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Detection and Classification of Epileptic Seizure in Electroencephalogram Using Adaptive Neuro-Fuzzy Inference System

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Abstract- This paper presents an intelligent diagnosis system using hybrid approach of adaptive neuro-fuzzy inference system (ANFIS) model for classification of electroencephalogram (EEG) signals. The system uses discrete wavelet transform (DWT) in combination with independent component analysis (ICA) for features extraction and normalization respectively. The extracted features serve as input feature vectors which were used as input of ANFIS classifier. Five types of EEG signals were used as input patterns of the ANFIS classifier. The method used is in three stages including EEG signals preprocessing, decomposition and feature extraction using DWT in combination with ICA, and classification using a trained ANFIS. The ANFIS model combined the neural network adaptive capabilities and the fuzzy inference system. The performance of the ANFIS model was evaluated in terms of the training performance and the classification accuracy. And the results indicated that the ANFIS model has great potentials in classifying the EEG signals.

Keywords*- Epileptic Seizure, Electroencephalogram, Adaptive Neuro-Fuzzy Inference System (ANFIS), Discrete Wavelet Transform (DWT), Independent Component Analysis (ICA)*

I. Introduction

Electroencephalogram (EEG) signal detection and classification is an interesting but difficult problem in biomedical engineering. The analysis of the EEG signal has become a routine procedure for the detection, evaluation, treatment and effective management of epileptic seizures. Epilepsy is one of the most neurological disorders in human beings. It is characterized by recurring seizures in which abnormal electrical activity in the brain causes the loss of consciousness or a whole body convulsion. Studies show that 4-5% of the total world population has been suffering from epilepsy (Khan et al, 2012).

EEG contains valuable information relating to different physiological state of the brain. The problem of diagnosing and/or classifying an epileptic seizure in humans is of great importance in the treatment and management of people suffering from neurological disorders. This is because the correct classification of each person's epilepsy by seizure type and epilepsy syndrome is important for proper treatment. Detecting the type of seizure has the most immediate influence on therapy. If the EEG is classified incorrectly, the seizure medicine that the doctor prescribes not only may not help but actually may make the seizures worse.

Many trained personnel and health care professionals have had conflicting interpretations of EEG tracing. This is due to the difficulties associated with distinguishing a transient seizure from a background activity and other artifacts. Many researchers have applied various techniques such template matching, parametric and mimetic methods etc. for feature extraction and classification of epileptic seizure. Besides, most of the existing techniques made used of feature extraction methods such as fast fourier transform (FFT), principal component analysis (PCA), independent component analysis (ICA) and linear discriminant analysis (LDA) which are not best for non-stationary signals analysis in time-frequency domain. Due to a high number of false detections, these systems cannot perform satisfactorily in the routine EEG settings. In order to minimize such limitations of the EEG analysis systems, a system of EEG detection and classification which incorporates discrete wavelet transform (DWT) in combination with independent component analysis (ICA) and neuro fuzzy is needed to be developed to detect epileptic seizure properly.

Over the years, many different methods have been developed for detecting and classifying the electroencephalogram (EEG) as either normal or epileptic. Since complete visual analysis of EEG signal is very difficult, automated means of detection is required. Fourier transform has been most commonly used in early days of processing of EEG signals (Nabeel et al, 2014).

Moreover, since EEG signal is a nonstationary signal, Fourier analysis does not give accurate results (Shoeb and Guttag, 2010). The most effective time-frequency analysis tool for analysis of transient signal is wavelet transform (Fathima et al, 2011). This was why wavelet transform was used for signal decomposition and features extraction with independent component analysis in this research work.The automated diagnosis of epilepsy can be subdivided into pre-processing, feature extraction, and classification (Nabeel et al, 2014). Seizure detection can be classified as either seizure onset detection or seizure event detection. In seizure onset detection, the purpose is to recognize the starting of seizure with the shortest possible delay. The purpose of seizure event detection is to identify seizures with the highest possible accuracy (Gandhi et al, 2010).

For treatment of epilepsy, patients take antiepileptic drugs on daily basis. But about 25% of them do experience frequent seizures thereafter. For these patients, surgery is the most important and generally adopted treatment method. Surgery can be done only if epileptogenic focus is identified accurately. For this purpose different types of tracers are used as soon as seizure onset is detected. This is why the seizure onset detection was considered very important (Khan et al, 2012). Hence the need for correct detection and classification of electroencephalogram (EEG).

This research aims to design an EEG analysis system that applies discrete wavelet transform technique in combination with independent component analysis based on fuzzy inference system to detect epileptic seizures in human EEG. This research is important because it can be used by health care professionals (whether experienced or inexperienced) for easier analysis of EEG and more accurate detection of interictal epileptiform discharge (IED) which indicates evidences of the presence of epileptic seizure in patients' EEG. And the focus is on epileptic events detection and seizure prediction. In the epileptic EEG, the presence of epileptiform activities, such as spikes, slow rhythm and high-frequency epileptiform oscillations confirms the diagnosis of epilepsy (Padmasai*et al*, 2010).

Traditionally, EEGs are scanned for epileptic spikes by experienced clinicians. If an automated seizure-detection and classification system is available, it could reduce the time required by a neurologist to perform an off-line diagnosis by reviewing EEG data. The system could also be used to produce an on-line warning signal to alert healthcare professionals of any possible seizures detected (Liang *et al*, 2010).

Seizure evolution is typically a dynamic and non-stationary process and the signals are composed of multiple frequencies. Visual and conventional frequency-based on direct spectral method has limited application (Tzallas*et al*, 2009). An algorithm proposed included application of wavelet packet analysis and determined dominant frequency bands during electro convulsive therapy (Zandi*et al*, 2007). Wavelet analysis method used to isolate EEG bands had shown good performance (Tafreshi*et al*, 2006). Shoeb and Guttag reported 96% sensitivity and mean detection delay of 4.6 seconds when worked on CHB-MIT database (Shoeb and Guttag, 2010). In 2011, Kharbouch and others proposed a method for seizure detection from iEEG (Kharbouch et al, 2011). The data of 10 patients were utilized to extract both temporal and spectral features. The method detected 97% of 67 test seizures with a median detection delay of 5 seconds and a median false detection rate of 0.6 per 24 hour (Kharbouch et al, 2011).

II. MATERIALS AND METHOD

The approach used in this research is qualitative. The qualitative research approach was used because the study is concerned with subjective assessment of the discriminative characteristics that reveals the inherent behaviours of EEG signals. To achieve the aim and objectives of this research work, benchmarked publicly available EEG dataset was collected, isolated, decomposed using wavelet transform and independent component analysis whose output was passed on to ANFIS classifier for classification. This approach involves training the ANFIS classifier that are required to classify the EEG signals when the wavelet coefficients defining the behavior of the EEG signals are used as inputs. The ANFIS classifier was trained with the backpropagation gradient descent method (backward pass) in combination with the least squares method (forward pass). And matlab software package (version 7.6) was used to implement the system.

A. EEG Signals Decomposition and Feature Extraction Using Discrete Wavelet Transform (DWT) and Independent Component Analysis (ICA)

The main reason the DWT was applied in this research work is to decompose the EEG signals and extract the discriminating features from appropriate sub-bands which will be used for further classification. The discrete wavelet transform is an effective way of analyzing non–stationary EEG signals. This wavelet transform (WT) technique 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 wavelet transform allows the decomposition of a signal into a number of scales, each scale representing a particular coarseness of the signal under study.

Discrete wavelet transform (DWT) technique provides high-frequency resolution if the frequency is low and high-time resolution if the frequency is high since it uses long time windows at low frequencies, and short time windows at high frequencies. The discrete wavelet transform decomposes a signal into sub-bands by way of filtering of the time domain signal f using sequential high-pass filter (HPF) and low – pass filter (LPF). This is shown in figure 1.

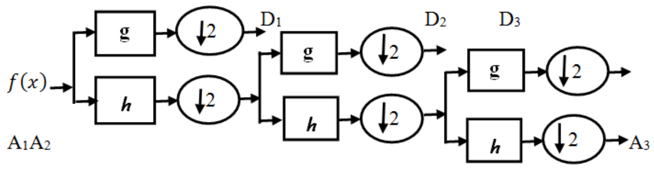

Figure 1. Sub-band Decomposition of Signal by Using DWT

Following the diagram illustrating the sub-band decomposition of the signal by the discrete wavelet transform, the high-pass filter, g and the low-pass filter, h are the discrete mother wavelet function and its mirror version, respectively. In the DWT technique, the signals are filtered by using these filters, and then sampled by using the down-sampler. The down-sampled signals 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 each next level are determined by using the approximation coefficient in previous level in the same way. The scaling function $\varphi_{j,k}(x)$ presenting low pass filter and wavelet function $\psi_{j,k}(x)$ presenting high pass filter are described as shown below:

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

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

Where x = 0, 1, 2, …, M – 1;

j = 0, 1, 2, …, J – 1, and

k = 0, 1, 2, …, 2^j – 1.

$$J = \log_2(M) \tag{3}$$

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

K is the sampling rate, and j is the resolution, and they indicate 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

$$A_i = \left\{ \frac{1}{\sqrt{M}} \sum_x f(x)\, \varphi_{j,k}(x) \right\} \tag{4}$$

and

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

The length of an EEG segment *M* equals to 4097, and *J* can be computed by *log_2 (M)*. In this case, *J* equals to 12, and therefore the maximum of the decomposition level *L* is chosen as 11.

In this research work, the discrete wavelet transform (DWT) technique with the wavelet of order 2 of Daubechies was used in the decomposition of the signals while the independent component analysis (ICA) was used to normalized and reduced resultant component dimensionality. The decomposition level providing the highest success of the ANFIS was investigated and a decomposition level was chosen for every experiment that was carried out in the process of this research.

B. EEG Classification using Adaptive Neuro Fuzzy Inference System (ANFIS)

ANFIS was used as classifier in this research work. ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems. It applies a combination of the least-squares method and the back propagation gradient descent method for training the fuzzy inference system (FIS) membership function parameters to emulate a given training data set.

In this work, 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 equal parts of 250 (50 samples from each dataset) each for training and testing. The first data sample of 250 was used to train the ANFIS, while the second part of 250 data samples was used for testing in order to verify the accuracy and the effectiveness of the trained ANFIS model for the detection and classification of epileptic seizure in EEG.

1) Architecture of 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 modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered. These are

Rule 1: If (x is A_1) and (y is B_1) then ($f_1 = p1x + q1y + r1$)

Rule 2: If (x is A_2) and (y is B_2) then ($f_2 = p2x + q2y + r2$)

where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in figure 2 in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

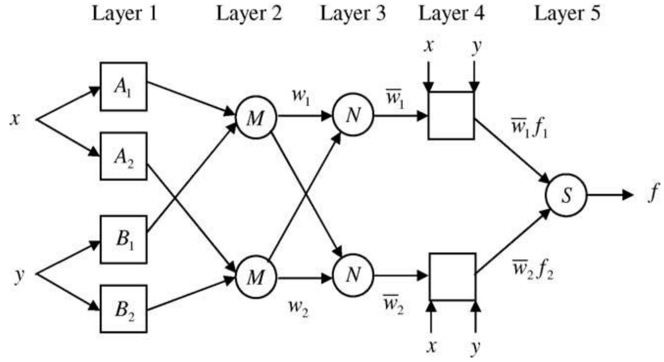

Figure 2. ANFIS Architecture

Considering the above ANFIS architecture, in the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$o_i^1 = \mu_{Ai}(x); i = 1, 2 \tag{6}$$

$$o_i^1 = \mu_{Bi-2}(y); i = 3, 4 \tag{7}$$

Where $\mu_{Ai}(x), \mu_{Bi-2}(y)$ can adopt any fuzzy membership function. For example, if the bell shaped membership function is employed, $\mu_{Ai}(x)$ is given by:

$$\mu_{Ai}(x) = \frac{1}{1 + \{(\frac{x - c_i}{a_i})^2\}^{b_i}} \tag{8}$$

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where a_i, b_i and c_i are the parameters of the membership function, governing the bell shaped functions accordingly.

In the second layer, the nodes are fixed. And they are labeled with *M*, indicating that they act as a simple multiplier. The outputs of this layer can be represented as shown below:

$$o_i^2 = \omega_i = \mu_{Ai}(x)\mu_{Bi}(y); i = 1, 2 \quad (9)$$

which are the so-called firing strengths of the rules.

In the third layer, the nodes are also fixed nodes. They are labeled with ***N***, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be written as shown below:

$$o_i^3 = \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2}; i = 1, 2 \quad (10)$$

which are the so-called normalized firing strengths. In the fourth layer, the nodes are adaptive. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Therefore, the outputs of this layer are given by:

$$o_i^4 = \varpi_i f_i = \varpi_i(p_i x + q_i y + r_i); i = 1, 2 \quad (11)$$

In the fifth layer, there is only one single fixed node labeled with *S*. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

$$o_i^5 = \sum_{i=1}^{2} \varpi_i f_i = \frac{\sum_{i=1}^{2} \omega_i f_i}{\omega_1 + \omega_2} \quad (12)$$

It can be seen that there are two adaptive layers in this ANFIS architecture, namely first and fourth layers respectively. In the first layer, there are three modifiable parameters(a_i, b_i, c_i)that are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters(p_i, q_i, r_i), pertaining to the first order polynomial. These parameters are the so-called consequent parameters.

2) ANFIS Learning Algorithm

The task of the learning algorithm for the above ANFIS architecture is to tune all the modifiable parameters, namely $(a_i, b_i, c_i)$and(p_i, q_i, r_i), to make the ANFIS output match the training data. When the premise parameters $(a_i, b_i \; and \; c_i)$of the membership function are fixed, the output of the ANFIS model can be represented as follows:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \quad (13)$$

Substituting equation (10) into equation (13) gives:

$$f = \varpi_1 f_1 + \varpi_2 f_2 \quad (14)$$

By substituting the fuzzy if-then rules into equation (14), it becomes:

$$f = \varpi_1(p_1 x + q_1 y + r_1) + \varpi_2(p_2 x + q_2 y + r_2) \quad (15)$$

After rearrangement, the output can be represented as follows:

$$f = (\varpi_1 x)p_1 + (\varpi_1 y)q_1 + (\varpi_1)r + (\varpi_2 x)p_2 + (\varpi_2 y)q_2 + (\varpi_2)r_2 \quad (16)$$

which is a linear combination of the modifiable consequent parameters $p_1, q_1, r_1, p_2, q_2 \; and \; r_2$**.** The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower.

A hybrid algorithm combining the least squares and the gradient descent techniques are adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares technique (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent technique (backward pass) was used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS will be calculated by employing the consequent parameters found in the forward pass. The output error was used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS

III. RESULTS AND DISCUSSION

Signal data acquisition is the first stage to record and capture data from the various human subjects used in this work. The data files of the EEG recordings which were processed and organized into dataset were imported into MATLAB software package (version 7.6) where all computations were carried out. The EEG dataset used was obtained from the EEG database in the website of the Albert-Ludwig's-University, Freiburg, Germany. For each set (A to E), there is a zip-file containing 100 TXT-files. Each TXT-file consists of 4096 samples of 0ne EEG time series in ASCII code. A in file Z. zip contains Z000.txt – Z100.txt; B in file O. zip contains O000.txt – O100.txt; C in file N.zip contains N000.txt – N100.txt; D in file F.zip contains F000.txt – F100.txt; E in file S.zip contains S000.txt – S100.txt. For simplicity and clarity of results of this research work, the dataset was assigned label as follows:

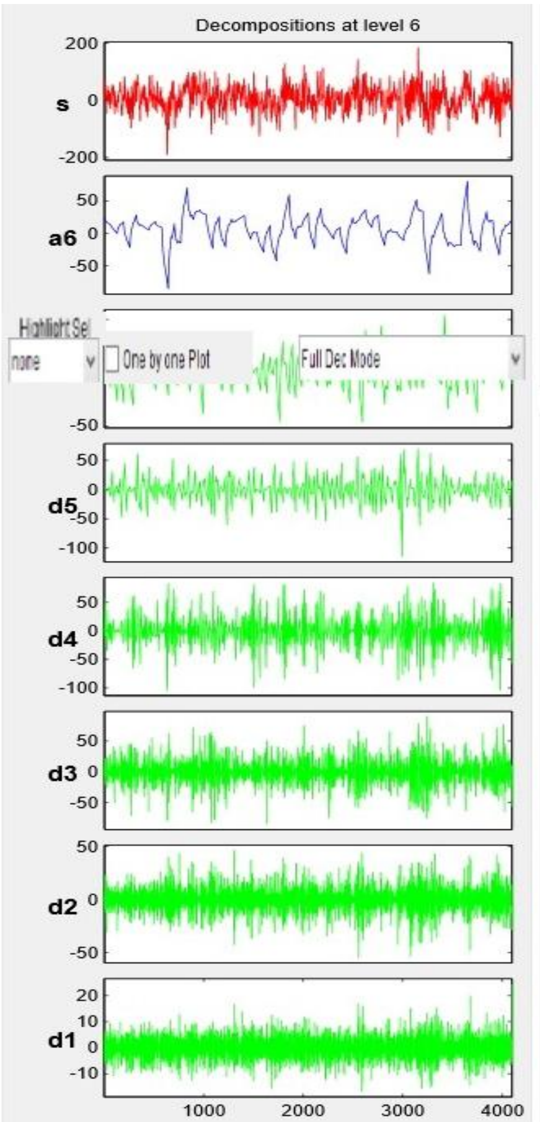
A is dataset Z (labelled DSZ) from healthy human subjects with eyes opened; B is dataset O (labelled DSO) from healthy human subjects with eyes closed; C is dataset N (labelled DSN) from epileptic human subjects in seizure free intervals from the hippocampal hemisphere of the brain that indicates non-interictal activity; D is dataset F (labelled DSF) from epileptic human subjects in seizure free intervals from the epileptogenic zone of the brain that represents the focal interictal activity; E is dataset S (labelled DSS) from epileptic human subjects in seizure activity i.e. during seizure intervals.

A. EEG Signals Decomposed and Features Extracted

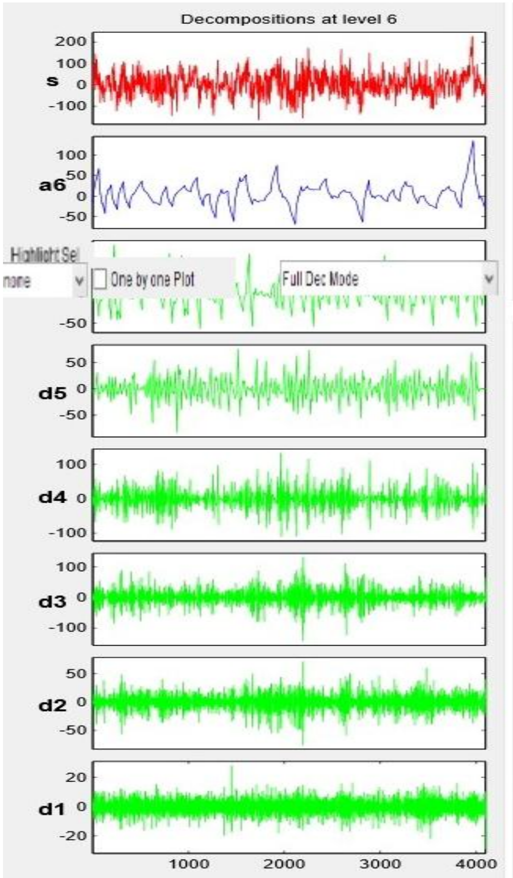
The EEG signal is a superposition of different structures occurring on different time scales at different times. In this work, the spectral analysis of the EEG signals was carried out using the discrete wavelet transform (explained in section 2.1 above).The decomposition of each signal into different frequency sub–bands was obtained by successive high-pass and low-pass filtering of the time domain signal. Selection of wavelet that is suitable and the number of levels of decomposition was carried out since it is an important factor to be considered in signal analysis using DWT.

1) Multiresolution Decomposition of EEG Signals

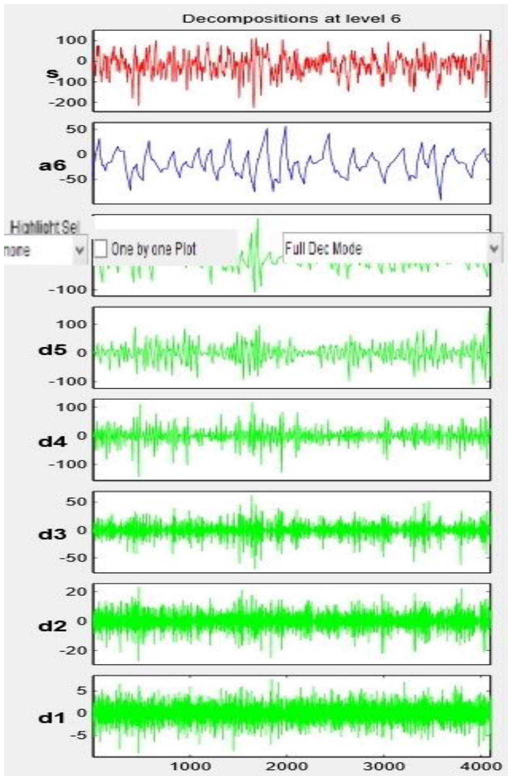
At the decomposition stage, all EEG signals were decomposed into frequency sub-bands by using the DWT with Daubechies wavelet of order 2 for level 6. During this stage of decomposition, visual inspections were carried out on the signals synthesized from each set of data. This is another reason the choice of DWT was a good one for the analysis of the EEG signals. The decomposition and filtering process of detail coefficient of level 1 was continued until the desired level, up to level 6 was reached for each of the EEG signal from the dataset. The approximate coefficient of A_6 and the detail coefficients of D_1 to D_6 of each EEG signal segment from each set of data is shown in figure 3(a to e) respectively:



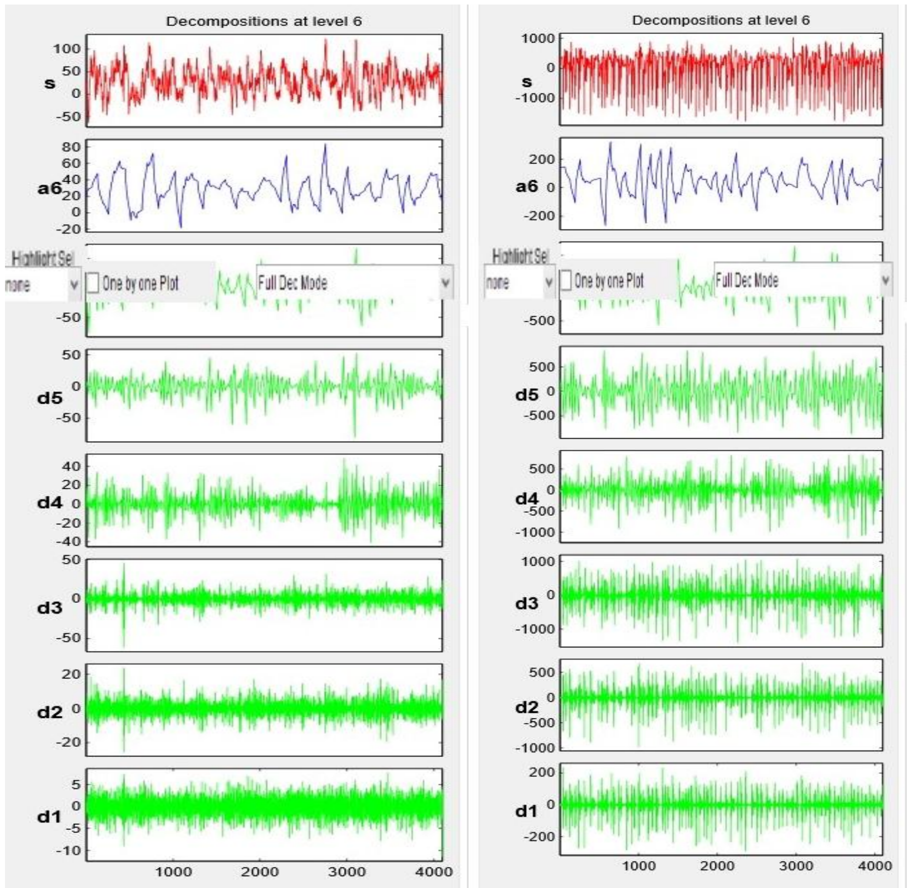
(a)



(b)



(c)



(d) (e)

Figure 3. a) The Approximate and the Detailed Coefficients of EEG Segment from DSZ. b) The Approximate and the Detailed Coefficients of EEG Segment from DSO. c) The Approximate and the Detailed Coefficients of EEG Segment from DSN. d) The Approximate and the Detailed Coefficients of EEG Segment from DSF. e) The Approximate and the Detail Coefficients of EEG Segment from DSS

2) *Features of EEG Signals Extracted*

The wavelet coefficients computed gave an acceptable representation that reveals the energy distribution of the EEG signals in both time and frequency. Therefore, the detail and the approximation wavelet coefficients of each EEG signal computed was used as the feature vectors representing the signals. The features used to represent the time-frequency distribution of the EEG signals include:

i. Energy of the wavelet coefficients in each sub-band;

ii. Maximum of the wavelet coefficients in each sub-band;

iii. Minimum of the wavelet coefficients in each sub-band;

iv. Mean of the wavelet coefficients of each sub-band and

v. Standard deviation of the wavelet coefficients of each sub-band

B. Classification Using ANFIS

In classification, the aim is to assign the input patterns to one of five classes, usually represented by outputs restricted to lie in certain range so that they represent the probability of the class membership. And while the classification is on, the specific pattern is assigned to specific class according to the characteristic features that represent the EEG signal. The classification of the EEG signals using the combination of ICA and DWT features coefficients and ANFIS that was trained with the back propagation gradient descent method in combination with the least squares method has been made. 25 features (dimension of the extracted feature vectors) representing the EEG signals were used as inputs. The fuzzy rule architecture of the ANFIS classifier was designed by using a generalized bell shaped membership functions defined in equation 8. The ANFIS classifier was implemented by using MATLAB software Package (MATLAB version 7.6 with fuzzy logic toolbox). The ANFIS used 250 training data in 200 training periods and the step size for parameter adaptation had an initial value of 0.011 and a final error convergence of 0.0084. The system shows possibility of getting zero training error since there were 243 rules applied in classifying 250 data samples.

The classification performance of the ANFIS model used was determined by the computation of statistical parameters such as sensitivity, specificity and accuracy. The classification specificity value of DSZ, DSO, DSN, DSF and DSS signals proposed by ANFIS is 99.5%, 99.0%, 99.0%, 100% and 100% respectively. And the classification sensitivity of DSZ, DSO, DSN, DSF and DSS signals is 100%, 100%, 100%, 100% and 90% respectively. The total classification accuracy determined by the ANFIS model is 98%.

IV. CONCLUSION

The primary interest of this research, which is the detection and classification of epileptic seizure in EEG using DWT in combination with ICA and ANFIS as a Neuro Fuzzy classifier have been successfully investigated. Several parameters have been investigated in this research work, which are the values of energy, maximum, minimum, mean and standard deviation of levels 1 to 6 DWT detail coefficients and the corresponding approximation coefficients. The results indicated that by using DWT in combination with ICA and ANFIS, the classification of EEG signals as either epileptic or normal can be successful. Therefore the primary objectives and aim of this research is achieved. The simulation results show that the class of EEG signals is well predicted using DWT in combination with ICA and ANFIS system, and the system working well since it achieve the 98% of classification accuracy rate. This result indicates that it has great potentials in the reduction of high rate of false diagnosis of epileptic seizure in patients and had been found to be successful in EEG signals detection and classification. The classification accuracy reached demonstrates the practicability of the system in the task of epileptic seizure detection, which can assist and speed up the decision making process of neurophysiologists in identifying seizure activity correctly.

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