NEURAL NETWORK CLASSIFICATION OF EEG SIGNAL FOR THE DETECTION OF SEIZURE

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Abstract—Brain is the strongest part of the human body which consists of the number of neurons. Electrical activity of the brain can be measured using many techniques in which EEG is widely used. Any change in electrical signal will define a particular abnormality in human. This paper, suggest a algorithm for the EEG signal analysis for the detection of seizure using wavelet transform and statistical parameters. Data set consists of two sampling rates, one with 128Hz and another with sampling rate of 1024Hz. Feature extraction was done using discrete wavelet transform. Once a feature extraction is done the data will be given to a neural network for the classification. A multilayered neural network was used classify seizure and normal person. The proposed algorithm is tested on 23 data sets. Classification accuracy of 100% has been achieved for the sampling rate of 1024 and 85% for the data with sampling rate of 128. Total system accuracy achieved is 92.5%.

***Keywords*—EEG, Seizure Detection, DWT, Statistical Moments, Neural Network.**

I. INTRODUCTION

EEG (Electroencephalography) is an important and effective tool to measure the activities of brain and understand the complex behavior of the brain. Even a small variations in EEG signal define a specific type of brain disorder and hence it is necessary to develop an algorithm which can be used for the detection of brain abnormality since it may affect the life of a person. EEG is a dynamic non-invasive and relatively inexpensive method used to monitor the state of brain. According to the survey about 1% of the world's population is having epilepsy and it is the 2nd most common neurological disorder [3]. This neurological disorder is associated with recurrent, unprovoked epileptic seizures which results due to the excessive - discharge of central neuron groups which are harmful to human. However, person who does not have epilepsy can suffer from seizures. The Behavior of the person with seizure ranges from simple finger twitching to convulsion where muscles will contract and relax in a manner which can not be controlled, results in an involuntary movement of the body.

Automatic seizure detection can be divided into five groups: frequency domain based, time domain based, time-frequency domain based, nonlinear methods and artificial neural network based [4]. Since EEG is a non stationary signal, it is more appropriate to use time-frequency based method such as discrete wavelet transforms (DWT). DWT analysis is important to address the different behavior of EEG signal on both time and frequency domain [5]. Once the feature has been extracted, then the resultant data will be given to the classifier to classify signal as normal or abnormal. Many methodologies have been used for the classification purpose. In the proposed work neural network classifier has been used

II. REVIEW

Many researchers are trying to propose different methodologies for the automatic detection of brain disorder using EEG signals. In a paper by M. Mursalin [1] an algorithm has been proposed for automated epileptic seizure detection using improved correlation-based feature selection with random forest classifier. The algorithm has tested on 5 set of EEG data. Each consists of 100 channels. Two set was recorded from a normal person and 3 were recorded from epileptic seizure patient. Feature extraction was done using time domain, frequency domain and entropy based. Best feature were selected using ICFS (Improved Correlation-based Feature Selection method) and classifier used was Random Forest classifier (RF).

In another paper by J. G. Bogaarts [2] has worked on a method for the seizure detection in which the EEG data that is to be incorporated into the baseline buffer are automatically selected based on a novelty detection algorithm. For the classification purpose SVM classifier has been used.

Zandi [2] has proposed a wavelet based technique for the real time detection of epileptic seizure. Decomposition of EEG signal was done using wavelet packet transform and frrequency band which represnets maximum separation was obtained. The algorithm was experimented on 14 pateints with 75.8 h with 63 seizures. The method resulted in 90.5% of sensitivity and false detection rate of 0.51/h.

Yinxia Liu [6] has described an algorithm using wavelet transform and SVM for sizure detection. The data set they have used consist of 2 to 5 h of seizure data and 24 to 26 h of non-seizure data and. The decomposition of multi-channel iEEG (intracranial EEG) was done and frequency bands were extracted from that only three bands are selected. Features were extracted and then sent to SVM for classification purpose. The specificity achieved was 95.26% and seneitivity of 94.46% with false detection rate of 0.58/h.

ANN (Artificial neural network) has been widely used as classifier for EEG analysis. Various ANN approaches have been reported in the literature review for detection of epileptic seizure. Subasi [7] have described how ANN can give accurate

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result as a classifier. In his work he mentioned how the AR model has an advantage over spectral loss problem and also how it gives a better frequency resolution. The results gave accuracy of 92.3% with a specificity of 96.2% and a sensitivity of 90.3%.

III. METHODOLOGY

Fig 1 represents the block diagram of analysis of EEG signal for seizure detection. The raw EEG data will be given for the preprocessing and is filtered to remove noise. The actual information in an EEG signal lies between 0-60Hz. A low pass filter with 60Hz cut off is applied to remove unnecessary signal information. After denoising of signal segmentation was performed by taking window size of 60 sec. From each data 4 segments were extracted for the feature extraction. Therefore total of 92 segments were considered. DWT is applied to extract different bands of EEG signal such as gamma (>32Hz), beta (16-31Hz), alpha (8-15Hz), theta (4-7Hz) and delta (<4Hz). Different features are calculated on the resulted coefficient of DWT to perform classification. Features considered here are mean, variance, standard deviation, skewness, kurtosis and magnitude. Once features were extracted they were sent for the classification using MLPNN and classifier classifies signal as normal and patient with seizure.

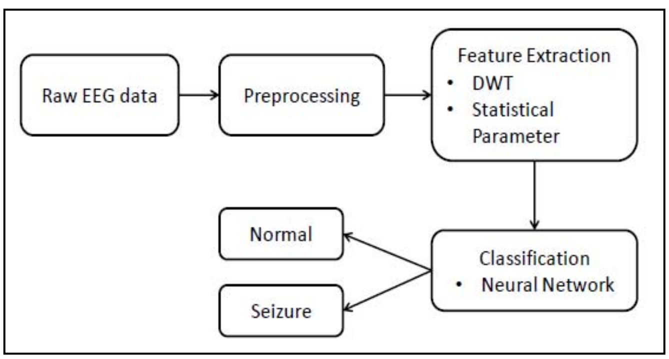


Figure 1. Block diagram of EEG signal analysis

IV. IMPLIMENTATION

In proposed work data set used with different sampling rate; one with 128Hz and another data set has a sampling rate of 1024Hz. After removal of noise the data was segmented. Feature extraction was done using DWT and statistical features were calculated. Finally data will be given to classifier for classification. Simulation environment used in this paper is MATLAB 2015a.

A. Feature Extraction using DWT

Fast Fourier Transform (FFT) is a strong tool for data analysis. However, it does not represent abrupt changes efficiently. And since EEG is a non-stationary signal it is advantageous to use time-frequency domain technique such as DWT. In simple term wavelets are rapidly decaying waves like oscillation that has zero mean. Scaling and shifting are the two key features of wavelets. Wavelet works on multi-scale basis. This feature of WT allows the decomposition of signal into several scales [3].

DWT can represent a natural signal with fewer coefficients. Key application of DWT is denoising and compression of image and signal. A given signal will pass through two filters. The first filter h[n] is the low pass (discrete mother wavelet) and the second filter g[n] is the high pass (mirror version). The data will be down sampled to get low pass and high pass filter coefficient, i.e approximation (A) and detail coefficient (D) respectively. Approximation coefficient is again decomposed and the procedure will repeat. The coefficients can be calculated by

$$a_{j,k} = \langle f(t), \phi_{j,k}(t) \rangle = \int_R f(t) 2^{\frac{-j}{2}} \overline{\phi(2^{-j}t - k)} dt \qquad (1)$$

$$d_{j,k} = \langle f(t), \varphi_{j,k}(t) \rangle = \int_R f(t) 2^{\frac{-j}{2}} \overline{\varphi(2^{-j}t - k)} dt \qquad (2)$$

Where $\phi(t)$ is the basic scaling and $\varphi(t)$ is mother wavelet. J is the scaling index and k is the translation parameter. Selecting the appropriate type of wavelet is also an important factor and according to studies it is shown that Daubechies-4 wavelet can be used for the most of the algorithm for seizure detection. Smoothing feature of a Daubechies-4 wavelet is more appropriate for detection of seizure hence db4 has been used in our algorithm [8]. The EEG signal with the sampling rate of 128Hz was decomposed into four levels, giving approximation coefficient representing a4(0-4 Hz), and detail coefficient representing d1(32-64 Hz), d2(16-32 Hz), d3(8-16 Hz), d4(8-4 Hz). Although seizure has spectrum between 3 and 29 Hz [8]. Hence, wavelet band 2, 3 and 4 could represent ictal frequency range,

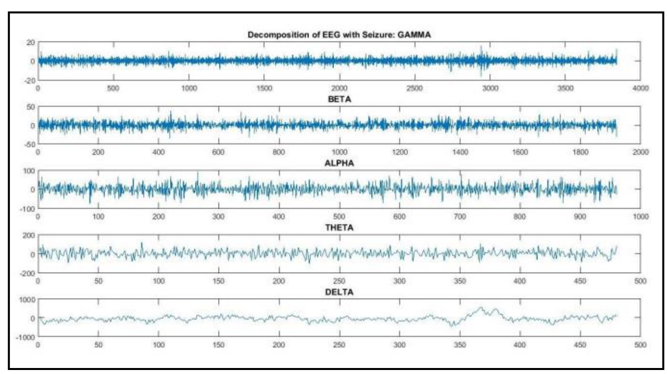


Figure 2. Decomposition of EEG signal

Therefore d2, d3 and d4 is used for feature extraction such as mean, variance, standard deviations, skewness, kurtosis and magnitude. Fig. 2 shows the decomposition level of EEG signals.

B. Statistical Features

The bands which are extracted will represent the distribution of energy of signal in the time - frequency domain. However numbers of coefficient are large, therefore feature reduction is important hence statistical parameters were calculated. Here we have considered statistical moments up to 4th order, i.e, mean, variance, skewness and kurtosis. Except this we have also considered standard deviation and magnitude of each band.

1) **Mean:** Mean is considered as first statistical moment, around zero. Mean calculate the value around which centrally clustering occurs.

$$\bar{x} = \frac{1}{N}\sum_{j=1}^{N} x_j \qquad (3)$$

2) **Variance:** The second moment around the mean is variance which gives the spread or scale of distribution.

$$Var(x_1 \ldots . x_N) = \frac{1}{N}\sum_{j=1}^{N}(x_j - \bar{x})^2 \qquad (4)$$

3) **Standard Deviation:** Standard deviation measures dispersion or width of the distribution. It can also be termed as the square root of variance.

$$\sigma(x_1 \ldots . x_N) = \sqrt{Var(x_1 \ldots . x_N)} \qquad (5)$$

4) **Skewness:** The third moment defines the skewness of distribution. It shows the asymmetry of distribution around its mean. A positive value signifies the tail of distribution extends towards more positive and negative values signifies tail towards more negative of x.

$$Skew(x_1 \ldots . x_N) = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{x_j - \bar{x}}{\sigma}\right]^3 \qquad (6)$$

5) **Kurtosis:** It is a nondimentional quantity which measures the flatness or the peakedness of distribution. A positive kurtosis value is termed as leptokurtic, and negative kurtosis is termed as platykurtic.

$$Kurt(x_1 \ldots . x_N) = \left\{\frac{1}{N}\sum_{j=1}^{N}\left[\frac{(x_j - \bar{x})}{\sigma}\right]^4\right\} - 3 \qquad (7)$$

Where -3 value make the value zero for normal distribution.

6) **Magnitude:** We have considered the magnitude as one of the parameters for feature extraction.

C. EEG database

The database used in this study was obtained from an open source. EEG data used here was recorded according to international 10-20 system. Sampling rate of signal is 128Hz and 1024Hz. The monopolar EEG method used in this study included 28 channels (EMG, EKG, A1, Fp1, Fp2, A2, F7, F3, Fz, F4, F8, T3, C3, Cz, C4, T4, T5, P3, Pz, P4, T6, O1, O2, T1, T2, Pg1, Pg2, MK). Data set included EEGs recorded from 20 patients (10 normal person and 10 seizure patients). And in another dataset consist of 10 normal data with sampling rate of128Hz and 13 seizure patient data with sampling rate 1024Hz. Here all channels have considered at once and also an individual channel to see which channel is more accurate for the seizure detection. Fig. 3 shows the raw EEG signal of a normal and seizure patient.

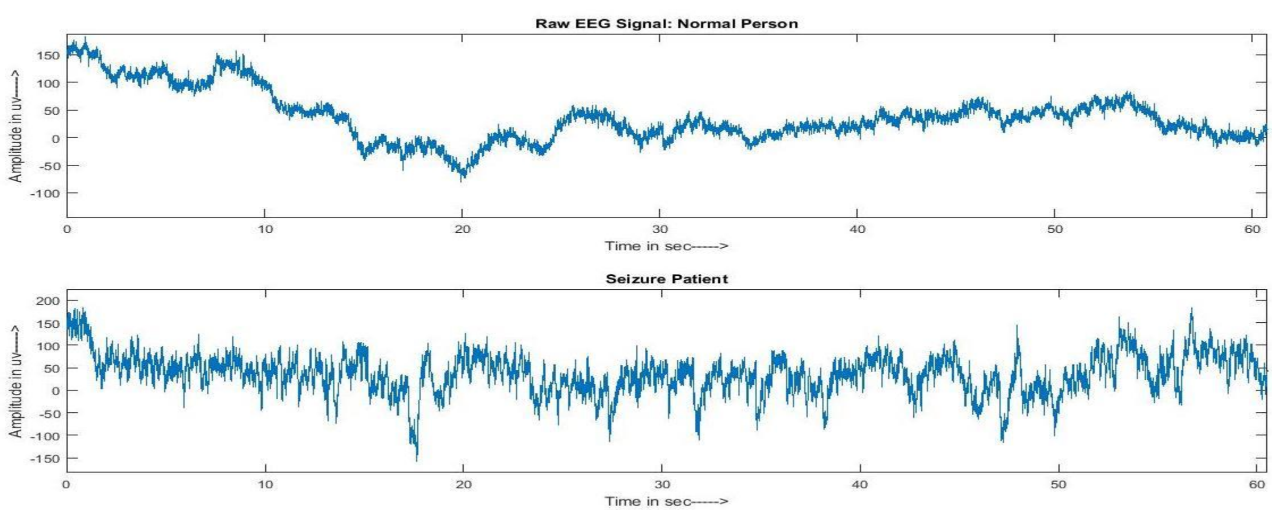


Figure 3. EEG of a normal and seizure patient

D. Classification

An Artificial neural network consists of a more number of processing elements called as neurons. These neurons are connected to one another and the strength of the connections is called weights.

For the physical system modeling multilayered NN is used. MLPNN consists of three layers; input layer, hidden layer and output layer. In order to increase performance multiple hidden layers are used which leads to MLP architecture which is as shown in Fig. 3. Multilayered ANN is used because it is more appropriate to solve any pattern recognition problem. Neural networks work on trial and error methodology.

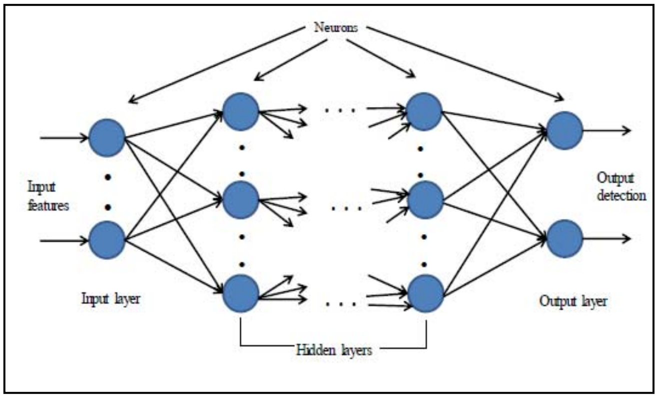


Figure 4. MPL Neural Network

The performance of network completely depends on the number of hidden neurons present in the network. If hidden neurons are less in number the network will be incapable of differentiating between complex patterns.

In contrast, if network has more number of hidden neurons it may lead to the addition of noise within the actual data because to over parameterization. Performance analysis of a classifier can be done by calculating parameter such as specificity (true negative ratio (TNR)), sensitivity (true positive ratio (TPR)) and accuracy. These parameters can be calculated using confusion matrix. The sensitivity of a system is calculated by dividing the true total number of diagnosis to total diagnosis. Sensitivity, also called the TPR (true positive ratio), and is calculated by the formula:

$$sensitivity = TPR = \frac{TP}{TP + FN} \times 100\% \qquad (8)$$

Where TP represent true positive value, TN represents true negative value, FP represents false positive and FN represents false negative value.

Whereas, specificity is calculated by dividing the total of diagnosis numbers to total diagnosis numbers. Specificity, also called the TNR (true negative ratio), and is calculated by the formula:

$$specificity = TNR = \frac{TN}{TN + FP} \times 100\% \qquad (9)$$

Accuracy defines the true classification rate. That is how accurate system can detect the signal correctly. Accuracy, also calculated by the formula:

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \qquad (10)$$

We used different combinations as input for the neural network. First, we have used a total of 30 features (6 feature calculation for each band). Complexity of neural network depends on the hidden neurons. As we increase the number of neurons complexity of the network will also increase. After input is given network will be trained and tested for different samples. If we are not getting the results we expect we can retrain the network till we get proper results. Here we considered 70% data for training, 15% for the validation and remaining 15% for the testing purpose.

In next combination we have considered data from only 3 bands (total 18 inputs) and the data was given to the network. Table II shows the accuracy of the system when considering five and 3 bands.

In last combination we considered each band separately and sent the data for classification. We can see more accurate results in alpha beta and gamma band. Graph 1 represents the classification result for alpha band with sampling rate of 1024Hz.

V. RESULTS

In this study, two data sets were used with different sampling rate (128Hz and 1024Hz). EEG data was first filtered and then decomposed into different level to extract the band information of EEG. For the sampling rate 128 signal was decomposed into 4 levels (D1, D2, D3, D4 and A4 consisting gamma, beta, alpha, theta and delta band respectively), and for 1024 sampling rate, the signal was decomposed into 8 levels (D5, D6, D7, D8 and A8, consisting gamma, beta, alpha, theta and delta band respectively). Once band information was extracted, then the statistical parameter was calculated on wavelet coefficients which are used as input for the classifier. In this experiment NN is used as the classifier to classify the signal as normal or seizure. The two layers, 10 perceptron feed forward networks were used and the network will be trained with scaled conjugate gradient backpropagation. Three subsets were done for the classification, one subset consist all channels, the second consisting three bands (beta, alpha and theta) and in third set individual channels were considered and accuracy has been noted down.

Table I shows the classification result when all the channels are considered. Table II shows the accuracy of the system when all and only three bands are considered. Fig. 5 shows the confusion matrix of both databases. From this we can see that for sampling rate of 1024 we can get more accurate results. Fig. 6 shows the performance of the algorithm for both the data set. From the plot we can see that the performance of the system with 1024 sampling rate is more accurate.

TABLE II. Result of a classifier when considering only three channels for different sampling rate.

Channels	5 band(gamma, beta, alpha, theta and delta) (Accuracy)		3 band(alpha, beta and theta) (Accuracy)	
	Sampling rate		Sampling rate	
	128	1024	128	1024
A1	82.6	100	78.8	100
Fp1	87.9	100	92.4	100
Fp2	90.2	67.9	87.9	100
A2	84.8	100	81.1	100
F7	81.8	100	84.1	100

F3	78	100	85.6	100
Fz	89.4	100	87.1	100
F4	92.4	98.9	92.4	100
F8	81.8	100	90.2	100
T3	97	100	90.2	100
C3	93.2	100	86.4	100
Cz	76.5	100	73.5	100
C4	91.7	100	88.6	100
T4	96.2	100	93.9	100
T5	93.2	100	93.9	100
P3	89.4	100	80.3	100
Pz	77.	98.9	78	98.9
P4	97.7	98.9	87.9	100
T6	88.6	100	91.7	100
O1	77.3	100	84.8	100
O2	75	100	83.3	100
T1	81.8	88	72.7	81.5
T2	92.4	100	84.1	100
Pg1	89.4	100	83.3	100
Pg2	88.6	100	81.8	100

ROC plots the receiver operating characteristic for individual output class. The more each curve goes towards of left and top edges of the plot, the better results we can say for the classification. Fig. 7 shows a ROC plot of the system. From the figure we can see that classification is better with the sampling rate of 1024Hz.

TABLE I. Result of classifier when considering all channels for different sampling rate.

	Sensitivity (%)		Specificity (%)		Accuracy (%)	
Sampling rate(Hz)	128	1024	128	1024	128	1024
All channels	86.5	100	83.7	100	85	100

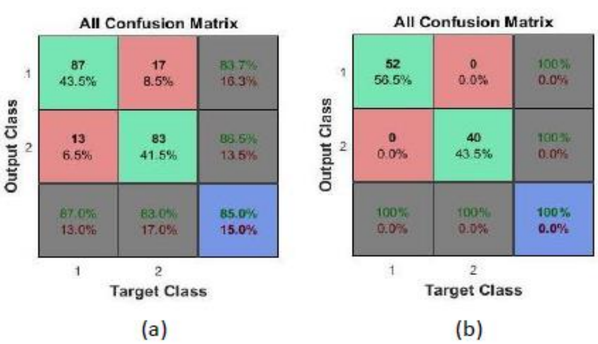


Figure 5. Confusion matrix: (a) With 128 sampling rate, (b) With 1024 sampling rate

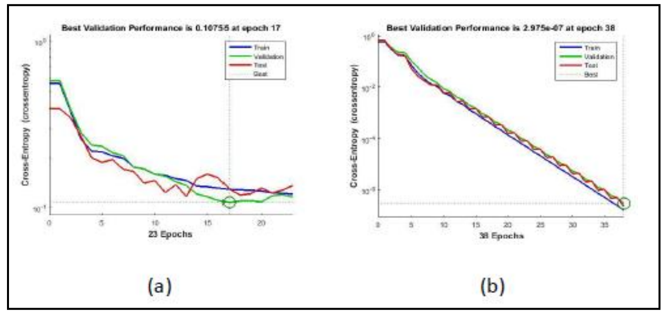


Figure 6. Performance plot: (a) With 128 sampling rate, (b) With 1024 sampling rate

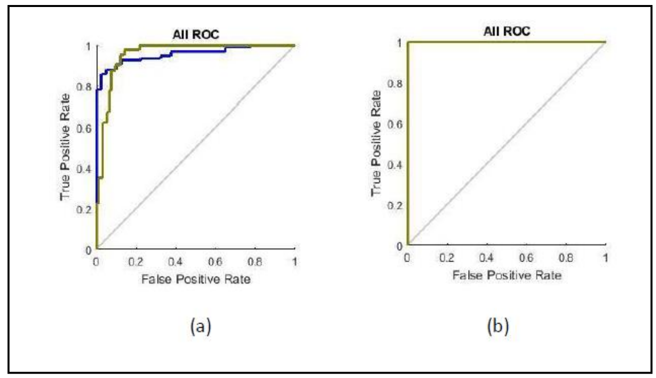
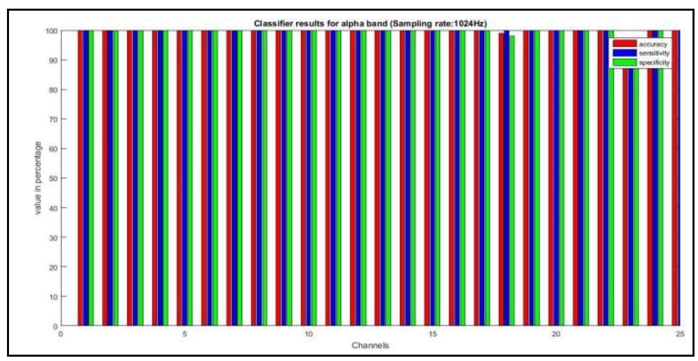


Figure 7. ROC plot: (a) With 128 sampling rate, (b) With 1024 sampling rate



Graph 1: Classification results for alpha band

VI. CONCLUSION

In this paper, two database have been used, one with 128Hz and another is with 1024Hz. Feature extraction was done using DWT method and statistical parameter were calculated on wavelet coefficients. For classification purposes, three different sets have been considered. Considering all the bands at once, considering only three bands at a time and finally considering the individual band. From the Table I, II conclude that for the sampling rate of 1024 Hz results are more accurate. This paper also concludes that the accuracy is less when sampling rate is less. But when sampling rate is increased decomposition level increases which in turn increases the processing time.

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