fig 2.2 Feature Extraction using DWT

A rectangular window of length 256 discrete samples is selected from each channel to form a single EEG segment. The total numbers of time series present in each class are 100 and each single channel time series contained 16 EEG signal segments. Therefore total 1600 EEG segments are produced from each class. Hence, total 4800 EEG segments are obtained from three classes. The 4800 EEG segments are divided into training and testing data sets. The 2400 EEG signal segments (800 vectors from each class) are used for testing and 2400 EEG signal segments (800 segments from each class) are used for training.[5]

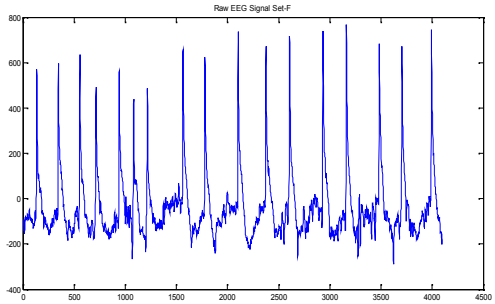

Figure 2.3 Raw EEG Set-F

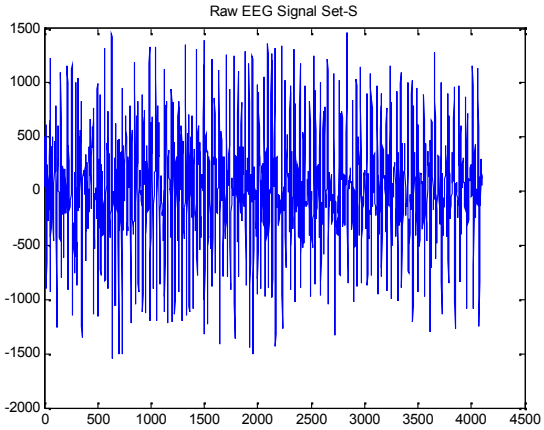

Figure 2.4 Raw EEG Set-S

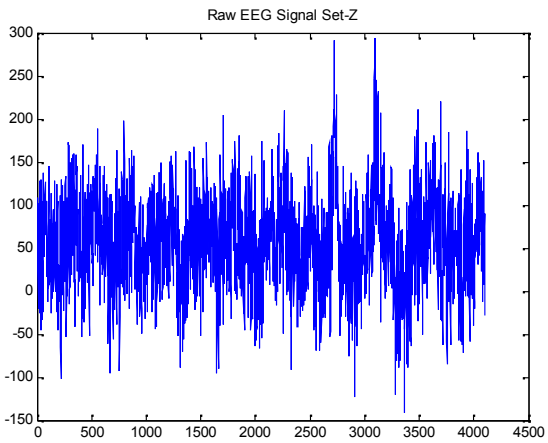

Figure 2.5 .Raw EEG Set-Z

Figure 2.3,2.4 and 2.5 shows the plot of raw EEG signals from the given set of data. These signals were analyzed using matlab to decompose it using DWT with db2 as mother wavelet and the level of decomposition as 5.

2.3. Feature Extraction using AR Model

Autoregressive (AR) coefficients describe the important features of EEG signals, the correct choice of model order is important. Too low and too high order gives the poor estimation of power spectral density (PSD) . In the present work, Burg's method is used for calculating the AR coefficients.The model order of 10th is set to the input signals by minimizing the forward and backward prediction errors for the AR parameters to satisfy the Levinson-Durbin recursion. The discrete wavelet coefficients and 11 Auto-regressive coefficients were compiled to form feature vector The plot of AR coefficnts for the three datasets are shown below-

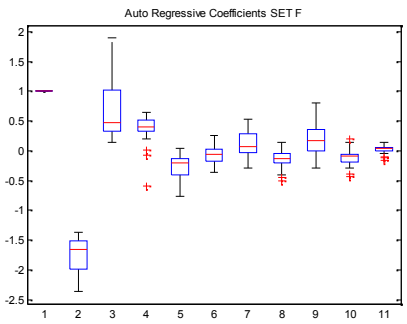

Figure2. 3.3 Plot of AR Coefficients of Set-F

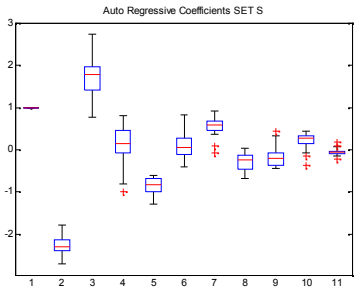

Figure2. 3.4 Plot of AR Coefficients of Set-S

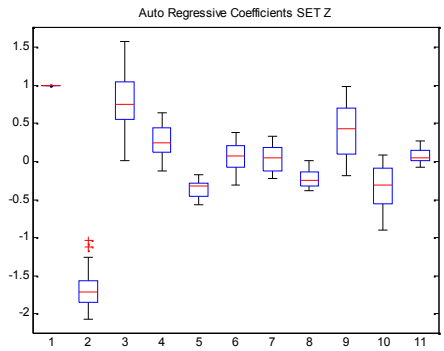

Figure2. 5.3 Plot of AR Coefficients of Set-Z

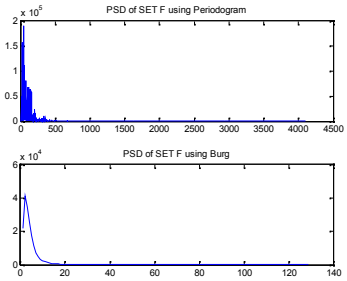

Figure2.3.5 Plot of Power Spectral Density for Set-F

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III. CLASSIFICATION USING NEURAL NETWORK

In our research work we have implemented classification of Epileptic EEG with help of Scaled Conjugate-Back Propagation Neural Network with hidden layer equal to 10 and initial weights assumed to be zero. For classification of features using neural network we need two important pre-defined parameters which are as follows-[9]

3.1. Input Vector- In our research the feature vector was implemented as input vector. This input vector consists of a matrix of size 25X300 such that rows indicate the features and column indicates number of samples.
3.2. Target Vector- In our research the results was implemented as target vector. This target vector consists of a matrix of size 3X300 such that rows indicate the target class and column indicates number of samples to be tested. The overview of target vector is discussed as follows-

- ✓ Class 1 – Epileptic Patient without Seizures- (1 0 0)
- ✓ Class 2 – Epileptic Patient during Seizures- (0 1 0)
- ✓ Class 3 – Normal Patients without Seizures - (0 0 1)

The overall classification was done using input vector and target vector with scaled conjugate gradient based back propagation neural network.

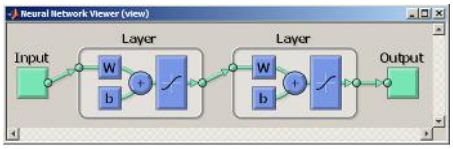

Figure 6.1.Model of Neural Network

In our classification process there are 25 input layers with 10 hidden layer and 3 output neurons for wavelet based features.

- Input Neurons = Number of features
- Output Neuron = Number of Target Classes.

IV. RESULTS

The overall samples are divided into three categories-

- ✓ **Training Data**-70 % of total 240 samples from given dataset.
- ✓ **Testing Data**- 15 % of 240 samples from given dataset.
- ✓ **Validation Data**- 15 % of 240 samples of given dataset.
- ✓ **Unknown Testing Data**-20 samples from each class of EEG samples.(Total 60 samples)

4.1. Summary of Results of Classification based on AR based Statistics –

Type of Dataset	**Percentage Accuracy**		
	During Training Testing and Validation With 80 Samples of Each Class	**During Testing With 15 % of Known Samples**	**During Testing With 60 Unknown Samples (20 from Each Class)**
Set-F(Epileptic Patient without Seizures)	96.3%	92.9%	95%
Set-S(Epileptic Patient with Seizures)	97.5%	100%	95%
SetZ (Healthy Patient without Seizures)	100%	100%	100%
Overall Accuracy of the Network	97.9%	97.2%	96.7%

4.2. Summary of Results of Classification based on Wavelet based Statistics –

Type of Dataset	**Percentage Accuracy**		
	During Training Testing and Validation With 80 Samples of Each Class	**During Testing With 15 % of Known Samples**	**During Testing With 60 Unknown Samples (20 from Each Class)**
Set-F(Epileptic Patient without Seizures)	98.8%	100%	100%
Set-S(Epileptic Patient with Seizures)	100%	100%	95%
SetZ (Healthy Patient without Seizures)	96.3%	100%	90%
Overall Accuracy of the Network	98.3%	100%	95%

V. COCNLUSIONS

In our research work 300 datasets were analyzed with different features characterized as-

- Wavelet Based Statistical Features
- Auto-Regressive Based Features.

In the given table mentioned below we have summarized the classification accuracy of both feature vectors on same epileptic eeg data which can serve as a basis for comparison of their effectiveness.
From the comparative analysis of the accuracy of both classification systems with same dataset and classifier we have drawn following observations-

- ✓ AR based model was found to be more efficient and accurate in classifying healthy patients without seizures from the collection of mixed database.
- ✓ Wavelet based classifier was more effective in classifying pre-ictal(Epileptic patient Without Seizures) data from the mixed database.
- ✓ In classifying epileptic eeg data with seizures both the features worked with optimum and similar accuracy.
- ✓ The overall accuracy of wavelet based feature for classify 60 unknown samples was found to be 95 % and that of AR based Features was found to be 96.7 % respectively.

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