Classification of intracranial Electroencephalographic signals using adaptive neuro fuzzy inference system

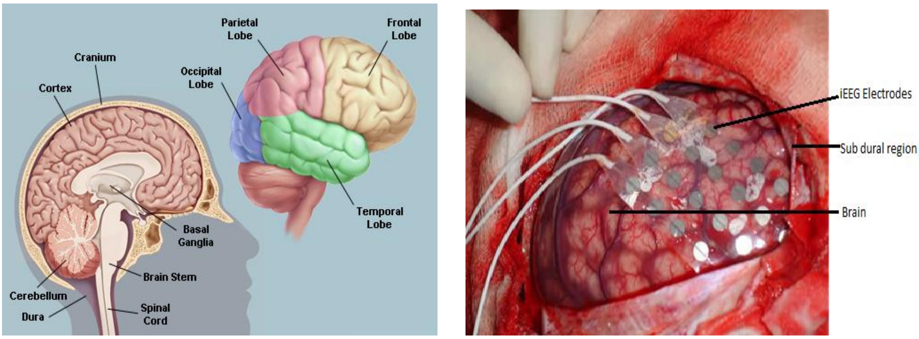
Sathish Eswaramoorthy[1], Sivakumaran N[1], Raji Sundarajan[2]
[1] Dept. of instrumentation and control engineering
National Institute of Technology, Trichy, Tamilnadu, INDIA
[2] Dept of electrical and computer engineering technology
College of Technology, West Lafayette, Indiana, US
phone: +91-9976966371
e-mail: 410112003@nitt.edu

***Abstract*— Electroencephalography (EEG) is the recording of electrical activity of brain cells caused by the electrostatic interactions of ions and molecules in the brain cells. It is useful to diagnose the normal or abnormal functionality of the brain. One of the abnormalities of the brain is epilepsy, a chronic, non communicable disorder of the brain that affects people of all ages. Intracranial Electroencephalographic (iEEG) signals are multidimensional, nonstationary, time domain biological signals obtained by electrodes placed on the subdural regions (below the parietal bone of head) of the patient, which are not reproducible. This signal consists of some useful information about behaviour of brain and pathological conditions. In this work, classification of focal (epileptic) and non-focal (epileptic) iEEG signals is reported using wavelet transform and adaptive neuro fuzzy inference system (ANFIS). The iEEG signals recorded were subjected to wavelet transform (WT) and features were extracted from the obtained wavelet coefficients. Further, the wavelet features were utilized to classify the iEEG signals using ANFIS, and the results shows maximum accuracy of 98.2%. Matlab software package was used for programming and analysis purpose of classification. This study seems to be of high clinical relevance since this method is useful for ease in analysis and monitoring of iEEG of epileptic patients.**

Keywords—Intracranial EEG, Epilepsy, Wavelet transform, Adaptive neuro fuzzy inference system.

I. Introduction

Human brain is most complex in its physiology and functions, in the same way diagnosis of abnormalities of brain is highly complex. Fig.1 shows a human brain and its parts [1, 2]. Reading of electrical actives of brain will be helpful in accessing brain functionality and disorders. iEEG is one of the most important tool for diagnosis of various disorders including epilepsy. It is mostly preferred for highly complex disorders of brain since it is not affected by impedances skin and skull.



(a) (b)

Fig.1. (a)Human rain and its parts [1] (b) acquisition of iEEG signals [2].

Epilepsy is a chronic, non communicable disorder of the brain that affects people of all ages. It is second most prevalent neurological disorder in humans after stroke. But in most of the cases, possible causes are unknown. Any abnormal pattern of neuronal activity, from brain illness to brain damage, can unfortunately lead to seizures. World health organization study says Around 50 million people worldwide have epilepsy. Nearly 80% of the people with epilepsy are found in developing regions [3]. The seizure occurs because of a sudden surge of electrical activity in the brain and does leads to a temporary disturbance in the messaging systems between brain cells. To analyze these disturbances and its characteristics Electroencephalography and intracranial electroencephalography (iEEG) proves to be the most useful tool. Most of the treatments for intractable seizures are very limited. The most critical involves focal resections of abnormal brain tissue when the epileptogenic region can be accurately defined [4]. This is a critical task that requires subdural EEG recordings of seizures to define their onset, electrodes of interest, and their region of involvement. iEEG is an invasive method, a craniotomy (a surgical incision into the skull) is required to implant the electrode grid [5].

The main objective of the study is focused on classification of seizures offline, based on subdural EEG data that would satisfy high accuracy, sensitivity and specificity of classification. Since epileptic seizure occurrence is erratic and random it challenges the automation through reliable and computational efficient seizure detection. In this study work was carried out for classification of focal and non-focal iEEG signals were reported using wavelet transform and adaptive neuro fuzzy inference system. Wavelet transform was chosen for analysis of iEEG data since literature studies shows good results in feature extraction and classification signals with high randomness. The pre recorded iEEG signals from multi-channel EEG signal acquisitions were subjected to wavelet transform and corresponding wavelet coefficients were extracted. Daubechies wavelet transform was used to obtain the wavelet coefficients of the selected signals. Further, the wavelet features were utilized to classify the iEEG signals using adaptive neuro-fuzzy inference system.

II. METHODOLOGY

A. Data collection

All iEEG signals acquired from the database, where signals are digitally band-pass filtered between 0.5 and150 Hz using a fourth-order Butterworth filter. Forward and backward filtering was used in order to minimize phase distortions. Those EEG signals that had been recorded with a sampling rate of 1024 Hz were down-sampled to 512 Hz prior to further analysis. EEG signals were then re-referenced against the median of all the channels free of permanent artifacts as judged by visual inspection. There is no reference that can be considered "best" on general grounds. We randomly selected 160 recorded signals x and y from the pool. The signals were divided into time windows of 20 seconds, corresponding to 10240 samples in which 80 signals belong to focal category and another 80 belong to non focal (non epileptic) category [6].

B. Wavelet transform feature extraction

The WT can be thought of as an extension of the classic Fourier transform, except that, instead of working on a single scale (time or frequency), it works on a multi-scale basis. This multi-scale feature of the WT allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study [7]. The procedure of multiresolution decomposition of a signal $x[n]$ in to different levels of decomposition D1-D5 and approximations A1-A5 is schematically shown in Fig. 2.

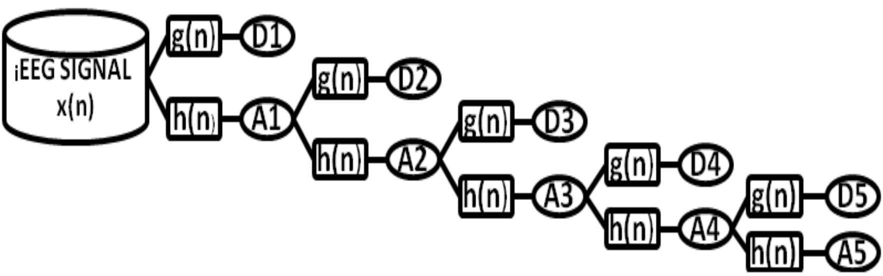


Fig. 2: Subband decomposition of discrete wavelet transform implementation; $g[n]$ is the high-pass filter, $h[n]$ is the low-pass filter.

The iEEG signals can be considered as a superposition of different structures occurring on different time scales at different times. One purpose of wavelet analysis is to separate and sort these underlying structures of different time scales. Spectral analysis of the iEEG signals was performed using the discrete wavelet transform (DWT). Selection of appropriate wavelet and the number of decomposition levels is very important in analysis of signals using the WT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlates well with the frequencies required for classification of the signal are retained in the wavelet coefficients. In the present study, the number of decomposition levels was chosen to be 5. Thus, the iEEG signals were decomposed into the details $D1$–$D5$ and one final approximation, $A5$. Usually, tests are performed with different types of wavelets and the one which gives maximum efficiency is selected for the particular application. The smoothing feature of the Daubechies wavelet of order 2 (db2) made it more suitable to detect changes of the iEEG signals. Therefore, the wavelet coefficients were computed using the db2 in the present study. The computed wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency.

The computed detail and approximation wavelet coefficients of the iEEG signals were used as the feature vectors representing the signals. For each EEG segment, the detail wavelet coefficients (Dk, k = 1, 2, 3, 4, 5) at the first, second, third, fourth and fifth levels and the approximation wavelet coefficients ($A5$) at the fifth level were computed. Then 10240 wavelet coefficients were obtained for each channel of iEEG signal. In order to reduce the dimensionality of the feature vectors, statistics over the set of the wavelet coefficients were used. The statistical features used to represent the time-frequency distribution of the iEEG signals are maximum, minimum, mean, standard deviation, variance, skewness and kurtosis. These feature vectors, which were calculated for the $D1$–$D5$ and $A5$ frequency bands were used in classifying the iEEG signals.

C. ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation. Such framework makes the ANFIS modelling more systematic and less reliant on expert knowledge. Like neural networks, ANFIS networks are also used in modelling, classification and control [8].

The ANFIS classifier was trained with the training feature sets of EEG signals. The features obtained from data sets (sets A and B) were divided into two separate feature data sets - the training data set and the testing data set. The adequate functioning of the ANFIS depends on the sizes of the training set and test set. The training data set was used to train the ANFIS model, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for classification of the five classes of EEG signals.

The present study changes of the final (after training) membership functions (mf) with respect to the initial (before training) membership functions of the input parameters were examined. In this work ANFIS network was trained using different membership functions such as gbell, triangular, Gaussian, trapezoidal and pi were tried out for different orders of those membership functions in order to compare the test performance of classifier using those membership functions. For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer shown in Fig. 3[8].

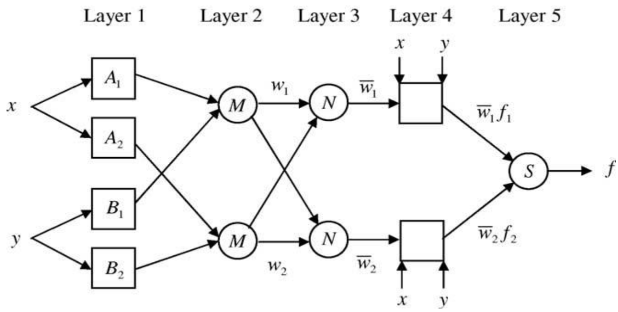


Fig. 3. ANFIS architecture [8].

In the backward pass, the error is sent back through the network in a similar manner to back propagation [9].

Layer 1:
The output of each node is:

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4$$

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y. The membership functions could be anything but for illustration purposes we will use the bell shaped function given by:

$$\mu_A(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{1}$$

Where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2:
Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{2}$$

Layer 3:
Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \tag{3}$$

Layer 4:

The nodes in this layer are adaptive and perform the consequent of the rules:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \quad (4)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters.

Layer 5:

There is a single node here that computes the overall output:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (5)$$

This then is how, typically, the input vector is fed through the network layer by layer [8]-[11].

D. Performance estimates of classifier

The outcome is abnormal for the input corresponding to abnormal subject then it is called a True Negative (TN). If the outcome refers to normal subject then it is called False Positive (FP). True Positive (TP) and False Negative (FN) are the case where the normal is classified as normal and abnormal respectively. The test performance of the classifiers can be determined by the computation of sensitivity, specificity, accuracy, positive predictive value, and negative predictive value [12]. The sensitivity, specificity, accuracy, positive predictive value (PPV), and negative predictive value (NPV) are defined as:

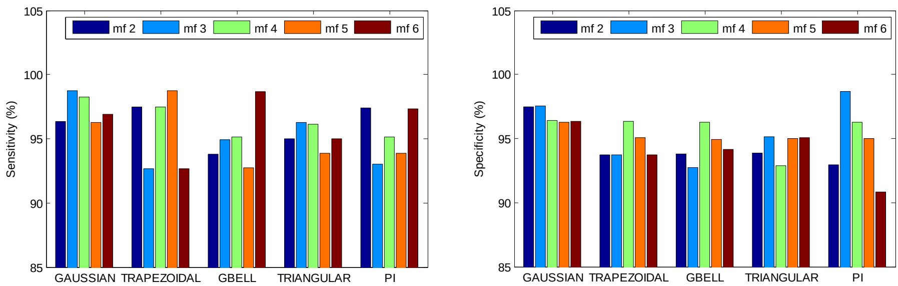
- Accuracy = (TP+TN) / (TP+FP+TN+FN)
- Sensitivity = TP / (TP+FN)
- Specificity = TN / (TN+FP)
- Positive Predictive Value = TP / (TP + FP)
- Negative Predictive Value = TN / (TN + FN)

III. RESULTS AND DISCUSSION

A total of 540 signals were randomly taken for analysis, where focal (set A) and non focal (set B) signals are equal in number (270 signals each). The signals set A and B are subjected to spectral analysis using discrete wavelet transform and decomposition levels were chosen to be four. The wavelet coefficients are extracted from iEEG signals and features like maximum, minimum, mean, standard deviation, variance, skewness and kurtosis were obtained from wavelet coefficients. The obtained features were used for training of ANFIS classifier where seventy percentage of signals (378 signals) from set A and B were chosen as training signals and the same is used for training of ANFIS network and thirty percentage of signals (162 signals) were used as test signals for testing the trained ANFIS network. The test performance of the classifiers can be determined by the Performance estimates like Accuracy, Sensitivity, and Specificity. These performance estimates of the classier vary depending on the type of membership function and also on the levels of the membership function used for classification.

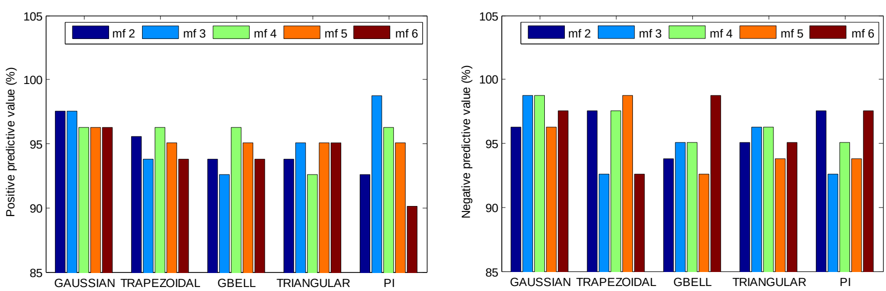
Figs. 4-6 illustrate the results obtained. Fig. 4(a) shows that the maximum sensitivity of 98.75% is obtained for Gaussian membership functions with the three membership functions. The sensitivity of the classifier is high for Gaussian membership function. And from Fig. 4(b) maximum specificity is 98.68% is noted at pi membership function with three membership functions.

Fig. 5(a) and (b) show that the maximum ppv of 98.77% is achieved in pi membership function and the maximum npv of 98.77% is reached in gbell, trapezoidal and Gaussian membership functions. From Fig. 6, the overall gain in accuracy is noted for Gaussian membership function and the maximum accuracy of 98.15% is achieved in Gaussian membership function with three membership functions as accuracy gives importance to true positive and true negative of classification. Table 1 shows the numerical values of performance estimates with Gaussian membership function.



(a) (b)

Fig. 4(a) Variation of percentage sensitivity for different types of membership functions (b) Variation of percentage specificity for different types of membership functions



(a) (b)

Fig. 5(a) Variation of percentage PPV for different types of membership functions (b) Variation of Percentage NPV for different types of membership functions

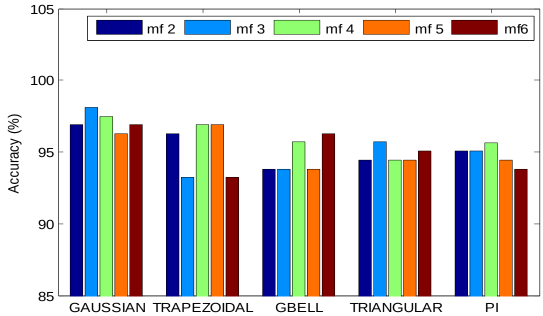


Fig. 6. Variation in percentage accuracy for with different membership functions

TABLE 1: VARIATION IN PERFORMANCE ESTIMATES FOR WITH DIFFERENT ORDERS OF GAUSSIAN MEMBERSHIP FUNCTIONS

Item	TP	FP	FN	TN	accuracy (%)	sensitivity (%)	specificity (%)	PPV (%)	NPV (%)
mf 2	79	2	3	78	96.91	96.34	97.50	97.53	96.29
mf 3	79	2	1	80	98.12	98.75	97.56	97.53	98.77
mf 4	78	3	1	80	97.50	98.73	96.39	96.30	98.77
mf 5	78	3	3	78	96.30	96.30	96.30	96.30	96.30
mf 6	78	3	2	79	96.91	97.50	96.34	96.30	97.53

Fig. 7 shows the Gaussian membership function and its membership level placement for achieving the highest accuracy in the classification. Analysis of electroencephalogram (EEG) signals in normal and abnormal conditions is essential for disease research, medical device design and treatment planning. The future studies may include optimization of type and levels of different membership function in ANFIS network and feature extraction from the signals using different types of wavelet transforms.

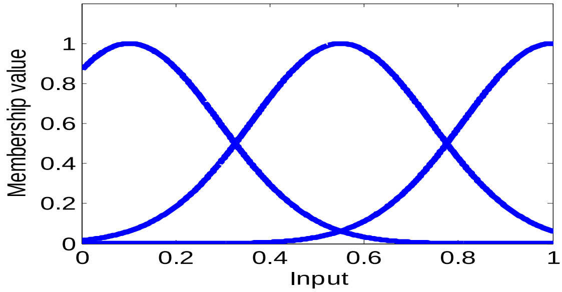


Fig. 7. Gaussian membership function which gives better test performance

IV. CONCLUSION

In this paper, we have presented a classification technique for diagnostics and detection of epilepsy more efficiently. We have used wavelet transform as a tool to extract features for classification purpose. After experimenting with a large number of features for each technique, our experiment shows that this system can achieve a detection rate accuracy of about 98.2 %. Different levels or scales of wavelet decomposition and their significance in extracting the features were studied. It can be concluded that for scales 3-5 of wavelet decomposition, the features were more prominent. This study seems to be of high clinical relevance since the analysis of EEG in normal and diseased states is essential for disease diagnosis and surgery planning. Thus this technique can very well used as a second opinion to radiologists for analysis of iEEG and has the ability to automatically detect presence of epilepsy.

REFERENCES

[1] WebMD, 2009. Available: http://www.webmd.com/brain/picture-of-the-brain.

[2] Jon Lieff, 2011. Available: http://jonlieffmd.com/blog/brain-electricity-and-the-mind.

[3] World health organization, fact sheets, media centre, epilepsy. (October 2012). Available: http://www.who.int/mediacentre/factsheets/fs999/en/.

[4] Inan Guler and Elif Derya Ubeyli, "Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients", Journal of neuro science methods, April 2005.

[5] K. Lehnertz, "Non-linear time series analysis of intracranial EEG recordings in patients with epilepsy—An overview," *Int. J. Psychophysiol.*, vol. 34, pp. 45–52, 1999.

[6] Andrzejak RG, Schindler K, "Nonrandomness, nonlinear dependence, and nonstationarity of electroencephalographic recordings from epilepsy patients", *Physical Review E, 86*, 046206, pp. 1 to17, 2012

[7] Daubechies I, "The wavelet transform, time-frequency localization and signal analysis, *IEEE Transaction Information Theory, 36*, 1990, pp. 961–1005.

[8] Jang J-SR, "ANFIS: Adaptive-network-based fuzzy inference system", *IEEE Transaction on Syst Man Cybern, 23*, 1993, pp. 665–85.

[9] D'Alessandro," Epileptic Seizure Prediction Using Hybrid Feature Selection Over Multiple Intracranial EEG Electrode", *IEEE Trans. Biomedical Enginering, 50(5),* MAY 2003.

[10]Maria Tito, "A Comparative Study of Intracranial EEG Files Using Nonlinear Classification Methods", *Annals of Biomedical Engineering, 38(1),* pp. 187–199, 2010.

[11] Rosso O. A, Figliola A, Creso J, Serrano E, " Analysis of wavelet-filter tonic-clonic electroencephalogram recordings", *Med Biol Eng Comput. 42*, pp. 516–23, 2004

[12] Lotte1 F and Congedo M, "Wavelet Transform Use for Feature Extraction and EEG Signal Segments classification, A review of classification algorithms for EEG-based brain–computer interfaces", *J. Neural Eng, 3*,.2007.