International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-2, December 2018

Computer Aided Diagnosis of Epileptic Seizure in Human Electroencephalogram using Discrete Wavelet Transform with an Adaptive Neuro - Fuzzy System

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Abstract: ***This study presents a computer aided epileptic seizure detection technique that usesdiscrete wavelet transform (DWT) with an adaptive neuro fuzzy system. The technique comprises electroencephalogram (EEG) signals data acquisition and synthesis of EEG signals, decomposition of the EEG signals and extraction of features, and classification of the features vectors. The technique which was implemented in Matlab (version 7.6) environment, exploits DWT strength in both time and frequency domain for the decomposition and extraction of characteristic features and an adaptive neuro-fuzzy inference system (ANFIS) for classification of transformed feature vectors that were used as input to the ANFIS. FiveEEG signals types were synthesized and decomposed. Features extracted from the decomposed signals were used to train and test the ANFIS classifier. The ANFIS blend neural network (NN) adaptive capabilities and fuzzy inference system (FIS). The performance of the ANFIS was measured in terms of sensitivity, specificity and total classification accuracy. And the results obtained showed that the hybrid model and/or technique which consist of DWT and ANFIS attained high level of accuracy in the classification of EEG signals as either epileptic or normal with minimal false detection.***

Keywords: Discrete Wavelet Transform (DWT), Adaptive Neuro-Fuzzy Inference System (ANFIS), Epileptic Seizure, Electroencephalogram.

I. INTRODUCTION

Electroencephalogram signal refers to brain signal. It is the pictorial illustration of electrical activities of the human brain within a short period of time. These signals are generated from neurons that have been bombarded in the human brains. When this happened, the signal is determined and assessed through an EEG.The signals are usually small energy signals which have been mixed with different kinds of noise signals referred to as artifacts. For proper analysis of an EEG, the noise signals areseparated from real brain signal. (Lanlan Yu, 2009). Several computer aided diagnosis techniques have been applied for the investigation of EEG signals.

Manuscript published on 30 December 2018.
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Johnson *et al*., (2011) discussed the multiplicative and differentiating methods to classification of epilepsy. The multiplicative technique relates the model produced to the training of data in each of the class in relation to the mean square error. This categorizes the EEG in relation to the count generated in each of the model produced and chooses the model that has more optimum count while the discriminative technique speedily assesses the borderlines between different categories. Different controlled learning techniques have been used to this set of feature in order to categorize the electroencephalogram data windows. The efficiency of the Multi-channel Epileptic (MCE) is as a result of its capability to utilize lightweight classifier for a determined efficiency. This is somehow fascinating when it comes to real-time seizure detection context, whereby a simple but highly efficient classifier is adjusted to suit lightweight tools applied by clinicians in caring and attending to patients. The outcome is in compliance with MCE viewpoint due to the fact that it underscores each category in the same way, weighting them for possible slightest error resolutions. Ajala F. A. et al (2018) applied a hybrid model including independent component analysis (ICA), discrete wavelet transform (DWT) and an adaptive neuro-fuzzy inference system to detection and classification of epileptic seizures in human electroencephalogram (EEG). Andthey obtained a fairly high classification accuracy with some low level false detection. Furthermore, Opiarighodare D. K. et al., (2018)suggested a discrete wavelet transform (DWT) technique that useswavelet of order **2** of Daubechies for the decomposition of the EEG signals into various subbands, displaying the detailed wavelet coefficients and the approximate wavelet coefficients respectively. Nasehi and Pourghassem (2011) discussed a review of different seizure investigation procedures and their use in different areas and/or fields. Many of the contemporary techniques apply ECG and EEG signals in the detection of seizures. Three seizure detectors were distinguished by them. These include EEG-based seizure-occurenceindicators, EEG based seizure-commencement indicators and EEG/ECG-based seizure-commencement indicators. Omerhodzic *et al.,* (2010) suggested a Wavelet-based Neural Network (WNN) classifier for the identification of the EEG signals realized and analyzed in three different EEG signals sets (healthy humans, patients with epileptic seizure and patients with epileptic syndrome at the time of manifestation of the seizure).

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The DWT together with the Multi-Resolution Analysis (MRA) was earlier applied in the EEG signal decomposition at resolution levels of the components of the EEG signal including delta, theta, alpha, beta and gamma, and the Parsevals theorem were applied in the extraction of the percentage distribution of the energy features of the EEG signal at different resolution levels. Neural Network (NN) was later applied in the classification of the extracted features in order to recognize the kind of EEGs based on the percentage distribution of the energy features that were extracted (Opiarighodare D. K. *et al.*, 2018).

Guo *et al.*, (2010a) proposed a new technique of computerized seizure detection that applied the approximate entropy features. In this technique, multi-wavelet transform was used in order to produce the entropy features. Artificial intelligence neural network was used in the classification. Guo *et al*., (2010b) discussed a method that uses line length features obtained using wavelet transform with an artificial neural network for the classification of EEG signals.

Filligoi *et al.*, (2011) described a computer program that analyzed the long term Holter-EEG and a template matching procedure that used statistical technique to compare the EEG with those of people in a known epileptic database. Cherian *et al.,* (2011) presented a classification and validation technique that uses EEG circumstantial classification. Eight categories were applied in the classification of the EEG signals along with their incoherence, sleep and wake up cycle. Manimegalai (2012) proposed a wavelet decomposition based EEG classification system. A Delta signal was discovered by multi-level decomposition and neural network was applied for the classification of the extracted delta signal.

Raghunathan *et al.,* (2010) presented a two facet design optimization method that considered signal investigation efficiency and the cost of hardware in the evaluationof the procedures. Detected features were analyzed for electroencephalographic seizure detection capability from microelectrode data documented in kainite treated rats. Active and outflow power utilizationwas established through the application of the circuit models. Raghunathan *et al*., (2010; 2011) proposed a method of two-facet design optimization that considers both the efficacy of detection and the cost of hardware in assessing the methods for their praticability in the embedded application. Detected characteristic featureswere first analyzed for their capability to discover electroencephalographic seizures from micro-electrode data documented from kainite-treated rats. The active and outflow power utilization of the characteristic features analyzed were evaluated by the use of circuit models. A value was attached to the efficacy of detection and the cost of hardware for each set of features which were thereafter plotted on a two-dimensional design plane.

Sharanreddy and Kulkarni (2011) put forward an evaluation of the significant studies linked to computerized epileptic seizures detection with EEG signals. Mercy (2012) did performance investigation of the computerized EEG tracing detection with the use of DWT and ICA. For extraction of feature, ICA and DWTtechniques were applied and support vector machine and neural network (NN) were applied in the classification.

Chandler *et al.*, (2011) projected a platform of small energy that works in constant multichannel analysis of epileptic seizures for people suffering from epilepsy. When a seizure is detected, the detection part activates the investigation circuit which processed the signal locally and send the frequency content and energy.

Majumdar (2011) revealed how differentiation can be used to improve some features of the electrophysiological signals of the brain, mixed with noise, artifacts and acquisition defects, thereby making way for economical analysis and/or detection of the changes. In this case, Majumdar applied the windowed variance procedure in the determination of epileptic seizure in EEG signals. He applied windowed variance and spontaneous seizure determination in order to make authentic validation for epilepsy to decrease the period for processing. Lewis *et al.*, (2010) made a system which applied both seizure's power spectra and deterministic finite automata. They combined the two methods for the analysis of epilepsy from activity.

Summarily, all the related works above obtained a fairly high performance but still produce a significant high level of false detection. Although they made use of some of the publicly available standard bench marked data sets which were also used in the present research, the input dataset used in each of the systems are not as complex as those encountered in the real world today, and cannot be considered reliable and efficient for the detection of epilepsy since all the set of data were not used. Therefore, there is need for further research in order to get a more reliable and efficient system that is capable of applying and detecting the presence of interictal epileptiform discharge in all the sets of data.

II. METHOD AND CONCEPT OF COMPUTER AIDED DIAGNOSIS OF EPILEPTIC SEIZURE

The concept of computer aided diagnosis of epileptic seizures with human electroencephalogram (EEG) devised in this research comprises EEG signal data acquisition and synthesis of EEG signals, decomposition of the signals and extraction of features, and classification of EEG based on the features vectors transformed. The method involves the application of MATLAB software package (version 7.6) where the implementation of the system was done.

A. EEG Signals Data Acquisition and Synthesis

The electroencephalogram (EEG) signals processed in this computer aided diagnosis of epileptic seizure were synthesized from a set of widely used EEG data acquired from the database of Albert-Ludwig's University, Freiburg, Germany. The datasets were condensed and represented in ASCII code. Five datasets were acquired and each dataset consists of a zip-file containing 100 TXT-files.The datasets are labelled Z, O, N, F, S. It is from these datasets which are made up of different categories of human epileptic and normal patients that the EEG signals were synthesized.

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B. Decomposition of the Electroencephalogram (EEG) Signals and Extraction of Features using Discrete Wavelet Transform (DWT)

Application of DWT method to signals processing gives a very high-level frequency outcome when there is a very low-level frequency and a very high-time outcome when there is a very high-level frequency. This functioning pattern of the DWT is as a result of its application of long time windows when the frequency is low, and application of short time windows when the frequency is high. DWT breaks a signal into sub-bands by means of passing through a filter, the time signal f using a successive high-pass filter (HPF) witha low-pass filter (LPF). This is illustrated with Figure 1.

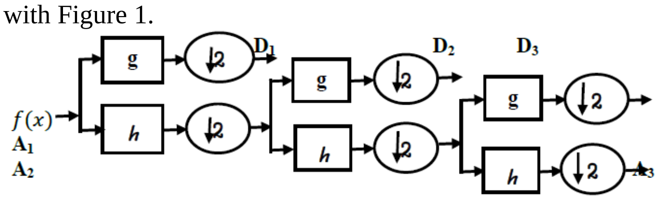

Figure 1 Sub-band Decomposition of Signal Using DWT

Considering figure 1, which illustrates sub-band decomposition of EEG signals by the DWT, the discrete mother wavelet function is the high-pass filter, denoted g while its mirror version is the low-pass filter, denoted h. In DWT technique, each signal is sorted through the use of HPF and LPF, and then broken down by the use of down-sampler. Signals broken down in the first level are first level approximation coefficients A_1 and first level detail coefficients D_1. The approximation and the detail coefficients for other consecutive levels were established by the use of the approximation coefficient in an earlier level in like manner.

The scaling function $\varphi_{j,k}(x)$ showing LPF and wavelet function $\psi_{j,k}(x)$ showing HPF are expressed in the equations shown below:

$$\varphi_{j,k}(x) = 2^{j/2}\, h\,(2^j x - k) \qquad (1)$$

$$\psi_{j,k}(x) = 2^{j/2}\, g\,(2^j x - k) \qquad (2)$$

Where x = 0, 1, 2…, M – 1; j = 0, 1, 2, …, J – 1, and k = 0, 1, 2, …, $2^j - 1$.

$$J = \log 2\ (M) \qquad (3)$$

Where M = length of an EEG segment (Gonzalez and Woods, 2008);

J is the sampling rate, and j is the resolution, and bothsignify the function positions and the function width on the x – axis respectively. The function heights depend on$2^{j/2}$value.

For k = 0, 1, 2 …, 2^j - 1, the approximation coefficients A_i (k) and the detail coefficients D_i (k) for ith level are

$$A_i = \{\tfrac{1}{\sqrt{M}} \textstyle\sum_x f(x)\varphi_{\ j,k}(x)\} \qquad (4)$$

and

$$D_i = \left\{\tfrac{1}{\sqrt{M}} \textstyle\sum_x f(x)\psi_{\ j,k}(x)\right\} \qquad (5)$$

The length of EEG segment*M* equals 4097, while *J*is calculated using$log_2\ (M)$. and as a result, *J* equals 12. Thus the highest level *L*of decomposition was taken to be 11.

In this research work, order **2**of Daubechies wavelet of discrete wavelet transform technique was applied during breakdown of signals. The breakdown (i.e decomposition) level which shows the highest and/or best performance of the system was analyzed and a level of decomposition selected for every experiment that was carried out during theresearch.

C. Classification of EEG using Adaptive Neuro - Fuzzy System

The adaptive neuro-fuzzy system applied as a classifier in the EEG classification in this research is Adaptive Neuro Fuzzy Inference System (ANFIS). The ANFIS utilizes hybridized learning procedure to distinguish constraints of Sugeno-type fuzzy inference systems. It uses both the forward pass and the backward pass procedures together for the training of the fuzzy inference system (FIS) membership function constraints in order to mimic the dataset supplied during the training.

In this research, the training and the test sets were formed by 500 data samples (100 samples from each class of human subjects represented by each dataset). The data samples were divided into two parts of 350 (70 samples from each dataset) for training and 150 (30 samples from each dataset) for testing. The first part of 350 samples of data was utilized in the training of the ANFIS, while the remaining 150 samples of data from the second part was utilized in the testing of the system to check the correctness of trained ANFIS model that was used for the classification of the epileptic seizure represented in the EEG.

ANFIS learning algorithm is used to tune every modifiable parameters in order to ensure the output of the ANFIS matches those of the data used during the training. Whenever the hypothesized (premise)parameters of the membership functions are made constant, ANFIS model output is represented as shown in equation 6:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \qquad (6)$$

The forward pass technique was applied in order to ascertain optimal values of the parameters with little or no difficulties. Whenever the premise parameters are undecided, the region to be search invariably becomes bigger and the training convergence becomes slower.

However, the problem of slower training convergence was solved by the application of hybridized procedure that consists of both forward pass and backward pass techniques. Thus the hybridized procedure comprises backward pass and forward pass. The forward pass utilized in this hybridized procedure was meant for optimization of the resultant (consequent)parameters while the hypothesized (premise) parameters were made constant. When ideal resultant (consequent) parameters are obtained, the backward pass begins straightaway. Backward passwas utilized in order to fine-tune the premise parameters matching the fuzzy sets in the domain where inputs are passed on to fuzzy inference system. The output of ANFIS was determined by putting to use, the resultant (consequent) parameters located during the forward pass.

The output error was utilized to adjust the hypothesized (premise) parameters through the use of standard backpropagation procedure. The list of instructions specifying the sequence of operation of the developed concept is as shown below:

Step 1: Start;
Step 2: Acquire EEG signals data;
Step 3: Synthesize EEG signals;
Step 4: Decompose EEG signals into frequency sub-band components through the use of DWT;
Step 5:IF frequency is less than 30Hz THEN GOTO step 6 ELSE step 3;
Step 6: Extract discriminating features of appropriate individual sub-band component using discrete wavelet transform (DWT);
Step 7: Process each frequency sub-bands with LPF and HPF using discrete wavelet transform (DWT);
Step 8: Classify individual component based on features extracted using ANFISclassifiers;
Step 9: IF interictal epileptiform discharge (IED) is present in individual component THEN process epileptic seizure ELSE normal;
Step10: Output epileptic seizure, normal;
Step 11: Stop.

In addition, the performance evaluation metrics that was used to analyzed the system include sensitivity, specificity, and accuracy. The sensitivity, specificity and accuracy values were determined by use of the relations shown in equations (7 to 11). Sensitivity is the number of abnormal data samples classified as abnormal data samples while specificity is the number of normal data samples classified as normal data samples. The calculation of the sensitivity and specificity is as follows:

For Healthy Human Subjects with Eyes Opened,

(i) $$\text{Sensitivity} = \frac{Number\ of\ Correctly\ classified\ DSZ\ Signal}{Number\ of\ Total\ DSZ\ Signal} \quad (7)$$

$$= \frac{TP}{TP+FN}$$

(ii) $$\text{Specificity} = \frac{Number\ of\ True\ Negative\ Decision}{Number\ of Actually\ Negative\ Cases} \quad (8)$$

$$= \frac{TN}{TN+FP}$$

For Healthy Human Subjects with Eyes Closed,

(i) $$\text{Sensitivity} = \frac{Number\ of\ Correctly\ classified\ DSO\ Signal}{Number\ of\ Total\ DSO\ Signal} \quad (9)$$

$$= \frac{TP}{TP+FN}$$

(ii) $$\text{Specificity} = \frac{Number\ of\ True\ Negative\ Decision}{Number\ of Actually\ Negative\ Cases} \quad (10)$$

$$= \frac{TN}{TN+FP}$$

For Epileptic Human Subjects at Hippocampal Hemisphere of the Brain during Seizure Free Interval,

(i) $$\text{Sensitivity} = \frac{Number\ of\ Correctly\ classified\ DSN\ Signal}{Number\ of\ Total\ DSN\ Signal} \quad (11)$$

$$= \frac{TP}{TP+FN}$$

(ii) $$\text{Specificity} = \frac{Number\ of\ True\ Negative\ Decision}{Number\ of Actually\ Negative\ Cases} \quad (12)$$

$$= \frac{TN}{TN+FP}$$

For Epileptic Human Subjects at Epileptogenic Zone of the Brain during Seizure Free Interval,

(i) $$\text{Sensitivity} = \frac{Number\ of\ Correctly\ classified\ DSF\ Signal}{Number\ of\ Total\ DSF\ Signal} \quad (13)$$

$$= \frac{TP}{TP+FN}$$

(ii) $$\text{Specificity} = \frac{Number\ of\ True\ Negative\ Decision}{Number\ of Actually\ Negative\ Cases} \quad (14)$$

$$= \frac{TN}{TN+FP}$$

For Epileptic Human Subjects during Seizure Activity,

(i) $$\text{Sensitivity} = \frac{Number\ of\ Correctly\ classified\ DSS\ Signal}{Number\ of\ Total\ DSS\ Signal} \quad (15)$$

$$= \frac{TP}{TP+FN}$$

(ii) $$\text{Specificity} = \frac{Number\ of\ True\ Negative\ Decision}{Number\ of Actually\ Negative\ Cases} \quad (16)$$

$$= \frac{TN}{TN+FP}$$

Where TP, FN, FP and TN implies true positive, false negative, false positive and true negative values respectively. An output value obtained is termed TP when the system classified an abnormal data as abnormal; an output value obtained is termed FN when the system classified an abnormal data as normal; an output value is termed FP when the system classified a normal data as abnormal and an output value is termed TN when the system classified a normal data as normal. For calculation of total classification accuracy, the term ‘accuracy’ is viewed as a depiction of the system operation in a general perception. This was computed using the equation below:

$$Total\ Classification\ Accuracy = \frac{Number\ of\ Correct\ Decision}{Total\ Number\ of\ Cases} \quad (17)$$

III. RESULTS AND DISCUSSION

A. EEG Signals Synthesized from the Datasets

A segment of the original EEG signal synthesized from each of the data set is shown in Figure 2 (a to e):

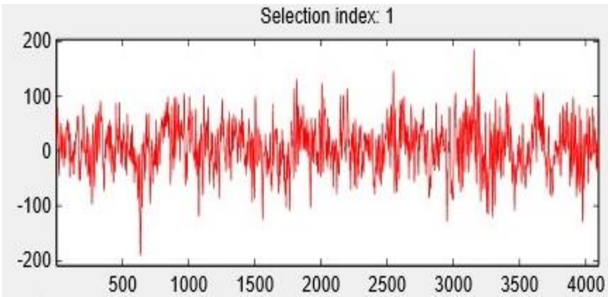

Figure 2 (a) Signal Synthesized from Dataset of Healthy Human Subjects with Eyes Opened

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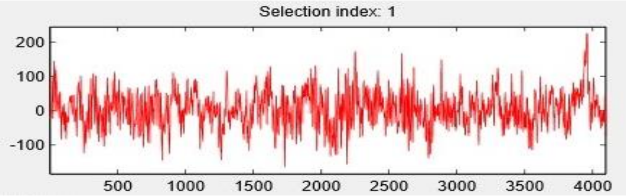

Figure 2 (b) Signal Synthesized from Dataset of Healthy Human Subjects with Eyes Closed

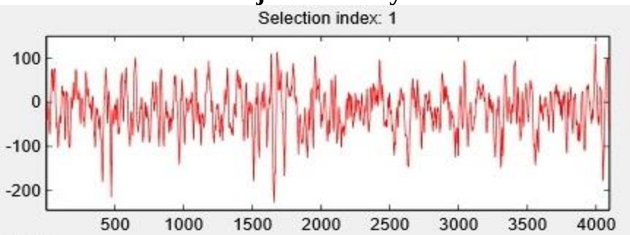

Figure 2 (c) Signal Synthesized from Dataset of Epileptic Human Subjects in Seizure Free Intervals from Hippocampal Hemisphere of the Brain

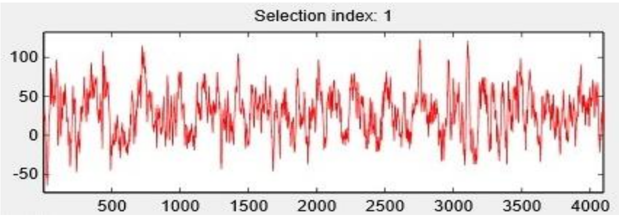

Figure 2 (d) Signal Synthesized from Dataset of Epileptic Human Subjects in Seizure Free Intervals from the Epileptogenic Zone of the Brain

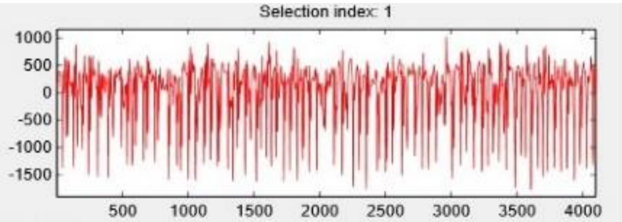

Figure 2 (e) Signal Synthesized from Dataset of Epileptic Human Subjects in Seizure Activity

B. Result of EEG Signals Decomposition and Features Extraction

The decomposition and filtering process of detail coefficient of level1was sustained up to level 6 for each EEG signal synthesized from each of the dataset. The approximate coefficient of A_6 and the detail coefficients of D_1 to D_6 of each EEG signal segment of the datasets is shown in Figure 3 (a toe) respectively. Wavelet coefficients computed represent energy distribution of the EEG signals in both time and frequency domain. The characteristic features applied to depict the time-frequency division of the EEG signals are:

i. Energy wavelet coefficients in each sub-band;
ii. Maximum wavelet coefficients in each sub-band;
iii. Minimum wavelet coefficients in each sub-band;
iv. Mean wavelet coefficients in each sub-band and
v. Standard deviation wavelet coefficients in each sub-band.

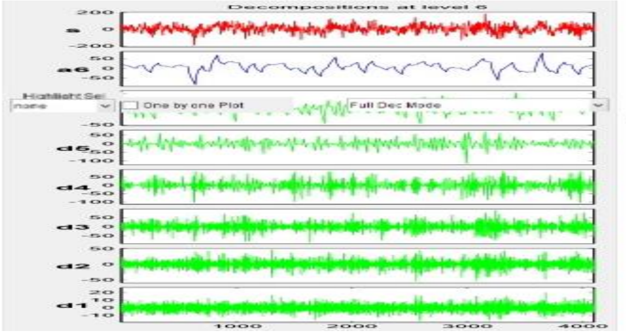

Figure 3 (a) the Approximate and the Detailed Coefficients of EEG Segment from Dataset of Healthy Human Subjects with Eyes Opened

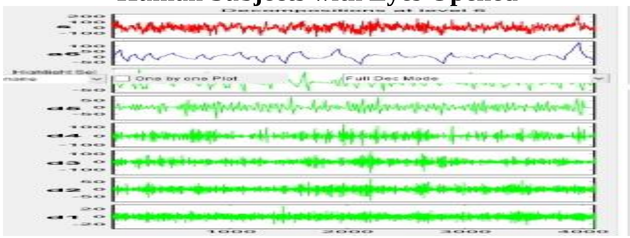

Figure 3 (b) the Approximate and the Detailed Coefficients of EEG Segment from Dataset of Healthy Human Subjects with Eyes Closed

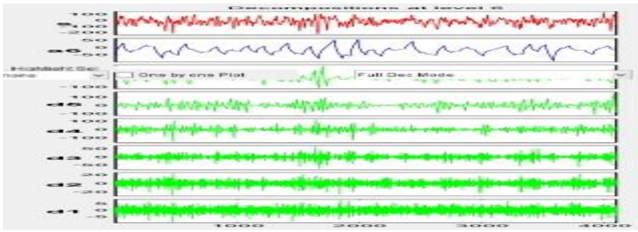

Figure 3 (c) the Approximate and the Detailed Coefficients of EEG Segment from Dataset of Epileptic Human Subjects during Seizure Free Period from Hippocampal Hemisphere of the Brain

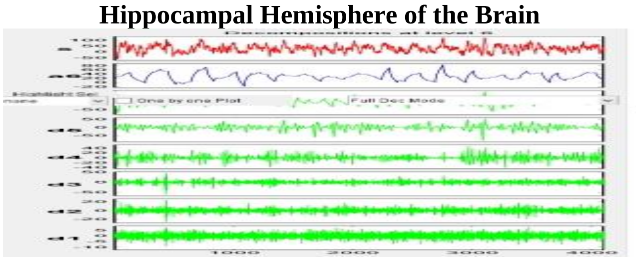

Figure 3 (d) the Approximate and the Detailed Coefficients of EEG Segment fromDataset of Epileptic Human Subjects during Seizure Free Period from the Epileptogenic Zone of the Brain

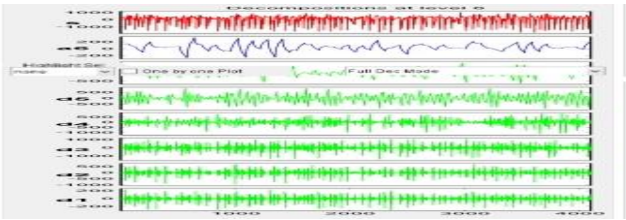

Figure 3 (e) the Approximate and the Detailed Coefficients of EEG Segment from Dataset of Epileptic Human Subjects in Seizure Activity

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C. ANFIS Model Designed and Classification by ANFIS

The design method of the neuro-fuzzy paradigmutilizes calculated data in creating FIS which mimic the input-output pairs of data given to it. And in this research, the inputs utilized by ANFIS network are those features extracted from the wavelet transform during the decomposition at different levels. There are different steps involved in the design of an ANFIS model. First, the ANFIS editor was opened and the initial Sugeno type FIS created based on the paired data set. And this was done through the use of "genfis1" function in Matlab software package (version 7.6). This function divides the fuzzy area into different zones according to the Number of membership functions given for each of the inputs. Three different membership functions were allocated to all adjustable inputs. The FIS of EEG classification is shown in Figure 4.According to the five input-one output system, the five adjustable parameters which were utilized as inputsinclude standard deviation, mean, minimum, maximum and energy of the DWT coefficients and the output class that is either epileptic or normal is received as the output variable. The input adjustable parameters were represented by the use of linguistic variables. The membership functions for the input variables before and after training are shown in Figure 5 (a-e):

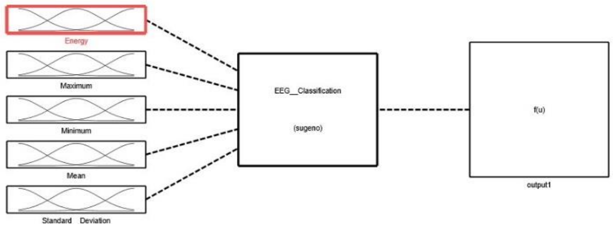

Figure 4 Fuzzy Inference System (FIS) for Epileptic Seizure Classification in EEG

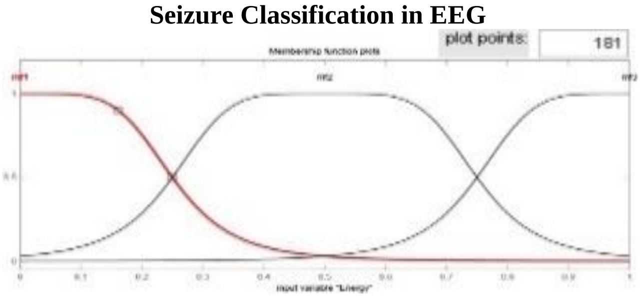

Figure 5 (a) (i) Energy Membership Functions before Training

Figure 5 (a) (ii) Energy Membership functions after Training

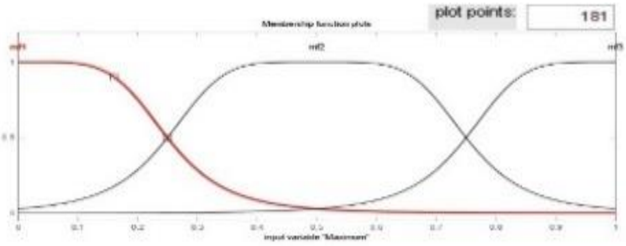

Figure 5 (b) (i) Maximum Membership Function before Training

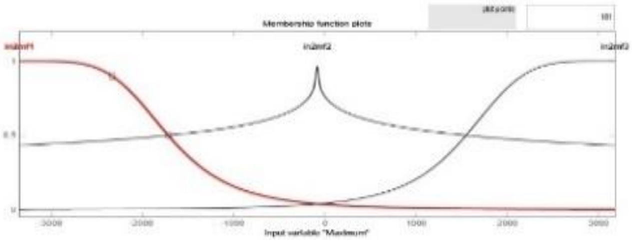

Figure 5 (b) (ii) Maximum Membership Functions after Training

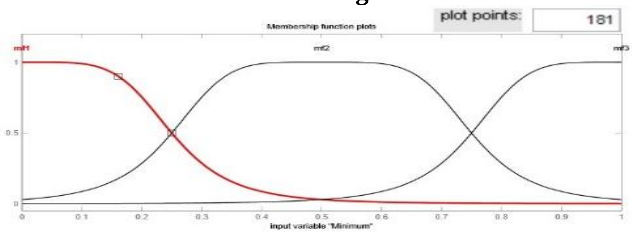

Figure 5 (c) (i) Minimum Membership Functions before Training

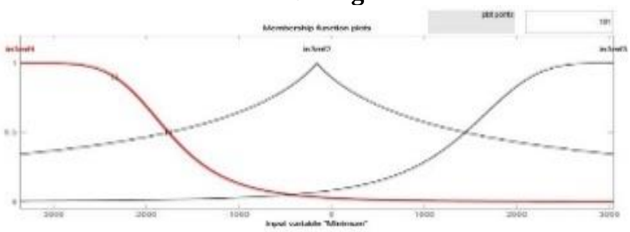

Figure 5 (c) (ii) Minimum Membership Functions after Training

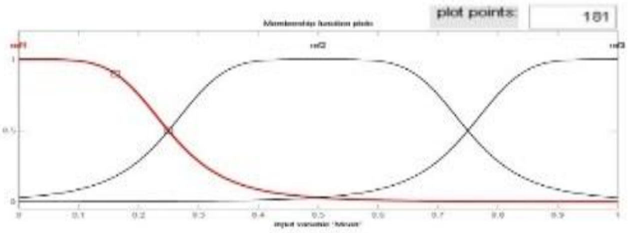

Figure 5 (d) (i) Mean Membership Functions before Training

Figure 5 (d) (ii) Mean Membership Functions after Training

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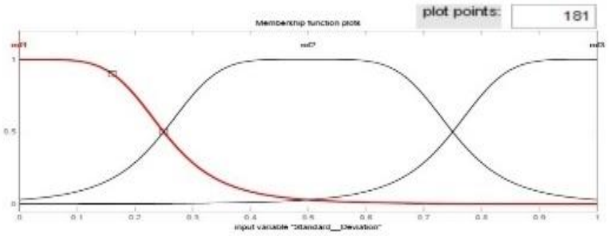

Figure 5 (e) (i) Standard Deviation Membership Functions before Training

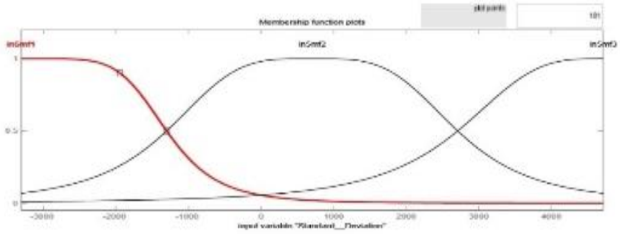

Figure 5 (e) (ii) Standard Deviation Membership Functions after Training

Based on Figure 5, the membership functions of each input parameter was divided into three regions, namely, small, medium and large. The examination of the initial (before training) membership functions and the final (after training) membership functions indicates that there are considerable changes in the final membership functions of the wavelet coefficients. And this shows the different levels of importance of the features used in classification. Parameter adaptation of ANFIS is illustrated in figure 6.

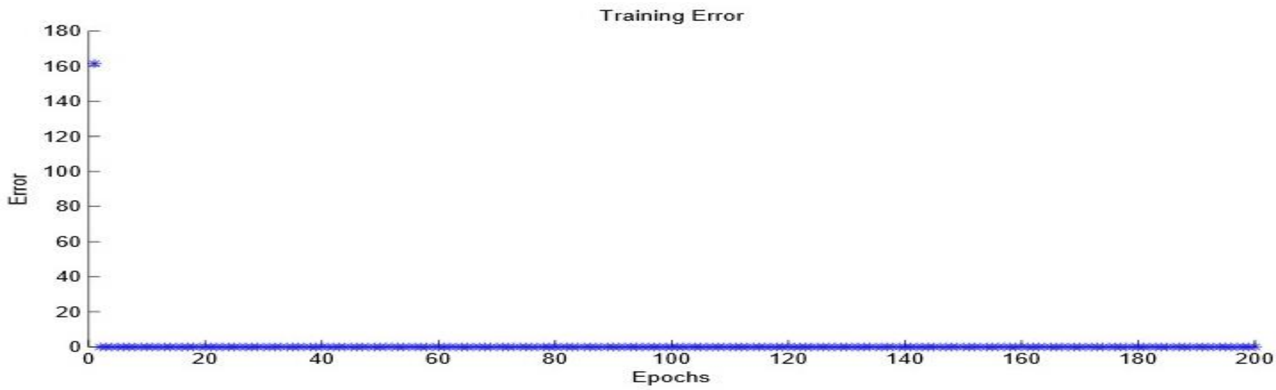

Figure 6 ANFIS Network Error Convergence

Following figure 6, 350 training data were utilized by ANFIS in 200 training periods and 0.011 was derived as an initial value for step size parameter adaptation. The network error convergence curve of ANFIS at the end of the 200 training periods is 0.0084. Figure 7illustrates 243 rule base plot of ANFIS performance during the traing. And the system indicates the possibility of getting a little and/or no error in training as there are 350 data samples to be classified by 243 rules. Following the plot of the ANFIS performance in training which utilized 243 rules, the red points denotes the output processed from the ANFIS structure. The blue points represent the required targets that are needed to be matched by the 350 training data samples. Figure 7 also indicate that there are little errors during training as there are samples that were not completely masked by the computed output from the ANFIS. The errors here are of no significance since they lie within their class boundary. When the training was completed, 150 testing data samples were utilized to authenticate the correctness of the ANFIS classifier that was used for the classification of the EEG signals. Figure 8 indicates the performance of the ANFIS model in testing.

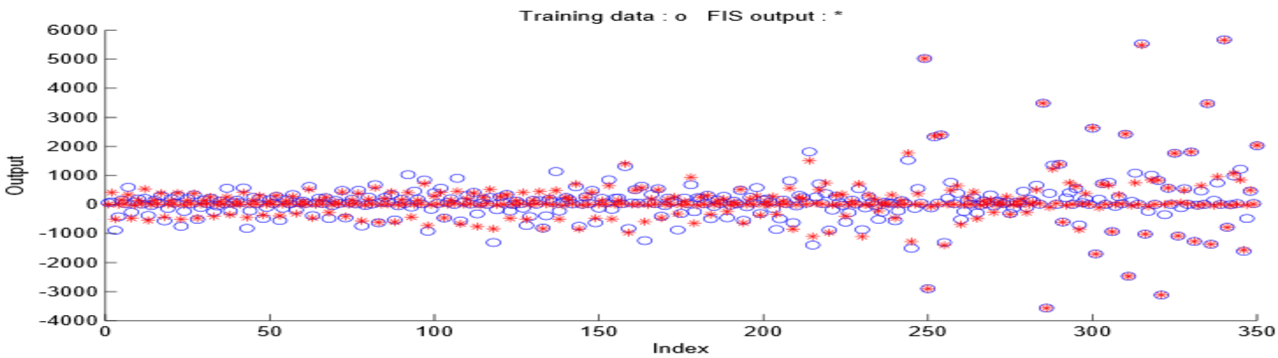

Figure 7 Plot for 243 Rule-based ANFIS Training Performance

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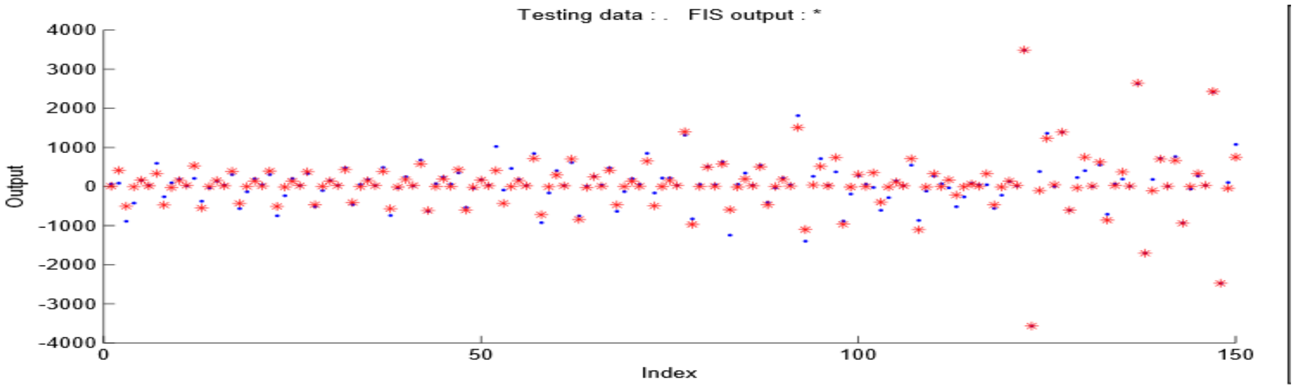

Figure 8 ANFIS Model Testing Performance.

The testing data samples distribution in figure 8indicates that there are little errors which occurred during the classification of the EEG signals. Considering errors at data sample boundary of little or no significance, the system can be regarded as efficient. No error was spotted between 0 and the 30th samples; no error was observed between the 30th and the 60th samples; no error between the 60th and the 90th samples; no error between the 90th and the 120th samples although there was a data sample mismatched that was observed around the data samples boundaries for each of the dataset mentioned above during training and testing of the dataset used. Errors were spotted between the 120th and the 150th samples as a result of a data sample mismatched arising from sharp spike in EEG. The results from classification by the ANFIS model which utilizes 350 data samples for training and 150 testing data are displayed in Table 1. The confusion matrix in Table 2 shows the results of classification by ANFIS model applied for the classification of EEG signals. The matrix reveals the number of times an EEG signal is misclassified. The matrix is demarcated by desired classification on rows and actual network outputs on columns.

Table 1. Statistic of Correct and Incorrect EEG Classification

Human Subject	Data Set	Correctly Classified	Incorrectly Classified
Healthy with Eyes Opened	Z	69	1
Healthy with Eyes Closed	O	69	1
Epileptic (Hippocampal) during Seizure free interval	N	69	1
Epileptic (Epileptogenic) during Seizure free interval	F	69	1
Epileptic in Seizure Activity	S	69	1

Table 2. ANFIS Training Performance

Confusion Matrix Desired \ output	Z	O	N	F	S
Z	69	0	1	0	0
O	0	69	0	1	0
N	1	0	69	0	1
F	0	1	0	69	0
S	0	0	0	0	69

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Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-2, December 2018

According to the confusion matrix, signal samples from Z, O, N, F and S were slightly classified incorrectly. 1 signal sample from Z was classified incorrectly as signal sample from N, 1 signal sample from O was classified incorrectly as signal sample from F, 1 signal sample from N was classified incorrectly as signal sample from Z, 1 signal sample from F was classified incorrectly as signal sample from O and 1 signal sample from S was classified incorrectly as signal sample from N.

Analyzing the performance of the concept applied in this research, the classification performance of the ANFIS model applied was established by thecomputation of statistical parameters including sensitivity, specificity and accuracy. The total classification accuracy determined by the ANFIS model used in this computer aided diagnosis of epileptic seizures is 98.6%. The classification specificity value of Z, O, N, F and S signals proposed by ANFIS are 99.64%, 99.60%, 99.29%, 99.60% and 99.99% respectively. And the classification sensitivity of Z, O, N, F and S signals is 98.57%, 98.60%, 98.57%, 98.60% and 98.57% respectively.

Table 3 shows the comparison of the system performance with some other existing techniques.

Table 3: Comparison of System Performance with Some Other Existing Techniques

Author(s)	Year	Feature extraction	Classification	Dataset	Accuracy (%)
Guo *et al*	2010a	Wavelet transform & approximate entropy	Artificial neural networks	Z-S ZONF-S	99.85 98.27
Najumnissa & Rangaswamy	2012	Wavelet transform	ANFIS	No standard bench marked data set	98
Polat & Gunes	2008a	PCA & Fast Fourier transform	Artificial immune recognition system	Z-S	100
Sadati *et al*	2006	Wavelet transform	Adaptive neurofuzzy network	Z-F-S	85.9
Subasi	2007	Wavelet transform	Mixture of expert model	Z-S	95
The present work	2018	DWT	ANFIS	Z-O-N-F-S	98.6

IV. CONCLUSION

The focus of this research is to inaccurate diagnosis of epileptic seizure caused by high level of false detection of the seizures in electroencephalogram (EEG). The methodology is in three stages. The first stage is the signal preprocessing which involves gathering the database containing the patients' information and synthesizing EEG signal from each of the dataset. The dataset containing the biosignals were carefully observed, selected and imported into MATLAB software where the data were made viable for decomposition and waveform characterization. The second stage is the EEG signals decomposition and features extraction. This stage involved the use of discrete wavelet transform for EEG signals decomposition and extraction of discriminating features of individual frequency sub-band. The final stage is classification which involved the use of adaptive neuro-fuzzy inference system (ANFIS) as an adaptive neuro fuzzy classifierwith the extracted feature vectors as inputs to the classifier. The ANFIS classifies the discriminative characteristics that represent the inherent behaviours of the EEG signals and thereby distinguishing a transient seizure from background activity accurately. This addresses the problems of false diagnosis of seizures arising from high false detection of epileptic seizures in EEG in the existing techniques. The results of the simulation carried out in this research show that the computer aided diagnosis involving the use of discrete wavelet transform (DWT) in combination with ANFIS, is more accurate and efficient since it achieve 98.6% of classification accuracy rate despite the complexity of the datasets used in the experiments conducted during the research.

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