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EEG Signal Classification into Seizure and Non-Seizure Class using Discrete Wavelet Transform and Artificial Neural Network

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ABSTRACT: In this paper, a wavelet-based neural network (WNN) classifier for recognizing EEG signals is implemented. Main part of paper presents basic principles of signal decomposition in connection with EEG frequency bands. Wavelet analysis method has been used for detection of seizure onset. Wavelet filtered signal is used for computation of spectral power ratio. First, Discrete Wavelet Transform (DWT) with Multi-Resolution Analysis (MRA) is applied to decompose EEG signal at resolution levels of components of EEG signal (δ, θ, α, β and γ) and n collected features are passed to ANN classifier. Based on features seizer or non-seizer signals are classified.

KEYWORDS: Discrete Wavelet Transform (DWT), artificial neural network (ANN), Multi-Resolution Analysis (MRA).

I.INTRODUCTION

Epilepsy is a common chronic neurological disorder. Epilepsy seizures are result of transient and unexpected electrical disturbance of brain. About 50 million people worldwide have epilepsy, and nearly two out of every three new cases are discovered in developing countries. Epilepsy is more likely to occur in young children or people over age of 65 years; however, it can occur at any age. Epilepsy is a medical condition that produces seizures affecting a variety of mental and physical functions. Epilepsy is also known as seizure disorder. When a person has more than two episodes of unprovoked seizures in lifetime, y is known to be seizure patients or person with epilepsy. Seizure occurs when a group of nerve cells in brain may change a person's consciousness, movements and actions. Seizure detection has a great importance in diagnosis and therapy of epileptic patients. Electroencephalography (EEG) is an important tool for studying human brain activity and epileptic processes in particular. EEG signals provide important information about epileptogenic networks that must be analyzed and understood before initiation of therapeutic procedures. Very small variations in EEG signals depict a definite type of brain abnormality .Visual inspection of electroencephalogram (EEG) signals for detection of interictal, pre-interictal and interictal activities is a strenuous and time-consuming task due to huge volumes of EEG segments that have to be studied [1].

Existing automatic detection techniques show high sensitivity and moderate specificity, and detect seizures a relatively long time after onset. High frequency (80–500 Hz) activity has recently been shown to be prominent in intracranial EEG of epileptic patients but has not been used in seizure detection in this study; we proposed a novel automatic detection method based on altered compressibility of EEG during two states with compressive sensing.
Electroencephalogram (EEG) has established itself as an important means of identifying and analysing epileptic seizure activity in humans. In most cases, identification of epileptic EEG signal is done manually by skilled professionals, who are small in number. Diagnosis of an abnormal activity of brain functionality is a vital issue. EEG signals involve a great deal of information about function of brain. But classification and evaluation of se signals are limited. Sincere is no definite criterion evaluated by experts, visual analysis of EEG signals in time domain may be insufficient. Routine clinical diagnosis needs to analysis of EEG signals. Therefore some automation and computer techniques have been used for this aim [2].

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II. LITERATURE SURVEY

Sivakumaran N [3] proposed a method named "Importance of Classification Algorithms in Epileptic Seizure Detection", in which he has given detailed study about classifying epileptic seizure detection algorithm. In method author has discussed about different methods that can be used to identify seizure signal. Selection of se techniques depends on various parameters like applicability, nature of research problem, ease in implementation and time consumption.

Ke Zeng et.al, [4] has given a method "Automatic detection of absence seizures with compressive sensing EEG". A novel automatic detection method based on altered compressibility of EEG during three states with compressive sensing. To evaluate proposed method, segments of interictal, pre-interictal and interictal EEG segments (100 segments in each state) were used. Two entropies, namely Sample Entropy (SE) and permutation Entropy (PE), and Hurst Index (HI) were extracted respectively from segments to compare with proposed method. Significant features were selected using ANOVA test. After evaluating performance of selected features by four classifiers (Decision Tree, K-Nearest Neighbor, Discriminate Analysis, Support Vector Machine) respectively, results show that proposed method can achieve highest accuracy of 76.7%, which is higher than HI (55.3%), sample entropy (71%), and permutation entropy (73%).

Sharanreddy and P.K. Kulkarni [5] has developed a paper named "EEG signal classification for Epilepsy Seizure Detection using Improved Approximate Entropy". This paper, presents a hybrid technique to classification EEG signals for identification of epilepsy seizure. Proposed system is combination of multi-wavelet transform and artificial neural network. Approximate Entropy algorithm is enhanced (called as Improved Approximate Entropy: IApE) to measure irregularities present in EEG signals. proposed technique is implemented, tested and compared with existing method, based on performance indices such as sensitivity, specificity, accuracy parameters. EEG signals are classified as normal and epilepsy seizures with an accuracy of ~90%.
L. Ayoubian, H. Lacoma, and J. Gotman [6] also made a study on EEG signals and proposed a paper "Automatic seizure detection in SEEG using high frequency activities in wavelet domain". Purpose of this study is to investigate if se frequencies can contribute to seizure detection. system was designed using 30 h of intracranial EEG, including 15 seizures in 15 patients. Wavelet decomposition, feature extraction, adaptive thresholding and artifact removal were employed in training data. An EMG removal algorithm was developed based on two features: Lack of correlation between frequency bands and energy-spread in frequency. Results based on analysis of testing data (36 h of intracranial EEG, including 18 seizures) show a sensitivity of 72%, a false detection of 0.7/h and a median delay of 5.7 s. Missed seizures originated mainly from seizures with subtle or absent high frequencies or from EMG removal procedures. False detections were mainly due to weak EMG or interictal high frequency activities. System performed sufficiently well to be considered for clinical use, despite exclusive use of frequencies not usually considered in clinical interpretation. High frequencies have potential to contribute significantly to detection of epileptic seizures.
I. Omerhodzic et,al. [7] has developed a method "Energy Distribution of EEG Signals: EEG Signal Wavelet-Neural Network Classifier". First, Discrete Wavelet Transform (DWT) with Multi-Resolution Analysis (MRA) is applied to decompose EEG signal at resolution levels of components of EEG signal (δ, θ, α, β and γ) and Parseval's orem are employed to extract percentage distribution of energy features of EEG signal at different resolution levels. Second, neural network (NN) classifies se extracted features to identify EEGs type according to percentage distribution of energy features. Performance of proposed algorithm has been evaluated using in total 300 EEG signals. Results showed that proposed classifier has ability of recognizing and classifying EEG signals efficiently.

III. PROPOSED METHOD

Signal amplitude is quantified to micro volts. EEG signal for each channel is filtered using a digital low pass finite impulse response filter with Hamming window to remove power line noise along with out-of band noise. Order of filter is 40 and cut off frequency is 32 Hz covering delta, theta, and alpha and beta bands of EEG. Wavelet transform is a mathematical tool that splits up data into different frequency components with required matched resolution .Wavelet transforms are an effective time-frequency analysis tool for analysing EEG signal. EEG signals are transient non stationary in nature. Symlet8 wavelets of order 8 are investigated for analysis of epileptic EEGs.

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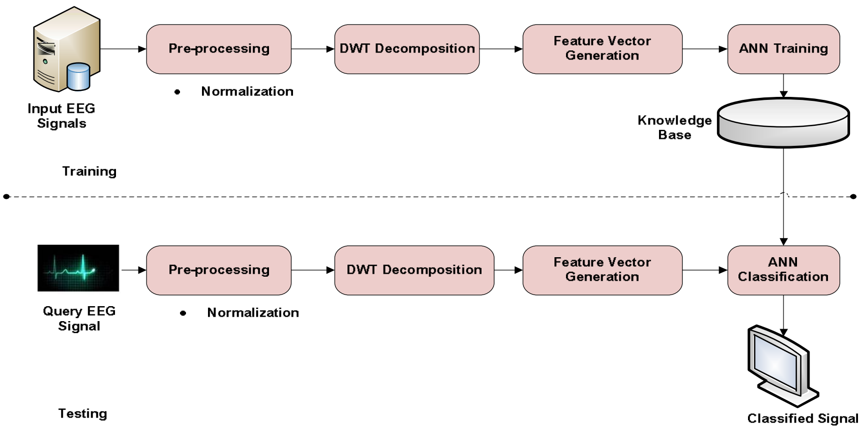

Figure 1 Architecture of proposed method

Figure 1, illustrates proposed method for Seizure, non-seizure detection of EEG signal. system comprises of two stages-training and testing. In training phase input signal is divided in regular time slot and undergoes DWT decomposition. Every wavelet is implemented through their wavelet filters (low pass and high pass). Feature vector is generated and these features are trained using Artificial Neural Network (ANN) and resulting trained co-efficient are stored as knowledge base. In testing phase query signal undergoes pre-processing; same as in training and signal is divided. Features extracted are passed to ANN classifier which classifies input signal as seizure or non-seizure signal.

1) DWT (Discrete Wavelet Transform)

In practical, we often want to get its multi-stage decomposition for a small wave, so that we can have a more accurate analysis of wavelet. N will introduce multi-level of wavelet decomposition specifically; we will introduce multistage decomposition diagram and multistage decomposition algorithm, so that we can get more profound understanding from multistage decomposition of wavelet.

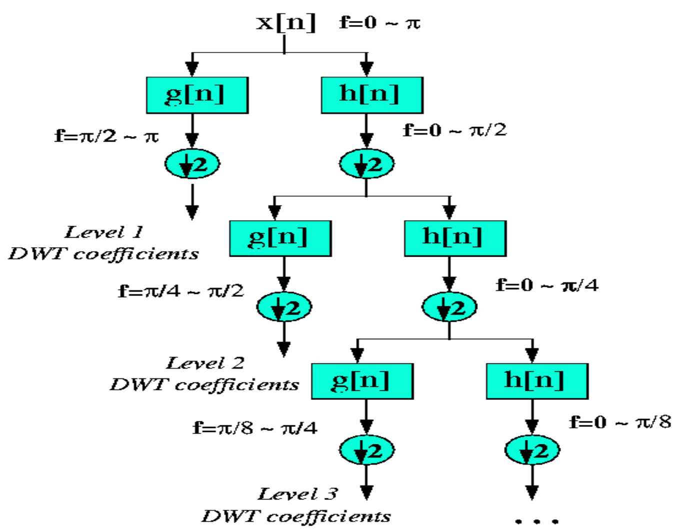

Figure 2 DWT transform block representation

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In figure 2, 'h' is low-pass filter, 'g' is high-pass filter, '↓2 'is down sampling [8]. For a given signal sampling, first approximate f and fj with f, through decomposition theorem, it decomposes ck into fj and dk.

$$f_j(x) = \sum_{k=1} C_k^j \varphi(2^j k - k) \in v_j - 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

f_j Can be broken down into $f_j = w_{j-1} + f_{j-1}$ in which

$$w_{j-1} = \sum_{k+y} d_k^{j-1} \tau(2^{j-1}x - k) \in w_j - 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$f_{j-1} = \sum_{k+y} c_k^{j-1} \tau(2^{j-1}x - k) \in v_j - 1 \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In symN, N is the order. Some use 2N instead of N. The symlets are nearly symmetrical, orthogonal and biorthogonal wavelets proposed by Daubechies as modifications to the db family. The properties of the two wavelet families are similar. Sym8 is better out of all as it also reconstructs signal within less reconstruction time. Sym8 shows maximum response for random noise hard thresholding also. MSE error for Sym 8 is somewhat higher but can be ignored as it has higher SNR as compared to other having same MSE. Sym18 is better in case of soft thresholding of random noise.

2) ANN (Artificial Neural Network)

Neurons work by processing information. y receive and provide information in form of spikes. ANN Classification is an example of Supervised Learning. Known class labels help indicate wher system is performing correctly or not. This information can be used to indicate a desired response, validate accuracy of system, or be used to help system learn to behave correctly. Known class labels can be thought of as supervising learning process; term is not meant to imply that you have some sort of interventionist role.

Clustering is an example of Unsupervised Learning where class labels are not presented to system that is trying to discover natural classes in a dataset. Clustering often fails to find known classes because distinction between classes can be obscured by large number of features (genes) which are uncorrelated with classes. A step in ANN classification involves identifying genes which are intimately connected to known classes. This is called highlight determination or highlight extraction. Highlight choice and ANN characterization together have an utilization notwithstanding when forecast of obscure specimens is a bit much: ANN utilizes variables to recognize key qualities which are included in whatever procedures recognize classes.

For the proposed method we have used Feed forward neural network. FFNN is one of the classification of ANN. These networks have proved useful in a wide variety of applications. The essential character of such networks is that they map similar input patterns to similar output patterns. This is why such networks can do a relatively good job in dealing with patterns that have never been presented to the networks. However the constraint that similar input patterns lead to similar outputs is also a limitation of such networks. For many practical problems, very similar input patterns may have very different output requirements. Simple XOR is used in Single layer FFNN.

V. RESULTS

Proposed method is classifying seizer signals using ANN classifier. Classifier will classify signal based on features calculated using mathematical functions such as Mean, Standard deviation and variance, giving different numerical values for different set of inputs. Complete flow of proposed method is controlled by using a GUI shown in figure below.

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Figure 4 Selections GUI in MATLAB

Signal is selected using GUI file once file is selected features of signal is calculated using mathematical instruction. Collected features are n stored in data file foe classification. ANN classifier is feed with se features which will finally collects features of tested signal and compares signal features. Once features match n ANN will classify signal. The signals which are selected are having two conditions; either it will be a seizure signal or non seizure signal. Figure 5 & 6 are given with sample signals selected. The selected signal are applied to DWT that will be decomposed. Decomposed signal are shown in the figure 7 & 8 for both seizure as well as non seizure.

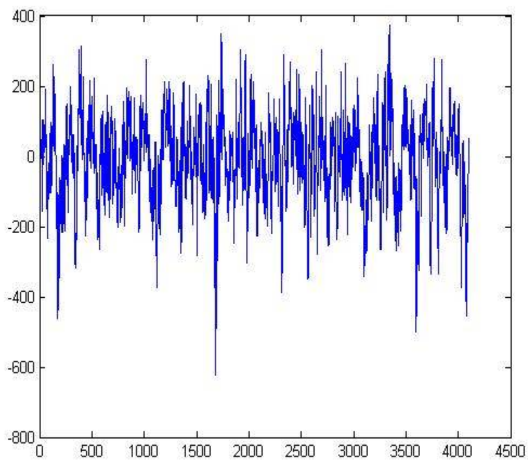

Figure 5 Sample signal 1 (Seizure Signal)

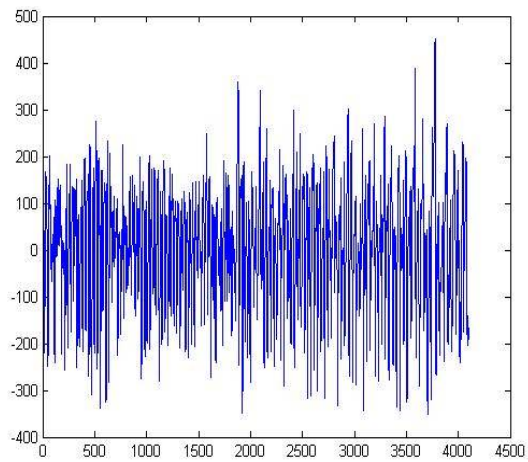

Figure 6 Sample signal 2 (Non Seizure Signal)

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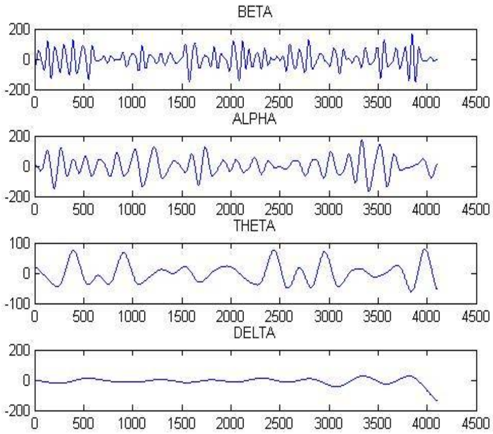

Figure 7 Decomposed signal for Seizure signal

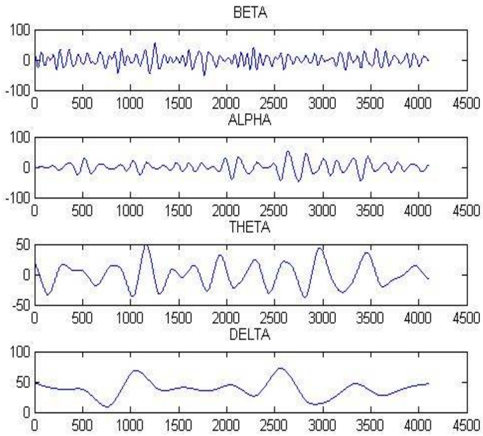

Figure 8 Decomposed signal for Non Seizure Signal

ANN results are shown in the figure 9 & 10. If the features of the signal is closet to trained seizure signal features then the ANN will classify the given query signal as a seizure signal Vice versa will happen with non seizure signal.

Figure 9 Classification results from ANN for Seizure signal

Figure 10 Classification results from ANN for Non Seizure signal

Some of the calculated features are listed below in the table, based on these co-efficient the classification is done. The feature vectors extracted are as follows:

1. Mean in each sub band of the wavelet coefficients.
2. Entropy in each sub band of the wavelet coefficients.
3. Standard deviation in each sub band of the wavelet coefficients.

These feature vectors are used to reduce the dimension of the extracted features from signal samples.

Table 1: Mean, Entropy and Standard Deviation features of four decomposition coefficients for two classes

Dataset	Feature Vectors	D6	D7	D8	A8
Non-seizure	Mean	-0.030,-0.433 0.7899,-0.2593	-0.2787, -0.7167 0.7978,-0.6022	0.028,-0.051 0.054,-0.359	18.119,18.080 19.217, 18.032
	Entropy	1.1351, 1.1427 1.1659,1.1138	1.4383, 1.1592 1.1525,1.1963	1.324,1.437 1.226,1.239	0.000,0.000 0.000,0.000
	Standard Deviation	25.485,29.365 25.360,21.197	9.5267, 22.0553 18.6197,15.5452	12.881,7.632 10.54,13.385	4.7865, 4.8902 7.1770, 2.0644

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Seizure	Mean	0.3632, -4.3678 0.3376, 4.7159	3.0117,2.7190 -1.9904,2.9948	5.7382,-3.3326 1.3525,-1.0712	-51.686,-45.765 -42.242,-47.585
	Entropy	1.0412,1.0392 1.0195,1.0207	1.1086, 1.0096 1.0299,1.0705	1.0516, 1.1144 1.1020,1.1317	0.000,0.000 0.000,000
	Standard Deviation	148.872,171.59 197.203,163.482	68.071, 79.767 66.208,39.097	43.205,25.890 37.826,23.176	27.029, 8.496 13.696,28.188

The feature vectors extracted from the above two datasets shown in table 1 are observed to have different values from each other. So these can be beneficial vectors in the classification of EEG signals.

V. CONCLUSION

This paper, proposes a hybrid technique to classification EEG signal for epilepsy seizure detection, which is combination of multi-wavelet transform and artificial neural network. EEG signal is decomposed into low frequency and high frequency components. FFNN is one of the artificial intelligence techniques, which is used for generating training dataset. From the generated dataset, the types of EEG signal classified as normal and epilepsy seizures signal. Using this neural network 96% accuracy is obtained.

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