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# Computer Aided Automatic Detection and Classification of EEG Signals for Screening Epilepsy Disorder

S. DEIVASIGAMANI[1], C. SENTHILPARI[2] AND HIN-YONG WONG[2]
[1]*Faulty of Engineering and Computer Technology*
*AIMST University*
*Kedah, 08100 Malaysia*
[2]*Faculty of Engineering*
*Multimedia University*
*Cyberjaya Campus, 63100 Malaysia*
*E-mail: deivasigamani@aimst.edu.my*

Infection in human brain causes brain disorder which is in the form of Epilepsy. The infected area in the brain region generates the irregular pattern signals as focal signals and the other healthy region in the brain generates the regular pattern signals as non-focal signals. Hence, the detection of focal signals from the non-focal signals is important for epileptic surgery in epilepsy patients. This paper proposes a simple and efficient methodology for EEG signals' classifications using ANFIS classifier. The performance of the proposed EEG signals classification system is evaluated in terms of sensitivity, specificity and accuracy.

***Keywords:*** brain disorder, epilepsy, epileptic surgery, EEG signals, focal signal

## 1. INTRODUCTION

Cerebral cortex portion of the brain generates the EEG signals. These signals are captured by EEG sensor which is placed over the head of the patient. The EEG signals are categorized into either normal or abnormal. The normal EEG signals have regular pattern and time interval and the abnormal EEG signals have irregular pattern and time interval. The irregular EEG signals are obtained from the patients who are affected by Epileptic disease. It is a kind of human brain disorder and its severity is varied with respect to age of the patients. The major root cause of the Epilepsy is the virus infection on the brain. About 1% of the persons are affected by epilepsy disease around the world and more than 40% of the epilepsy disorder cannot be cured by medication (WHO report, 2015). Hence, prior detection of epilepsy will save the life of the patient.

Formation of Seizures in captured EEG signals is the main symptom for epilepsy disease. The seizures are not occurred in the EEG signals continuously and they occurred in EEG signals in bit by bit manner. The seizures are held in EEG signals from few seconds to few minutes based on the patient's conditions. The seizure are present in a large time interval if the patient is severely affected by epilepsy and the seizures are progressively held in EEG signal for the short period of time if the patient is affected by epilepsy in mild manner. The seizures produces muscles stiffen and the patients to become fainted. The functioning of the brain will be stopped if the formation of seizures is often. Seizures are categorized into simple partial seizures and complex partial

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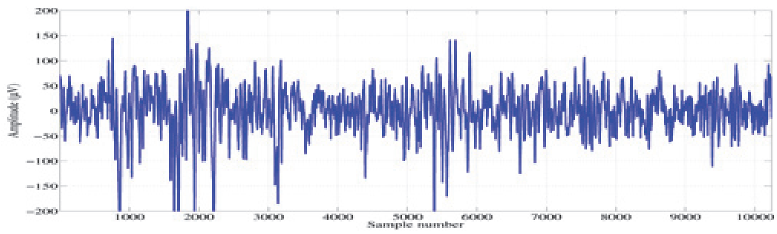
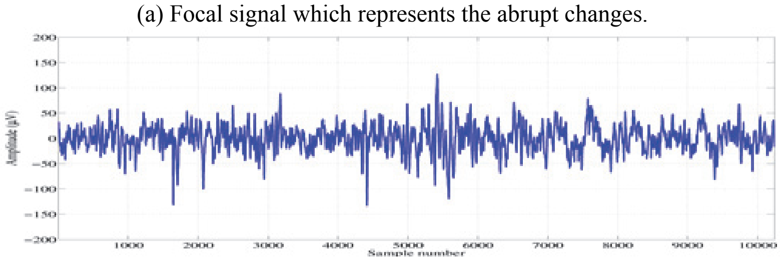
seizures. The simple partial seizures do not make the patients consciousness. The complex partial seizures make the patients consciousness. The epilepsy is categorized as idiopathic epilepsy, symptomatic epilepsy and Refractory Epilepsy. In case of Refractory epilepsy, the seizures can be controlled and it can be cured if the patient is taking proper medicine regularly. The seizures cannot be controlled in case of idiopathic epilepsy and symptomatic epilepsy.

Neuroradiology and magnetic resonance imaging (MRI) are the two methodologies to screen the Epilepsy in patients. The MRI technique provides high accuracy for epilepsy detection than Neuroradiology technique. Shake detector is another method which is used to detect and count the seizure in the epileptic patients. In this paper; EEG sensors are used to capture the EEG signals from the patients. The EEG electrodes are placed over the scalp of the epilepsy patient and the outputs from these electrodes are viewed in the Cathode Ray Oscilloscope (CRO) to detect the abnormal seizures in the captured EEG signals. There are two types of EEG electrodes are used in real time to capture the EEG signals. First one contains 256 sub channels and second one contains 128 subchannels to acquire the EEG signals. The accuracy of the 256 subchannel is high when compared with 128 sub channels. Even though the accuracy level is directly proportional to the number of electrodes in EEG sensor; the classification time is high if more number of electrodes are used in EEG sensor. The technique called Independent Component Analysis (ICA) is used to separate the EEG signals from the subchannels.

This paper proposes a computer aided automatic detection of epileptic disorder through the analysis of EEG signals. The location detection of epileptogenic area in the brain is very important for earlier epilepsy surgery. Epileptogenic area is the portion of the brain where the brain cells are severely affected by virus and this affected area of the brain generates the signals which are known as focal signals. This paper proposes a computer aided automatic classification of focal and non-focal signals using Adaptive Neuro Fuzzy Inference System (ANFIS) classifier.




(a) Focal signal which represents the abrupt changes.




(b) Non-focal signal which shows linear changes.

Fig. 1. EEG signals obtained from open access dataset.

The focal signals are shown in Fig. 1 (a). The non-focal signals are generated by the healthy tissue areas in the brain, as shown in Fig. 1 (b).

This paper is organized into 5 sections as stated in the following. Section 2 discusses the various conventional methodologies for the automatic classification of EEG signals for epilepsy disorder detection. Section 3 proposes a simple and efficient methodology to detect and classify EEG signals using ANFIS classifier. Section 4 discusses the experimental results in detail and finally, Section 5 concludes the paper.

## 2. LITERATURE SURVEY

Kharbouch *et al.* [4] proposed a methodology to detect and diagnose the onset type seizure in the EEG signals. The authors tested their proposed algorithm on 10 numbers of real patients and the classification rate was 95%. The methodology proposed in this work was not able to diagnose the EEG signals for epilepsy detection. The classification elapsed time was high in this methodology.

Goshvarpour *et al.* [14] used Probabilistic Neural Networks for the detection of abnormal points on EEG signals. The authors extracted the non-linear feature set from the obtained EEG signals and these signals are classified using neural networks.

R. Sharma *et al.* [5] classified the EEG signals into either focal or non-focal signals using Empirical Mode Decomposition (EMD) algorithm. This method decomposed the EEG signals into number of empirical modes and its intrinsic functions were computed for classifications.

Kumar *et al.* [12] proposed an efficient methodology for EEG signal classifications by using Discrete Wavelet Transform (DWT) transform. This transform was used to decompose the EEG signal into various numbers of sub-bands. Then fuzzy entropy technique was used to compute the features from the transformed coefficients.

The Support Vector Machine (SVM) classifier was then to classify the extracted features from these coefficients. The authors obtained 99.3% average accuracy for the case of normal and 99.65% for the case of eye closed. Ahammad *et al.* [11] proposed a framework for EEG signal classifications for epilepsy disorder detection and diagnosis. The author utilized linear classifier to train and classify the extracted features from EEG signals. The authors achieved 98.5% average accuracy.

S. Gautam *et al.* [1] proposed a method for focal and non-focal signal classifications using empirical mode decomposition technique. The intrinsic mode functions were obtained by decomposing the EEG signals for classification. Xiang *et al.* [3] used fuzzy logic for the detection of epilepsy disease.

The authors achieved an average sensitivity of 98.27% and an average specificity of 98.36% over the set of signals for EEG signal classifications. Zhang *et al.* [13] used autoregressive (AR) model with extracted energy feature set. AR coefficients were extracted from the trained and test EEG signals with its corresponding energy values. These values were classified by support vector machine classifier. This proposed methodology was robust in large numbers of EEG signals for epilepsy detection. The authors achieved 97% of average classification rate for the detection and classification of EEG signals. Tiwari *et al.* [15] proposed an EEG signals classifications through the analysis of local binary pattern feature set. These features were extracted from test EEG signals and compared with trained local binary pattern feature set. Abhinaya *et al.* [2] developed an efficient methodology for epilepsy detection using the entropy features. The optimum features were selected using Sequential Forward Feature Selection (SFFS) algorithm in this work for epilepsy signal classifications. The authors achieved 82% of average accuracy for EEG signals classifications.

W. L. Hwang *et al.* [18] proposed Constrained Null Space Component Analysis (CNSA) method for the issues in signal band separation. The authors also used sparsity-enforcing separation model for enhancing the separation results.

Vipin Gupta *et al.* [16] used least squares support vector machine classification methodology to classify the test EEG signals into either focal or non-focal. The authors transformed the test EEG signals using flexible analytic wavelet transform which decomposed the EEG signals into 15 subbands. These transformed subbands were used as features for classifier. The authors achieved 94.41% of classification accuracy.

Abhijit Bhattacharyya *et al.* [17] proposed Tunable-Q Wavelet Transform for the classification of focal and non-focal signals. The authors analyzed the performance of their proposed EEG signal classification methods using random forest and least squares support vector machine classifiers. The authors achieved average classification accuracy of 84.67% for the EEG signal classifications.

The following points are observed from the conventional methodologies for EEG signals classification as,

- The conventional methodologies failed to detect the sharp edges and failed to smooth the regions.
- Most of the existing methods detected the interior boundary of the signal, which further degraded the classification accuracy.

The proposed methodology stated in this paper will overcome such limitations for automatic EEG signal classifications of epilepsy disease.

## 3. PROPOSED METHODOLOGY

The EEG signals are captured from the brain by placing 19 electrodes over the skull of the brain. CWT is applied on these captured EEG signals and the spatial domain signals are converted into frequency domain signals for further classifications. The features are extracted from the transformed wavelet coefficients and then ANFIS classifier is used to classify the EEG signals into either focal or non-focal based on the extracted feature set.

The proposed methodology for EEG signals classification is illustrated in Fig. 2. The EEG recordings used in this paper to test the classification performance of epileptic

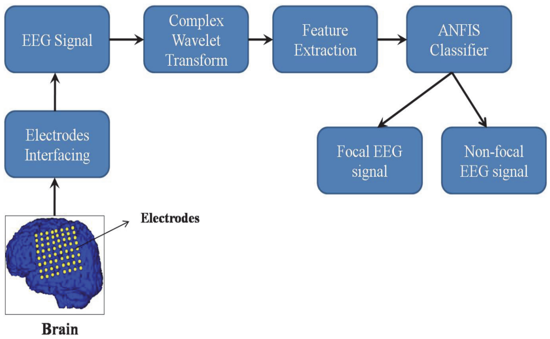



Fig. 2. Proposed flow for EEG signals classifications.

seizures are collected from the open database available at the University of Bern (Bern-Barcelona EEG dataset) (2012). The dataset is comprised of EEG recordings of patients who have been undergoing long-term intracranial treatments at the Department of Neurology, University of Bern, Switzerland. These EEG signals were sampled at a rate of 512Hz or 1024Hz based on the number of channels, *i.e.* more or less than 64, respectively. The database includes 750 focal EEG signals and 750 non-focal EEG signals obtained from adjacent channels. In this work, 100 focal and 100 non-focal pairs of EEG signals are randomly chosen from this dataset for automatic EEG signal classifications.

### 3.1 Preprocessing

It is used to smoothen the regions where the edges are sharp in EEG signals to validate the signal for further classifications. Butterworth filter is used in this paper to preprocess the EEG signals. The frequency response of the Butterworth filter used in this paper is described as,

$$|H(\omega)|^2 = \frac{C_0 + C_2\omega^2 + C_4\omega^4 + \dots + C_{2n}\omega^{2n}}{1 + D_2\omega^2 + D_4\omega^4 + \dots + D_{2n}\omega^{2n}}. \qquad (1)$$

Where, '$n$' is the order of the filter and the coefficients of the Butterworth filter are represented by $C$ and $D$.

The frequency response of this filter is ideal if it satisfies the following constraints:

- The magnitude at $\omega = 0$ is normalized to one.
- The maximum number of derivatives at $\omega = 0$ are zeros.
- The magnitude decreases to zero if $\omega$ reaches infinity.

The transfer function of the designed Butterworth filter used in this paper is depicted as,

$$|H(j\Phi)|^2 = \frac{1}{1 + \left(\frac{\Phi}{\Phi_c}\right)^{2N}} \qquad (2)$$

$$N = \frac{1}{2}\frac{\log\left(\frac{k_2}{k_1}\right)}{\log\left(\frac{\Phi_s}{\Phi_p}\right)} = 2.4546. \tag{3}$$

Where, the number of poles is represented as '$N$' and '$\Phi$' represents the cut off frequency. The passband and stop band frequency specifications are given as,

$$\Phi_p = \frac{\omega p}{T} = \frac{0.47124}{T}, \tag{4}$$

$$\Phi_s = \frac{\omega s}{T} = \frac{1.0996}{T}. \tag{5}$$

The passband edge frequency is noted as,

$$\left|H(j\Phi)\right|^2 = \frac{1}{1+\left(\frac{\Phi p}{\Phi c}\right)^{2N}} = (1-\delta_1)^2. \tag{6}$$

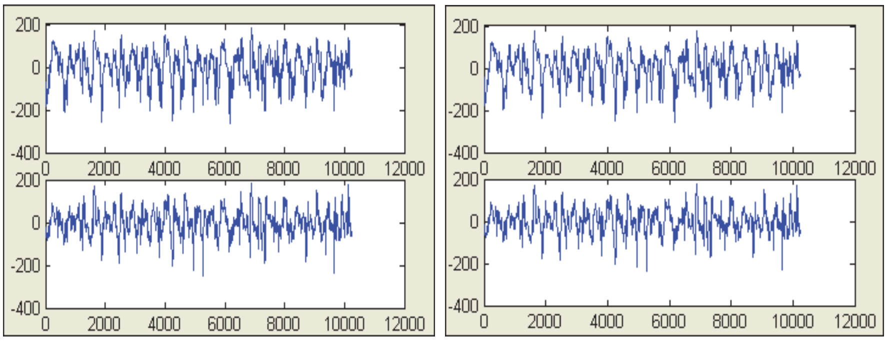
The number of poles interms of stopband and passband frequency.

$$\Phi_p = \frac{2}{T}\tan\left(\frac{\omega_p}{2}\right) = \frac{0.4802}{T} \tag{7}$$

$$\Phi_s = \frac{2}{T}\tan\left(\frac{\omega_s}{2}\right) = \frac{1.226}{T} \tag{8}$$

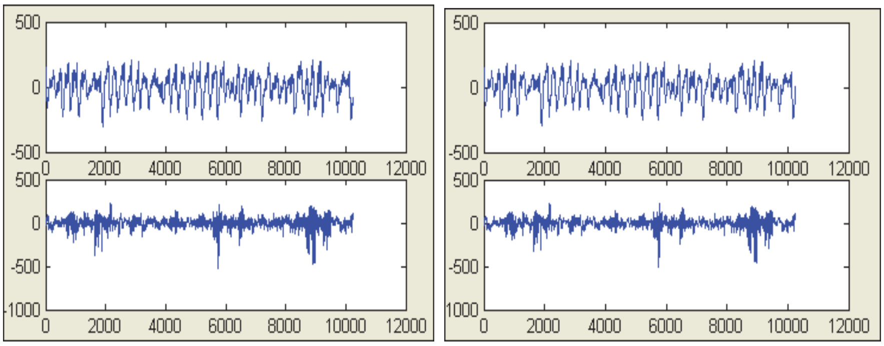
Where, $T$ shows the time period which is determined from the design itself and it is noted in seconds.

Fig. 3 (a) shows the input focal EEG signal with sharp regions and Fig. 3 (b) shows the preprocessed focal EEG signal with smooth region. Fig. 3 (c) depicts the input non-focal EEG signal with sharp regions and Fig. 3 (d) depicts the preprocessed non-focal EEG signal with smooth region.




(a) (b)

Fig. 3. EEG signal; (a) Input focal signal with unsmoothed regions; (b) Preprocessed focal signal with smooth region; (c) Input non-focal signal with unsmoothed regions; (d) Preprocessed non-focal signal with smooth region.



(c) (d)

Fig. 3. (Cont'd) EEG signal; (a) Input focal signal with unsmoothed regions; (b) Preprocessed focal signal with smooth region; (c) Input non-focal signal with unsmoothed regions; (d) Preprocessed non-focal signal with smooth region.

### 3.2 Complex Wavelet Transform

In this paper, dual tree complex wavelet transform (DT-CWT) is used in order to convert the spatial domain signal into frequency domain signal, as stated in Yuan *et al.* (2011). In this paper, the EEG signals are subjected to the DT-CWT for up to four levels of decomposition. In DT-CWT, EEG signals from the electrodes placed in human scalp are decomposed by the dual filters, which consist of low and high pass filters. The approximate filter coefficients from the first level decomposition is now passed through the second level filtering which further produces the second level decomposition co-efficients. In this paper, the decomposition is applied on the EEG signals with respect to the decimation value 2.

The proposed EEG signal classification framework using DT-CWT is carried out using MATLAB DT-CWT toolbox. The dual tree wavelet transform decomposes the EEG signals into four sub band levels and each sub band signals are represented by spatial and frequency mode transformation, which clearly illustrates the distribution of spatial and frequency response at output.

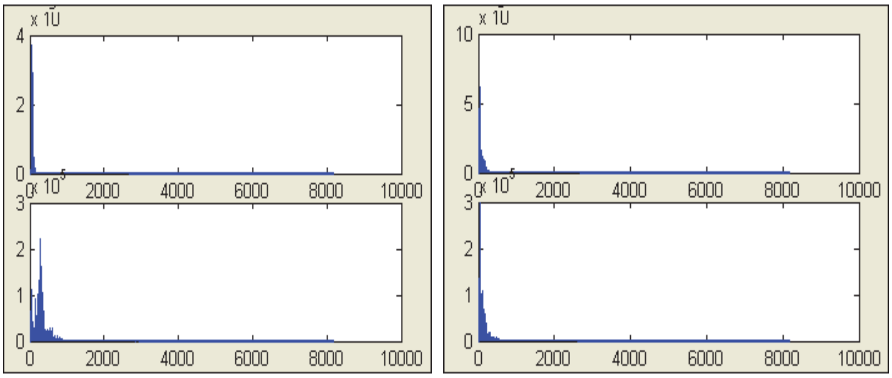
### 3.3 Feature Extraction

Features play the major role in EEG signal classifications for epilepsy disease detection and diagnosis at an earlier stage. Features as periodogram and statistical, differentiate the focal signal from non-focal signals and they are extracted from the coefficients of dual tree complex wavelet transform. In order to improve the classify-cation accuracy of the proposed EEG signal classification system, the mean, standard deviation (SD), energy, entropy, skewness, kurtosis and moment features are extracted from transformed EEG signal coefficients.

### 3.4 Periodogram Feature

The intensity distribution of points in signal is represented by periodogram. These intensity variations are considered as periodogram feature and it clearly differentiates the focal signal from non-focal signal by means of a classifier.

Fig. 4 (a) shows the periodogram of the focal signal and Fig. 4 (b) shows the periodogram of the non-focal signal.



(a) (b)

Fig. 4. Periodogram of (a) focal EEG signal; (b) non-focal EEG signal.

### 3.5 Statistical Features

The statistical features mean, standard deviation, energy, entropy, skewness, kurtosis and moment, are computed from the transformed coefficients and they are described as,

$$Mean = \frac{\sum Lowpassbandcoefficient + \sum Numberofdecompositionsleveles}{Number\ of\ decompositions\ levels}, \tag{9}$$

$$SD(\delta) = \left(\tfrac{1}{n}\right) * \left(std_{low-pass-coefficient} + std_{high-pass-coefficients}\right), \tag{10}$$

$$Energy = \sum_{i=1}^{n} | D_{i,j} |^2; j = 1, \ldots, n. \tag{11}$$

Where, '$n$' represents the number of sub-bands in the DT-CWT. '$D_{i,j}$' represents the extracted coefficients from EEG signal.

The third and fourth order moment are called as skewness and kurtosis, respectively. Skewness is the measure for signal symmetry and kurtosis features describes the shape characteristics of the signal and they are based on the standard deviation of transformed dual tree complex wavelet coefficients and they are given in Eqs. (12) and (13) as,

$$Skewness = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^3 / N}{\sigma^3}, \tag{12}$$

$$Kurtosis = \frac{\sum_{i=1}^{N} (x_i - \bar{x})^4 / N}{\sigma^4}. \tag{13}$$

'$\bar{x}$' is the mean of coefficients, '$\sigma$' represents the standard deviation and '$N$' is the number of data points in signal.

Entropy determines the signal energy per unit slot in EEG signal and moment describes the physical quantity of the signal and they are given in Eqs. (14) and (15) as,

$$Entropy = -\sum_{i=1}^{N} p(x_i) \cdot \log_{10} p(x_i) \tag{14}$$

$$\boldsymbol{Moment\ m_k} = \boldsymbol{E}(x - \mu)^k \tag{15}$$

Where, $\mu$ is the mean of the transformed coefficients and $N$ is number of data points.

The feature set expressed in Eqs. (9)-(15) forms the one dimensional feature set, which will be given to the input of the ANFIS classifier. Table 1 shows the feature values of both focal and non-focal CWT transformed EEG signals. The extracted features clearly differentiate the focal signals from non-focal EEE signals. The standard deviation, skewness, kurtosis and moment features of the non-focal signal are higher than feature values of the focal signal. The entropy features of the focal EEG signal are higher than the entropy features of the non-focal EEG signals. These extracted features of both focal and non-focal EEG signals are arranged as a one dimensional vector for further EEG signals classification.

**Table 1. Extracted features from decomposition coefficients.**

| Extracted features of CWT transformed focal EEG signal | | | | | | |
|---|---|---|---|---|---|---|
| Mean | Standard deviation | Energy | Entropy | Skewness | Kurtosis | Moment |
| $-3.33*10^{-16}$ | 0.51 | 345.30 | 15.53 | −0.44 | 32.85 | $-8.10*10^{-4}$ |
| $4.95*10^{-10}$ | 3.04 | $6.06*10^{3}$ | 18.54 | −0.60 | 30.33 | −0.23 |
| $7.007*10^{-5}$ | 36.18 | $4.26*10^{5}$ | 6.76 | −0.14 | 31.49 | −134.96 |
| −0.73 | 112.78 | $2.03*10^{6}$ | 4.90 | −0.44 | 36.65 | $-9.25*10^{3}$ |
| Extracted features of CWT transformed non-focal signal | | | | | | |
| $-3.52*10^{-17}$ | 0.64 | 578.14 | 16.21 | −1.26 | 44.13 | −0.01 |
| $-6.68*10^{-10}$ | 3.83 | $1.0008*10^{4}$ | 17.69 | −1.04 | 35.78 | −1.91 |
| $-6.33*10^{-5}$ | 46.21 | $7.39*10^{5}$ | 5.87 | 0.22 | 39.44 | 421.19 |
| 0.22 | 193.61 | $6.77*10^{6}$ | 4.39 | 0.53 | 39.58 | $1.43*10^{5}$ |

### 3.6 Classification

Classification plays an important role in detection of focal and non-focal EEG signals. In this paper, ANFIS classifier is used for the classification of EEG signals.

***ANFIS Classifier design:*** A number of conventional classifiers (Zhu *et al.* [8], Sharma *et al.* [5], Sharma *et al.* [6]) such as support vector classifier, neural network *etc.*, were used in the classification of EEG signals for epilepsy detection. The classification accuracy of conventional methods was not adequate for EEG signal classification. In order to improve the classification accuracy of EEG signal classifications, ANFIS classifier is used in this paper.

A multi-layer ANFIS classifier consists of an input layer, three hidden layers and an output layer, is used in this paper for focal and non-focal EEG signal classification. The ANFIS classifier is trained with the training feature sets of EEG signals. The extracted features from DT-CWT transform coefficients are initially trained by training mode of the ANFIS classifier. Then, the features are extracted from test EEG signals to form the transformed filter coefficients and then given to the testing mode of the ANFIS classifier, which classifies the signal into focal and non-focal category. The training speed of the ANFIS model is very fast, making it suitable for EEG signal analysis and classification problems in real time.

In this paper, ANFIS classifier is used to classify the given test EEG signals into either focal or non-focal EEG signals. This classifier consists of one input layer, three hidden layers and single output layer. The neurons in each layer are determined by the size of the extracted features. The output layer assigns either zero or one to the output variable based on the classification of extracted features. The output response zero represents the focal signals and output response one represents the non-focal signals.

## 4. RESULTS AND DISCUSSION

Bern-Barcelona EEG dataset is used in this paper to validate the proposed EEG signal classification system. This dataset contains 750 focal and 750 non-focal EEG signals, captured from various patients in Bern university hospital. These captured EEG signals in both cases are sampled at the rate of 512Hz. In this paper, we have used 50 focal signals and 50 non-focal signals. The performance of the proposed EEG signal classification system is analyzed in terms of sensitivity, specificity and accuracy. These parameters are given in Eqs. (16)-(18) as,

$$Sensitivity = TP/(TP+FN) \tag{16}$$
$$Specificity = TN/(TN+FP) \tag{17}$$
$$Accuracy = (TP+TN)/(TP+FP+TN+FN) \tag{18}$$

True positive is noted as TP and it defines the number of signals correctly classified as focal signals. True negative is noted as TN and it defines the number of signals wrongly classified as focal signals. False positive is noted as FP and it defines the number of correctly classified non-focal signal and false negative is noted as FN and it defines the number of wrongly classified non-focal signal. The performance of the proposed system is illustrated in Table 2.

The MATLAB R2014 version is used in this work for simulation with Intel Pentium core i5 processor with 1GB internal RAM. To analyze the performance in effective manner, The 100 EEG signals are chosen from focal (set A) and 100 EEG signals are chosen from non-focal (set B) in dataset. In training mode of the ANFIS classifier, the signal sets A and B are subjected preprocessing and then the preprocessed signals are applied to dual tree complex wavelet transform. The decomposition levels are chosen to be four in this paper, as optimum efficiency after several iterations. The transformed wavelet coefficients are extracted from EEG signals and features are obtained from wavelet coefficients at each level. The obtained features are used for training the ANFIS classifier where signals from set A are chosen as training signals and the same is used for training of ANFIS network and signals from Set B are used as test signals for testing the trained ANFIS network. The test performance of the classifier can be determined by the performance estimates-accuracy, sensitivity and specificity.

**Table 2. Performance analysis.**

| Performance evaluation parameters | Experimental results (%) |
|---|---|
| Sensitivity (Se) | 97 |
| Specificity (Sp) | 98 |
| Accuracy (Acc) | 96 |

Table 3 shows the performance comparisons of the proposed classification methodology with conventional methodologies for focal and non-focal signal classifications. The proposed methodology achieves 97% sensitivity, 98% specificity and 96% average accuracy for focal and non-focal signals classifications, as illustrated in Table 2. The conventional methodology Sharma *et al.* [5] achieved 87% average accuracy and the main limitation of this method is that it used empirical mode decomposition algorithm.

This method is not suitable for sharp signals and degraded the performance of the classification system. Sharma *et al.* [6] achieved 85% average accuracy. The authors used intrinsic mode decomposition technique to decompose the signals for its epilepsy classifications. The method was capable to detect the interior edge regions in the EEG signals and this reduced the classification accuracy rate. Zhu *et al.* [8] achieved 84% average accuracy. The ANFIS based EEG signal classification system improves the classification accuracy to the rate of 9% while compared with the conventional methodology Sharma *et al.* [5].

**Table 3. Performance comparisons with conventional methodologies.**

| Methodology | Year | Signals in Dataset | Accuracy (%) |
|---|---|---|---|
| Proposed | 2016 | 100 | 96 |
| Sharma *et al*. [5] | 2015 | 50 | 87 |
| Sharma *et al.* [6] | 2013 | 50 | 85 |
| Zhu *et al.* [8] | 2013 | 50 | 84 |

## 5. CONCLUSIONS

In this paper, computer aided automatic categorization of EEG signals into focal EEG and non-focal EEG signals are proposed for epilepsy disorder diagnosis. The dual tree complex wavelet transform is applied and then features are extracted from these transformed coefficients. Then, ANFIS classifier classifies the EEG signals into either focal or non-focal based on the trained features. The proposed system stated in this paper achieves 97% sensitivity, 98% specificity and 96% average accuracy for focal and non-focal signals classifications. In future, this proposed work can be extended for the detection of stroke in brain through the diagnosed focal EEG signals.

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**Deivasigamani S.** received the B.Engg., M.Engg degrees in Electrical and Electronics Engineering, Applied Electronics from Thiagarajar College of Engineering, Thanthai Periyar Government Institute of Technology, Anna University, India in 2006 and 2009 respectively. His research interests include signal processing in bio medical engineering and VLSI applications. He is an IEEE member and registered Chartered Engineer with Engineering Council, United Kingdom.

**C. Senthilpari** had a post-graduated in Applied Electronics and Material Science at National Institute of Technology, Tiruchirappalli. He is working as a Senior Lecturer in Multimedia University and he obtained Ph.D. degree from Multimedia University in 2009. He works on the VLSI design and simulation analysis of new hardware circuits. Dr. Senthilpari invited committee member in various international conference. He immersed himself in conducting research in chosen area of specialization, guiding Ph.D. projects and Master students and teaching at undergraduate and post graduate level. Dr. Senthilpari has so far published more than 51 papers in national and international journals and conferences. Dr. C. Senthipari is a Senior Member in IEEE (USA) and obtained Charted Engineer from IET (U.K).

**Hin-Yong Wong** received his B.Eng. (first class Hons.) in Electronics Engineering, M.Sc. (Eng) (*with Distinction*) and Ph.D. in Electrical and Electronic Engineering from the University of Sussex, University of Leeds and University of Glasgow, United Kingdom respectively. He is currently a Professor and the Dean of Faculty of Engineering, Multimedia University, Malaysia. He has to date published over 85 scientific articles in international journals and conferences. His current research expertise and interest areas include wireless communication, semiconductor device fabrication and processing technology, nanotechnology, nano-patterning, photonics integrated circuit and organic electronics devices, solar cell technology and sustainability. Among some of the recent recognitions he received are he was announced the winner and honoree of the 2015 Ten Outstanding Young Malaysians (TOYM) Award by the Junior Chamber International, he is elected to the Fellows of The Institution of Engineers Malaysia and The Institution of Engineering and Technology (UK). He is a Senior Member of The Institute of Electrical and Electronics Engineers He is a registered Chartered Engineer and Professional Engineer registered with Engineering Council United Kingdom and Board of Engineers Malaysia respectively.