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A NON-INVASIVE DETECTION OF EPILEPTIC SEIZURE IN HUMAN SCALP ELECTROENCEPHALOGRAM USING DISCRETE WAVELET TRANSFORM

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ABSTRACT

This study shows the effectiveness of Discrete Wavelet Transform (DWT) technique in the analysis of Electroencephalogram (EEG) by performing decomposition of the EEG signals and extracting unique features for efficient diagnosis of epilepsy using standard benchmarked EEG datasets. The total dataset comprising 250 segments was grouped into five sets (A–E). The datasets used in this technique were chosen from records of EEG after artifacts caused by muscle movements and blinking of the eyes were removed. The datasets were used as inputs of the system. The technique applied includes signals preprocessing which involves synthesizing the signals which were originally represented in ASCII form, decomposition of the signals and extraction of features characterizing seizures. The researchestablished that though the decomposed EEG signals were imprecise, the wavelet detail coefficients computedgave an acceptable representation thatreveals the energy distribution of the EEGsignals in both time and frequency domain while the wavelet approximate coefficients computed gave a clearer view of spikes which indicate the presence of epileptiform activities in the EEG signals sub - band.

KEYWORDS: Discrete Wavelet Transform (DWT), Electroencephalogram (EEG), Epileptiform, Epileptic Seizure.

1. INTRODUCTION

Epileptic seizure is a popular severe neurological disorder, which affects quite a large number of people in the world today (WHO, 2007). Epilepsy is a convulsive brain problem resulting from too much neuronal discharge (Fix, 1995). It is associated with some altered state of consciousness, recurrent and sudden malfunction of the brain. Although the use of Electroencephalogram (EEG) is considered to be the best, the diagnosis of epileptic seizures can also be achieved by different observations, such as Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI), and Computed Tomography (CT). Among all these categories of diagnosis, EEG is the most economical and significant one which gives high temporal resolution. There are lots of important facts in EEG which can be gotten through signal processing methods (Mansouri*et*al., 2012). A number of the important facts obtained are useful for detection and treatment of people suffering from epileptic seizures (Wang and Xu, 2009).

The present study is mainly on finding out whether or not there is an epileptic seizure in an EEG. The diagnosis of epilepsy is ascertained by the presence of epileptiform activities which are represented by spikes, sharp waves, slow rhythm and high frequency oscillations (Ajala F. A. *et* al., 2018) and (Padmasai*et*al., 2010). EEGs are monitored traditionally for epileptic seizures by health care professionals. However, EEG long – term collection has been made possible through the advancement of EEG acquisition systems.

Computerized seizures monitoring with the use of EEG had been of great significance in computational intelligence research over the past few decades. Gotman and Gloor put forward a technique that can be used to specify and quantify the characteristics of epileptic seizures such as spikes and sharp waves, in an EEG (Gotman and Gloor, 1976). In order to carry out a computerized identification, there is need to split the EEG of the individual channel into half waves. The waves are distinguished by periods and amplitude of its halves. The technique provided a study background in epileptic seizures analysis automation. One major setback of this technique is the nonappearance of specific characterization of an interictal epileptiform discharge (IED) (Ajala F. A. *et* al., 2018).

Gotman carried out a better technique of computerized seizures monitoring and identification in EEG. Later, several other techniques were put forward for seizures detection, but only a small number of them were based on onset seizures detection (Gotman, 1982). Qu and Gotman also carried out onset detection technique for a seizure of a specific patient and attained sensitivity of 100% with an average latency of 9.4 seconds. The mean false detection that was recorded is 0.02 per hour. The system that was designed was tested on 47 seizures of about twelve patients. The limitation of the technique that was devised was the template needed for the detection of the seizures. Gotman and Saab devised a system of an onset detection in 2004. At the time the technique was tested with 16 patients' EEG, having about 69 seizures, they arrived at a sensitivity of 77.9% including false detection rate of about 0.9 per hour and a median detection delay of about 9.8 seconds (Gotman and Saab, 2004).

A matching pursuit procedure was applied by Sorensen and others who attained 78 - 100% of sensitivity and 5-18 seconds delay onset detection of seizure with 0.2- 5.3 false positives per hour. This procedure was analyzed with intracranial and scalp EEG (Ajala F. A. *et al.*, 2018). A sensitivity of 96% with average detection delay of 4.6 seconds was achieved by Shoeb and Guttag at the time they worked on the database of CHB-MIT (Shoeb and Guttag, 2010). A system of seizures detection from iEEG was also put forward in 2011 by Kharbouch and others (Kharbouch*et al.*, 2011). Spectral and temporal features were extracted from data of ten patients. 97% of 67 test seizures including a median detection delay and false detection rate of about 0.6 per 24 hour was reached by the system (Kharbouch*et al.*, 2011).

Furthermore, a method was also proposed to study the latency of seizure detection using two statistical features and a wavelet based feature. And in this method, Daubechies wavelet was used for the seizure detection in EEG. The algorithm put forward applies the Daubechies wavelet (of order 4) for the detection of the onset seizures in the database. Numerous research works already exist in the literatures that make use of epilepsy detection in EEG signal as we have a few of them in the aforesa

A wavelet-chaos-neural network methodology for classification of electroencephalograms (EEGs) into healthy, ictal, and interictal EEGs has been offered by Samanwoy Ghosh-Dastidar and others (Ghosh-Dastidar*et al.*, 2007). For breakdown of EEG into delta, theta, alpha, beta, and gamma sub-bands the wavelet analysis is applied. The parameters that were utilized for the EEG demonstration include: standard deviation (specifying the signal variance), correlation dimension, and largest Lyapunov exponent (specifying the non-linear chaotic dynamics of the signal).

2. METHOD AND CONCEPT OF EPILEPTIC SEIZURES DETECTION

The concept of EEG analysis used here is in two broad stages. The first stage is the signal data acquisition from the human subjects stored in a database; and the second stage is the signal analysis which in turn consists of three sub-stages including synthesizing EEG signal from each set of data, decomposition of each of the signals, and detection of waves components. Figure 2.3 illustrates the conceptual view of the whole system developed for the detectionof epileptic seizures in electroencephalogram. The method used in this study involves application of MATLAB software package (version 7.6) which was used for the implementation of the system.

A. Data Acquisition

In this study, publicly available EEG data were used. The set of data were taped by measures of 128-channel 12 bit EEG system which used 173.5 samples per second. The total dataset comprising 250 segments was grouped into five sets (A–E). Each segment has 23.6 seconds duration. All of the datasets were chosen from records of EEG after artifacts caused by muscle movements and blinking of the eyes were removed. Set A (eyes opened) and set B (eyes closed) were recorded by using the placement system of international 10–20 electrodes from five healthy persons. Set C and set D were intracranial recordings that were obtained from five epilepsy patients measured in seizurefree intervals. For these recordings (sets C and D), the electrodes were placed on epileptic foci for set C and on hippocampus of opposite hemisphere for set D. Set E included only epileptic seizure recordings of the same five epilepsy patients.

Here, subjects within the age group of 21 to 50 years were selected for this research. And the EEG was collected using Nihon Kohden digital EEG system, signal processor and a personal computer from the diagnostic centre. All EEGs with artifact, electrode movement and bursts of alpha waves were discarded in order to ensure high detection accuracy. Figure 2.1 illustrates the general procedure of data signal analysis:

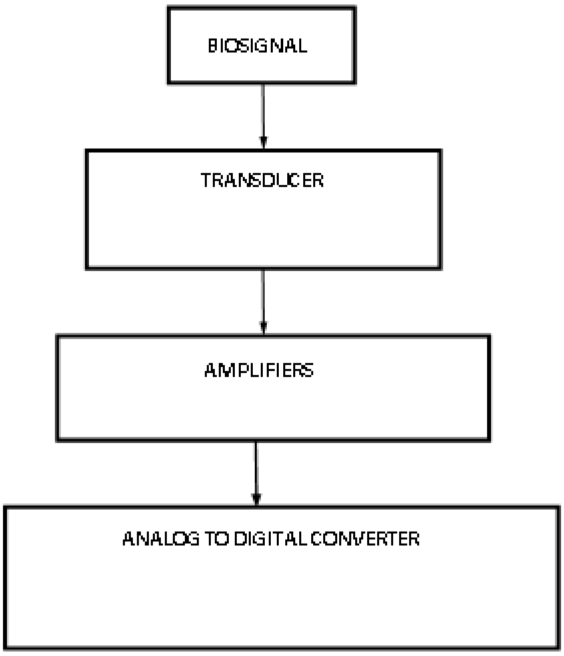


Figure 2.1: Block Diagram Illustrating General procedure of Data Acquisition.

However, the datasets used in this study are represented in ASCII. It is from the ASCII values that the initial and original signals were synthesized. And the signal synthesized from each set of data was decomposed in the following stage.

B. Decomposition of EEG Signals using Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) was applied in this work to decompose the EEG signals which were synthesized from the EEG data sets. Discrete wavelet transform is very efficient in the analysis of EEG signals which are non – stationary. The wavelet transform (WT) method is a wing of the Fourier transform, though it is more than the classic Fourier transform which operates on only time or frequency, since it operates effectively on both time and frequency domain. This ability of Wavelet Transform to operate on multi – scale characteristics makes it easy to decompose one signal into multiple scales, and each of the scales representing a particular characteristic feature of the decomposed signal.

DWT technique displays a high-frequency resolution when the frequency is low and a high-time resolution when the frequency is high. This action and/or operation of the DWT is as a result of its usage of long time windows in cases of low frequency, and usage of short time windows in cases of high frequency. The DWT breaks down each of the signals into sub-bands by way of passing through a filter, called the time domain signal f using a sequential high-pass filter (HPF) and a low-pass filter (LPF). This is illustrated in Figure 2.2.

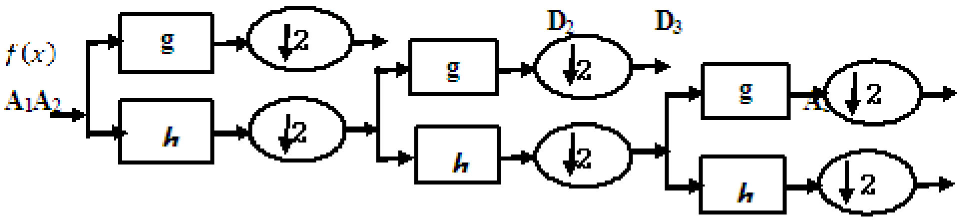


Figure 2.2: Sub-band Decomposition of Signal by Using DWT.

Considering figure 2.2, which displays the decompositionof the EEG signal into sub-bands by DWT, the high-pass filter, g represents the discrete mother wavelet function while the low-pass filter, h is represented by its mirror version. At this stage of the discrete wavelet transform (DWT) technique, the signals were filtered by using these filters, and then sampled by using a down-sampler. The signals which were down-sampled in the first level of decomposition are the first level approximation coefficients A_1 and first level detail coefficients D_1. The approximation and the detail coefficients for subsequent levels were determined by using the approximation coefficient derived from the preceding decomposition level in the same fashion.

The scaling function $\varphi_{j,k}(x)$ which presents low pass filter and wavelet function $\psi_{j,k}(x)$ which presents high pass filter are given as follows:

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

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

Where $x = 0, 1, 2, \ldots, M - 1$;

$j = 0, 1, 2, \ldots, J - 1$, and

$k = 0, 1, 2, \ldots, 2^j - 1$.

$$J = \log_2(M) \quad (3)$$

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 $k = 0, 1, 2, \ldots, 2^j - 1$,

The approximation coefficients $A_i(k)$ and the detail coefficients $D_i(k)$ for ith level are

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

and

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

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 decomposition level $L$of the EEG signals is selected to be 11.

In this study, the discrete wavelet transform (DWT) technique with the wavelet of order **2** of Daubechies was used in the decomposition of the signals. The decomposition level which shows the best observable characteristic features of the EEG signals was chosen and investigated in all the experiments that weredone during the study.

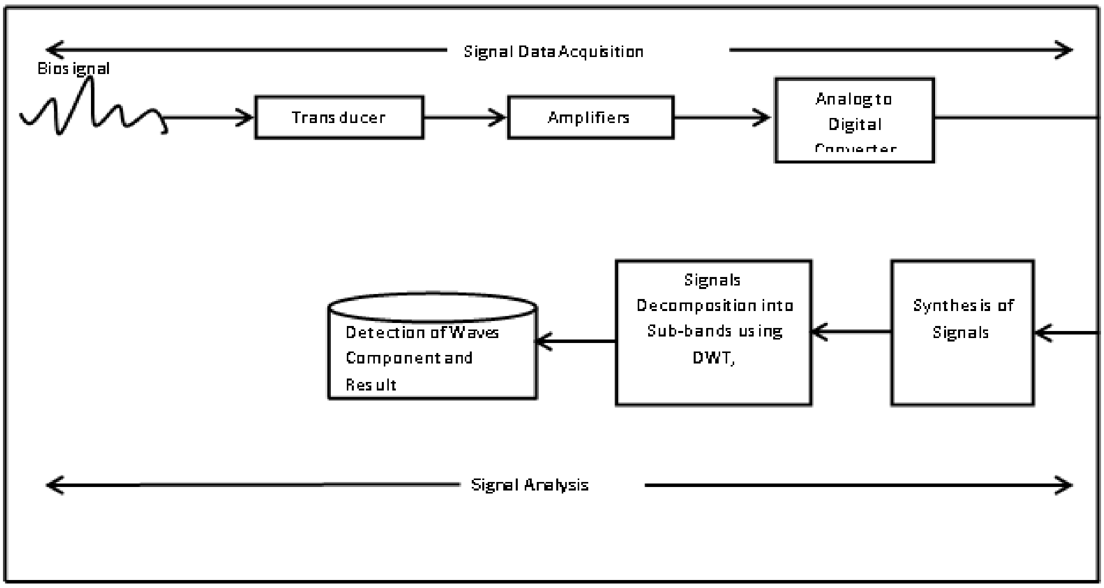


Figure 2.3: Conceptual View of the Whole System.

3. RESULTS AND DISCUSSION

Acquisition data signals is the first stage to record and capture data from the various human subjects that were used in thestudy. The EEG recordingsdata files which were processed and organized into datasets were imported into MATLAB software package (version 7.6) where the system implementation was done. The dataset employed 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, 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 Acquired from Dataset

The EEG signal synthesized from each of the set of data is illustrated in Figure 3.1 (a to e)

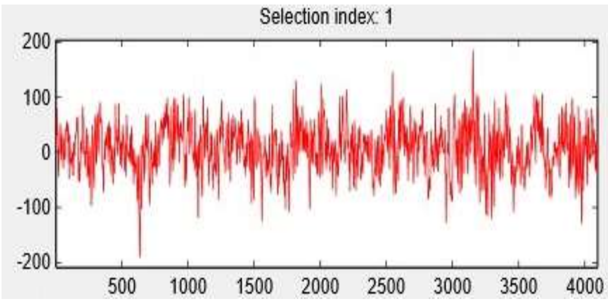


Figure 3.1: (a) Signal Synthesized from DSZ: Representing Healthy Human Subjects with Eyes Opened.

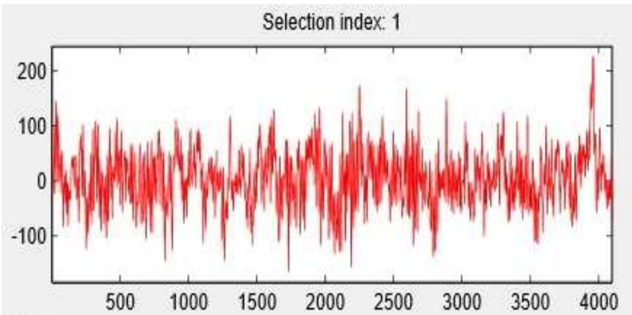


Figure 3.1: (b) Signal Synthesized from DSO: Representing Healthy Human Subjects with Eyes Closed.

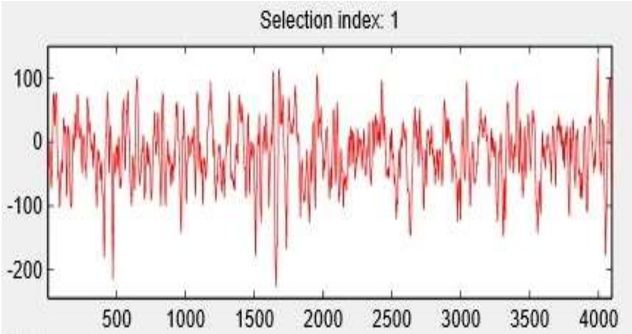


Figure 3.1: (c) Signal Synthesized from DSN: Representing Epileptic Human Subjects in Seizure Free Intervals from Hippocampal Hemisphere of the Brain.

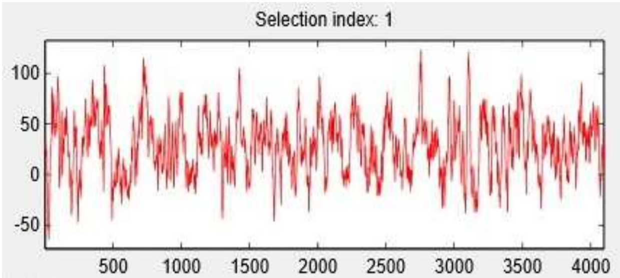


Figure 3.1: (d) Signal Synthesized from DSF: Representing Epileptic Human Subjects in Seizure Free Intervals from the Epileptogenic Zone of the Brain.

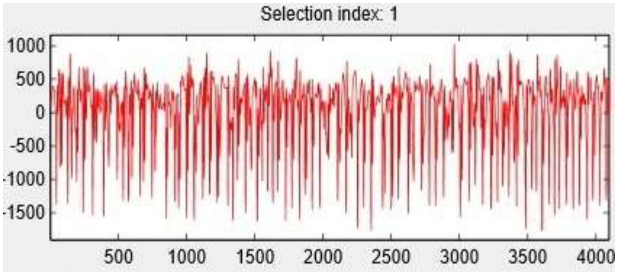


Figure 3.1: (e) Signal Synthesized from DSS: Representing Epileptic Human Subjects in Seizure Activity.

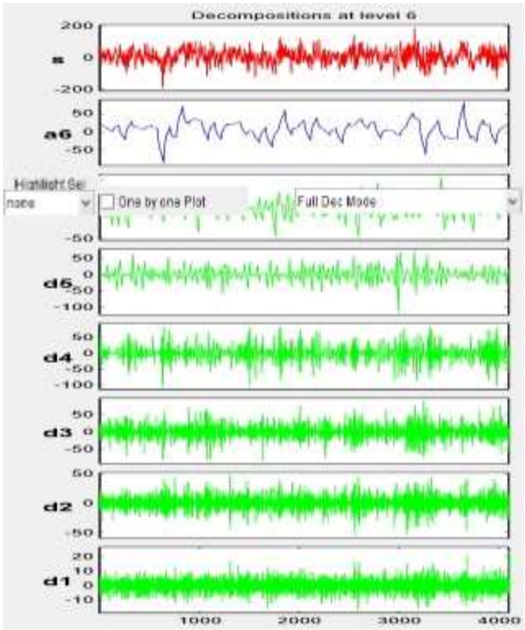
B. EEG Signals Decomposed and Detection of Wave Components

Generally, EEG signals are superimposed and their distinctive formations occur on different time scales at different periods. In this study, the spectral analysis of the EEG signals was done using the discrete wavelet transform (explained in section 2 above). Each signal's decomposition into distinct frequency sub–bands was achieved by successive high-pass and low-pass filtering of the time domain signal. Determination of a choice wavelet that is suitable and the decomposition levels was done because it is an important factor to be considered in the use of DWT for signal analysis.

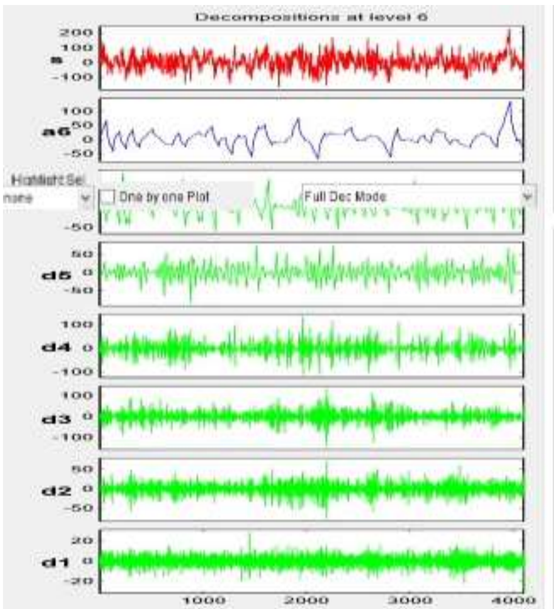
During the decomposition of the EEG signals into frequency sub-bands, the DWT used with Daubechies wavelet was set at order 2, level 6. And the desired number of intervals the coefficients of each frequency sub-band were discretized is displayed in Table 3.1. At this stage of the decomposition, visual inspections were done on the synthesized signals. This is one reason the choice of discrete wavelet transform (DWT) was a good one for the analysis of the EEG signals as the signals were seen to be continuous. The decomposition and filtering process of the detail coefficient of level1was continued until a desired level was attained at level 6for each EEG signal synthesized from the five different human subjects. The approximate coefficients of A1 to A_6 and the detail coefficients of D_1 to D_6 of each EEG signals are illustrated in Figure 3.2 (a to e) respectively:

Table 3.1: Frequencies Corresponding to Different Levels of Decomposition for Daubechies 2 Filter Wavelet.

Decomposed signal	Frequency range (Hz)
D1	43.38 – 86.75
D2	21.69 – 43.38
D3	10.84 – 21.69
D4	5.42 – 10.84
D5	2.71 – 5.42
D6	1.35 – 2.71
A6	0 – 1.35

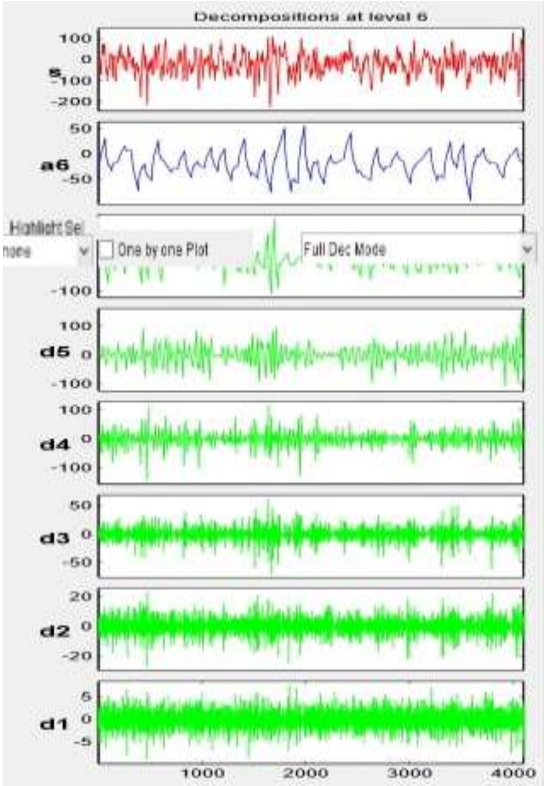


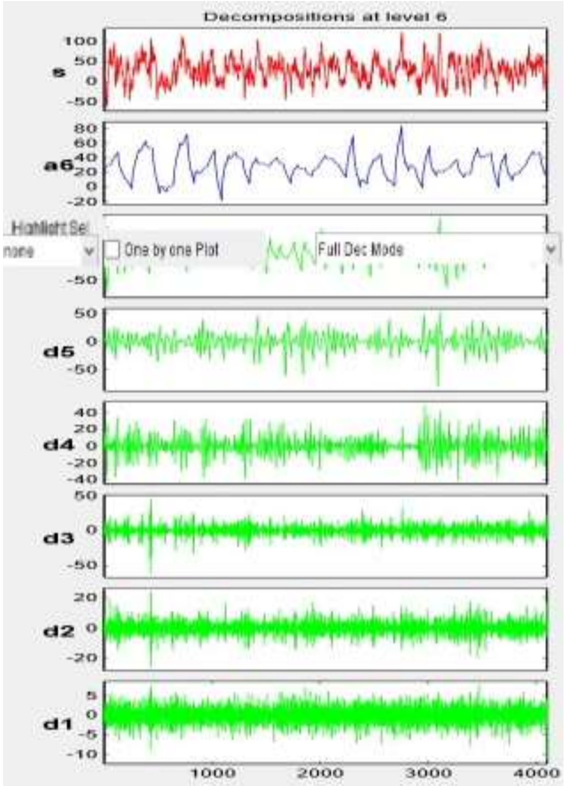
(a)



(b)

Figure 3.2: (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) **(d)**

Figure 3.2: (c) The Approximate and the Detailed Coefficients of EEG Segment from DSN (d) the Approximate and the Detailed Coefficients of EEG Segment from DSF.

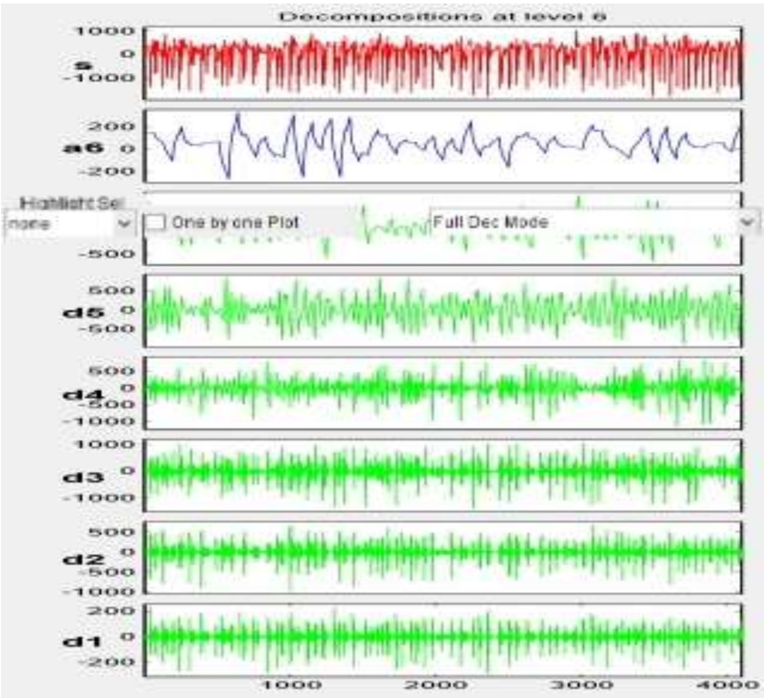


Figure 3.2: (e) The Approximate and the Detailed Coefficients of EEG Segment from DSS.

4. CONCLUSION

Discrete Wavelet Transform (DWT) was the proposed technique for the detection of interictal epileptiform discharge (IED) which is an indication of epileptic seizure in an EEG. Presence of spikes and sharp waves in an EEG indicate IED. And one major advantage of DWT over other technique that can be used for same purpose is that it is very efficient in the computation of non-stationary signals in both time and frequency domains.The wavelet coefficients computed also gave an acceptable representation that reveals the energy distribution of the EEG signals in both time and frequency. Thedetail and the approximation wavelet coefficients of each EEG signal computed shows clearly spikes and sharp waves representing epileptiform activities in the signals.Since the morphology of the decomposed EEG signals sub-bands in the segment of approximation coefficients computed shows the wave's component of the signals clearly, it can be used by medical doctors and other health care professionals in the diagnosis epileptic seizures. Hence, the success of the present study.

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