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Design and Implementation of Brain Signal Detection and Analysis Approach

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Abstract: The brain is the main control of the body and any disorder that occurs in the brain affects the body's vital activity. There are many diseases that infect the brain and effect on brain functions and which affects many people around the world. Brain signals extracted by EEG system are used to diagnose brain signals and classify them as normal or abnormal. The process of detecting and classifying EEG signals are difficult and exhausting process and require effort by the specialist doctor to diagnose them. Brain injury treatment is complicated and require surgical intervention when the injury is severe but when early detection of injury may be treated without surgical intervention. This study will use the EEG signals that have been collected as images. Then these signals will be extracted from these images. At the beginning the background will be removed by thresholding and then extracting the signals by tracking each signal. These signals are then analyzed using DWT for features extraction and using ANN for classification.

Key words: Brain signal, brain disease, signal processing, signal analysis, DWT, ANN, image segmentation

INTRODUCTION

Since 1970, start research within the automated detection of brain disorder and several algorithms are suggested for this issue. Depend these algorithms for automated disclosure of brain abnormalities on the recognizable of diverse patterns like a raise in amplitude, activity of periodic cadence or EEG flattening (Pramanick, 2013). Brain activities can be measured non-invasively by utilizing Electro Encephalo Gram (EEG) or invasively by utilizing Electro Cortico Graphy (ECOG). EEG is important for disease surveillance and cerebral death, to locate the damage area after a head injury. EEG signals recorded by electrodes set on the scalp these electrodes can be read brain signals. Presently, clinical EEG signals analysis can be implemented visually by trained the Electro Encephalo Graphy (trained EEG) to determine and recognize disorders in brain signals. Since, a lot of signals generated by various electrodes, the procedure of brain signals analysis visually is boring and uphill. The techniques of brain signals processing assist to speed up this boring process and permitting to medical vocational to determine brain disorders speedily and precisely. EEG waves analysis is employed in the diagnosis and medication of diverse neurological ailments (Balasubramanian, 2014; Vijila *et al*., 2007). Recently, there has been a rising attention in the techniques of machine learning applications for helping a doctors in the right diagnosis of brain turmoil ailments. The EEG data is utilized to detect sickness and abnormalities of brain. With growing request of brain diseases detection, EEG assists to suit this request in reasonable prices with best clinical and healthcare services (Lima *et al*., 2009; Rashid *et al*., 2015). Through abnormality seizures main changes happen in a patient's brain signal because concurrent voltage activity of the neurons. One of the specific features of the brain signal abnormality is incidence of sharp and spikes waves. The factors taken from brain waves can be utilized as useful diagnostic characteristics for automatic detection of brain turmoil. EEG waves which really are carrying information concerning brain abnormalities are also polluted by the noises such as deeply breathing, eye winking and artifacts of muscle (Joshi *et al*., 2014).

Literature review: There are many literatures used different techniques for detection and analysis brain signals, some of these researches are: Guo *et al*. (2010) used approximate entropy based on Multi Wavelet Transform (MWT) and combines with Artificial Neural Network (ANN) to classify the brain signals. By using multi wavelet transform the signals decompose into multi sub-signals, then extract the approximate entropy feature for each sub-signals this feature used as input to ANN for classification into normal and seizure. Proposal method used four level of MWT.

Bajaj and Pachori (2012) proposed the Empirical Mode Decomposition (EMD) algorithm to decompose the EEG signals into sub-bands signals, the Intrinsic MODE Functions (IMFs) generated by EMD method can be regarded as a set of Amplitude and Frequency Modulated (AM-FM) signals, the IMFs analytic by using Hilbert

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transformation. The frequency bandwidth and amplitude bandwidth computed from IMFs analytic are used as inputs to Least-Squares Support Vector Machine (LS-SVM) for classification.

Kalaivani *et al*. (2014) used Discrete Wavelet Transform (DWT) to decompose the EEG waves into sub-band waves and the feature extraction methods are used to extract the time domain and frequency domain features of the EEG signal. In this proposed genetic algorithm are used to extract the best features by select the pertinent features by removing features with few or no prophetic information and k-means classifier to classify EEG signals.

Gajic *et al*. (2014) discussed wavelet transform and statistical pattern recognition. The proposed system has three stages wavelet transform for feature extraction, scatter matrices for feature space dimension reduction and quadratic classifiers for classification. The extracted features include energy, entropy and standard deviation. The suggested method was applied on EEG databases belong to three sets: healthy set, epileptic set during a seizure-free interval and epileptics set during a seizure.

Kumar *et al*. (2015) proposed a classification system for brain disorders, proposed system is based on segmentation of brain waves using four parallel Gabor filters from particular range of frequencies. Discriminatory characteristics extraction by using from 1D-Local Binary Patterns 1D-LBP. The processed brain wave is separated into smaller pieces and histograms of 1D-LBPs of these pieces are calculate. The features extracted used as inputs to Nearest Neighbor classifier (NN) for classification.

Riaz *et al*. (2016) presented a method for EEG waves classification based on Empirical Mode Decomposition (EMD) for feature extraction. The feature extracted by EMD fed into Support Vector Machine (SVM) for classification, it utilizes a kernel to convert the input signal to a higher dimensional space, this way makes the samples of classification having capability of optimum generalization and therefore is used in a broad range of pattern recognition applications. The precision of the suggested way is used a publicly database which is prepared to handle different problems of classification including the determination of abnormalities patients and seizures detection (Riaz *et al*., 2016).

MATERIALS AND METHODS

This research contains two steps first detecting and extracting the signal, the second step involves preprocessing, extracting the features and classification, Fig. 1 shows block diagram of the works.

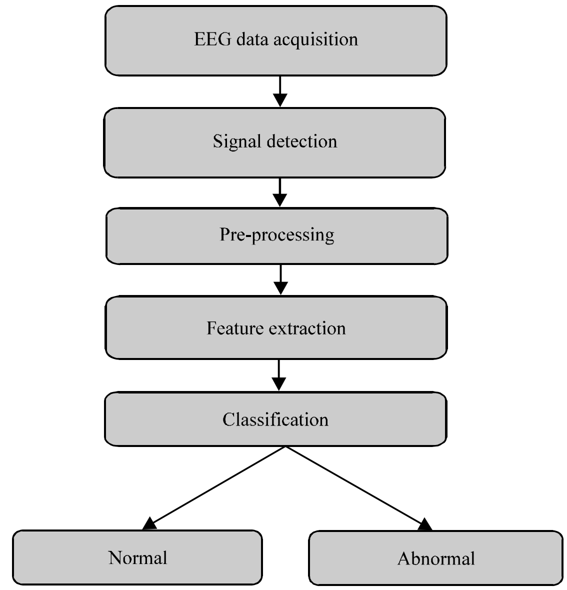

Fig. 1: System block diagram

Table 1: Channels and electrodes names

Channel names	Differential electrodes
Ch1	Fp2-F4
Ch2	F4-C4
Ch3	C4-P4
Ch4	P4-O2
Ch5	Fp2-F8
Ch6	F8-T4
Ch7	T4-T6
Ch8	T6-O2
Ch9	Fp1-F3
Ch10	F3-C3
Ch11	C3-P3
Ch12	P3-O1
Ch13	Fp1-F7
Ch14	F7-T3
Ch15	T3-T5
Ch16	T5-O1

Dataset: The EEG data collected from Medical City Teaching Hospital Baghdad, EEG acquisition systems, Neurophysiology laboratory. The data collected from ten volunteers five healthy and five unhealthy with two state open eyes and closed eyes. Each state contains 16 signals. The data recorded with duration of 30's (Fig. 2). The signals were recorded from 16 different regions of the brain. EEG data recorded by using the international 10/20 EEG system which uses several electrodes placed on the head from the following channels Fp2, F4, C4, P4, Fp2, F8, T4, T6, Fp1, F3, C3, P3, Fp1, F7, T3, T5 (Table 1).

Signal detection

Image segmentation: Image segmentation is one of the most important processes in image processing techniques which segment the images into several regions. There are many algorithms that are used in image segmentation,

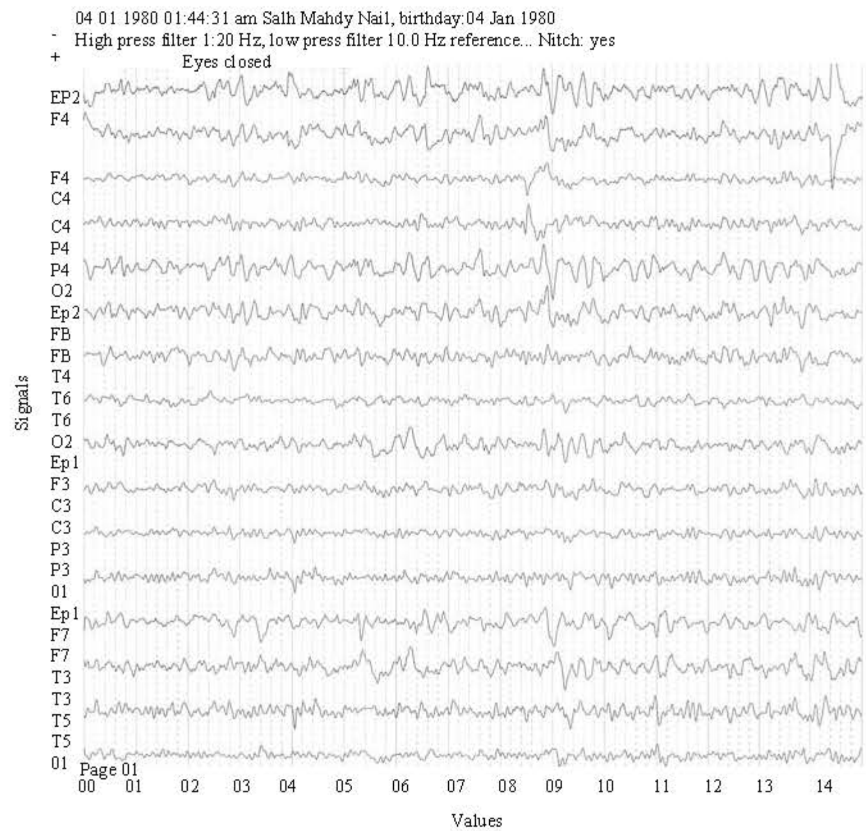

Fig. 2: EEG signals

some of them are based on segmentation into objects. In this research, we will use the threshold for segmentation the image.

Threshold: Threshold is one of the many ways used for segmentation the image. It is helpful for distinguishing objects from the background through choosing appropriate threshold rate, the image is converted from gray image to binary image. This binary image contains the required and important information that is extracted from the original image. One of the advantages of the binary image is that it contains less complex information and simplifies the process of classification and recognition. To convert grayscale image to binary image, choose threshold value and any value higher than the threshold is classified as white (one) and the lower threshold is classified as black (zero) (Al-Amri *et al*., 2010).

By using the threshold we will remove the background and get binary images containing only signals that will be extracted in next step:

$$g(x, y) = \begin{cases} 1 \text{ if } f(x, y) > T \\ 0 \text{ if } f(x, y) \leq T \end{cases} \quad (1)$$

Signal extraction: At this stage we will extract the signals from the images by tracking and reading the black pixels of each signal by taking a certain range of each signal in the image and read them separately to get 16 signals (Fig. 3). The extracted signals are filtered by median filter to smoothing the signal and remove the merged noise with the signal from the image background (Algorithm 1).

Algorithm 1; Signal detection:

```
Input: image
Output: 16 signals
1. read image: imread ('image')
2. convert to grayscale
3. convert image to binary by threshold
  [m n] = size(image)
  for i = 1 to m
      for j = 1:n
         if image(i, j)>threshold
            new image(i, j) = 1
         else new image(i, j) = 0
4. extract the signals
   x = []
   Define range
   c = 1
   for i = 1-16
       x1 = []
       for j = 1 to m
           v = 0
           for k = c to c+range
               if (image(k, j) == 0 and v== 0)
```

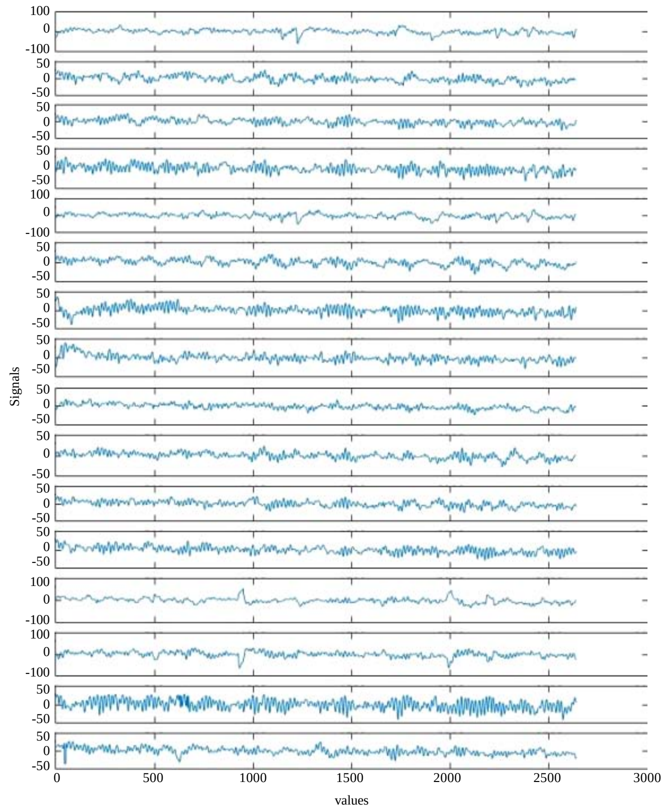

Fig. 3: Signals extracted

```
                location = k-c
                x1 = [x1, location]
                v = 1
            end if
        end
    end
    x = [x, x 1];
    c = c+range
end
return x
5. filtere the signals by median filter
  for i = 1-16
      Signal(i,:) = medfilt1(x(i,:))
  end
  return signal
```

Pre-processing: EEG waves are very noisy and mixed with massive quantity of useless data generated by physiological artifacts that cover the EEG waves, filtering the waves are useful to eliminate this noise and remove unwanted data to obtain filtered signal (Alomari *et al*., 2013). So, all this waves pass to pre-processing to remove noises caused by eye blinking, deep breathing, muscle movements, etc. (Fig. 4). The high frequency removed and filtered by Low Pass Filter (LPF), so, low frequencies will pass, that hold the original EEG signal that contain features and important data about brain activities.

The data pre-processing aim is to enhance the levels of signals of attention whereas attenuating or dismissing undesirable signals in noisy recordings of the signal. Signal processing filters are more helpful while it comes to repressing the high frequencies in the signal, smoothing the signal, decreasing the noise or repressing the low frequencies (Seitz, 2010) (Fig. 5).

Feature extraction: The method for extraction the important features form the signal that contain information about signal to reduce the dimensional size of the signal. The requirement of feature extraction method is to extract right features or verifying what's appropriate data that is used to classify EEG signal (Murugesan and Sukanesh, 2009). The basic characteristics of the signal are immersed in the noise. Therefore, in order to extract the features, the brain signals are analyzed in order to give an accurate description of the energy of the signal as a function of time and frequency domain (Fatehi and Suleiman, 2011).

DWT was used in this research to analyze the signal and feature extraction. DWT hold sufficient information and thus enables the reconstruction of an excellent signal from the coefficients of the wavelet.

DWT decompose EEG signals into multi subands waves delta, theta, alpha, beta and gamma, Fig. 6 shows

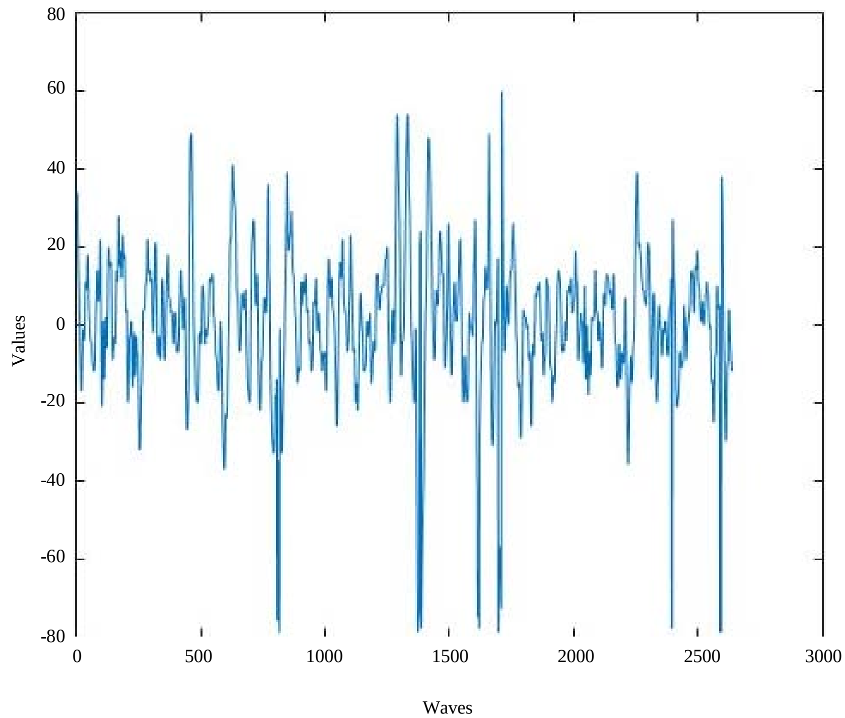

Fig. 4: Original signal

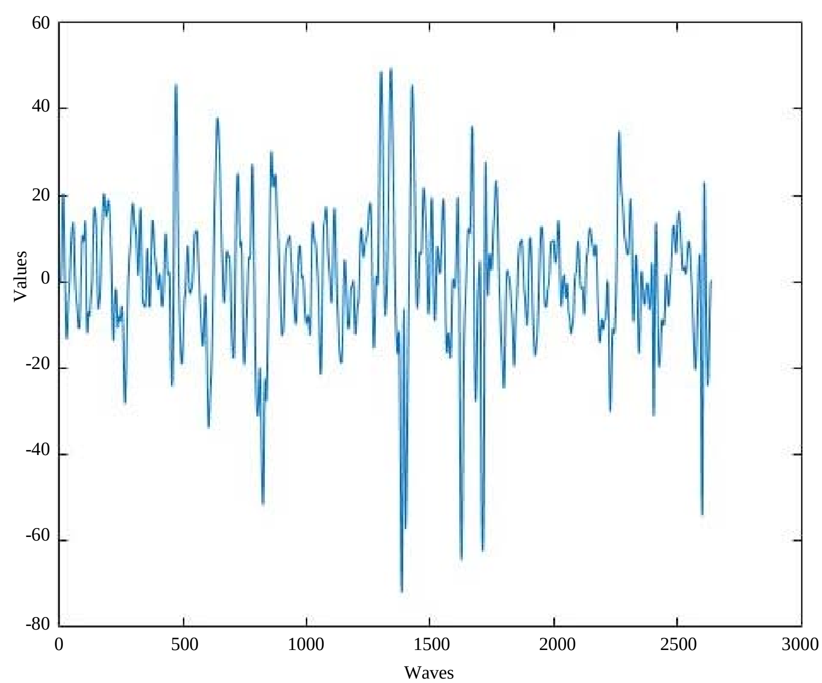

Fig. 5: Filtered signal

5 suband waves for one signal. The frequencies of the EEG waves are: delta wave varies between 0-4 Hz, theta waves between 4-8 Hz, alpha wave frequencies between 8-12 Hz, beta wave frequencies varies from 12-30 Hz and gamma wave have frequencies above 30 Hz (Lima *et al*., 2009).

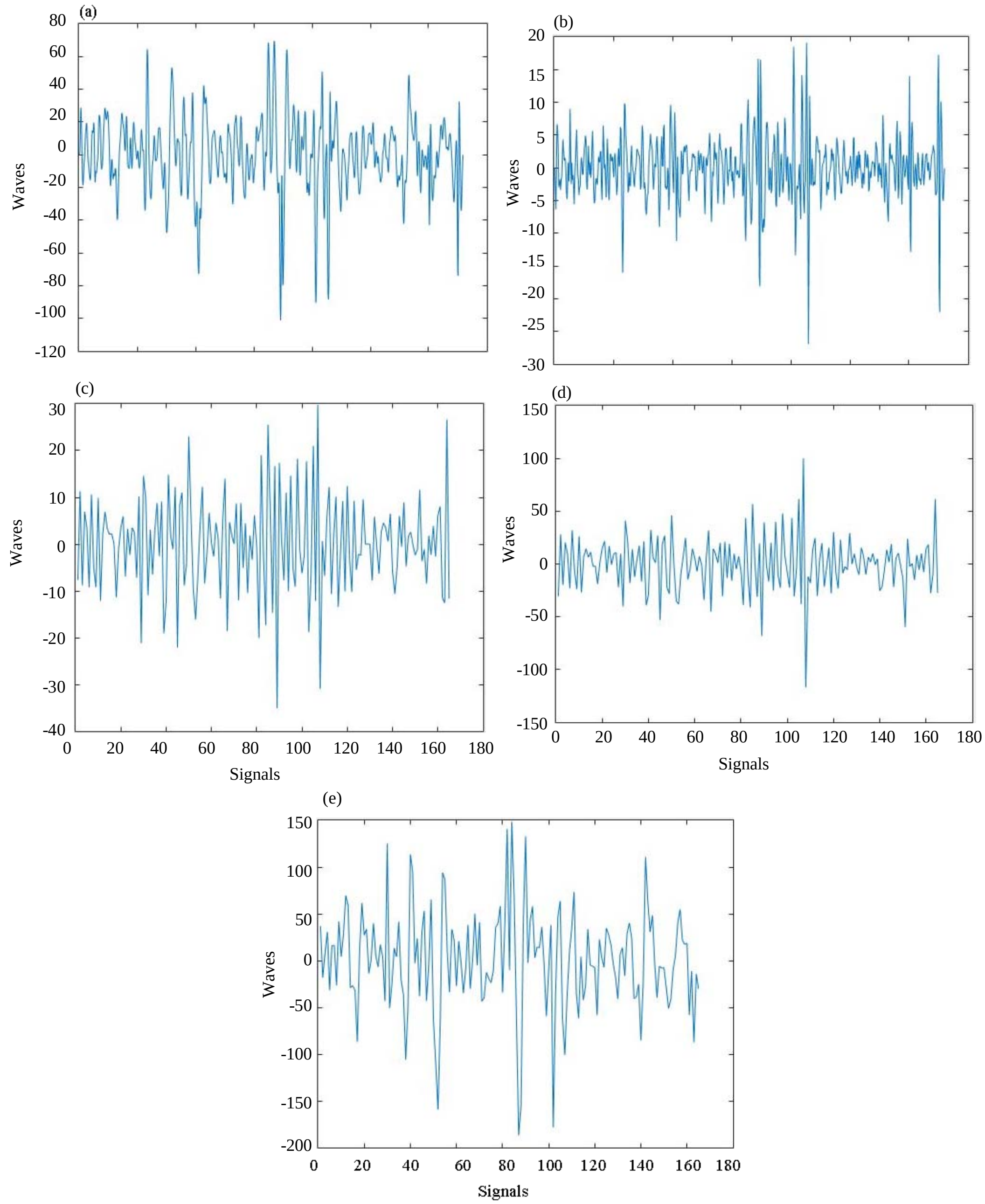

Fig. 6: EEG Subbands: a) Gama wave; b) Beta wave; c) Alpha wave; d) Theta wave and e) Delta wave

Delta rhythmic appear in deep sleep and can be present in the waking case. Theta rhythms were associated with creative revelation and deep thinking. Alpha rhythms appear during relaxation awareness. Beta rhythms are associated with a waking of brain, active attentiveness, active thinking, involved in issues solving, appreciation and decision-making. Gamma rhythms are fastest waves that processes information in different areas of the brain simultaneous (Zulkifli *et al*., 2015):

$$a_i = \frac{(S_i + S_{i+1})}{\sqrt{2}} \quad (2)$$

$$d_i = \frac{(S_i + S_{i+1})}{\sqrt{2}} \quad (3)$$

In this research will use four sub-bands (theta, alpha, beta and gamma) to extract features. The following statistical measurements will be measured for each sub-bands: Mean Absolute Value (MAV), Standard Divation (SD), Band Power (BP), the Difference between Max and Min value (DMM). So, we used 16 features from each signal to train the network:

$$MAV_i = \frac{1}{N}\sum_{n=1}^{N} S_i^2(n) \tag{4}$$

$$SD_i = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(s_i(n)-\mu)^2} \tag{5}$$

where, μ is mean value of the signal:

$$DMM = \max(S)-\min(S) \tag{6}$$

Classification: In this research, we used the feed forward backpropagation neural network to classify signals and distinguish normal signals from abnormal. Levenberg-Marquardt algorithm (LM) was used to train signals and separate them into two groups normal and abnormal. LM is a basic training algorithm to minimize Mean Square Error (MSE) (Fig. 7). It provides quick convergence and it is multi-use, powerful, efficient and easy to execute (Rajaguru and Prabhakar, 2016). The weights are updated by Eq. 7:

$$W_{(n+1)} = W_{(n)} + \alpha\frac{\partial E_{(n)}}{\partial W_{(n)}} + \mu\Delta W_{(n)} \tag{7}$$

Where:
$W_{(n)}$ = Weight at the n iteration,
α = The learning rate

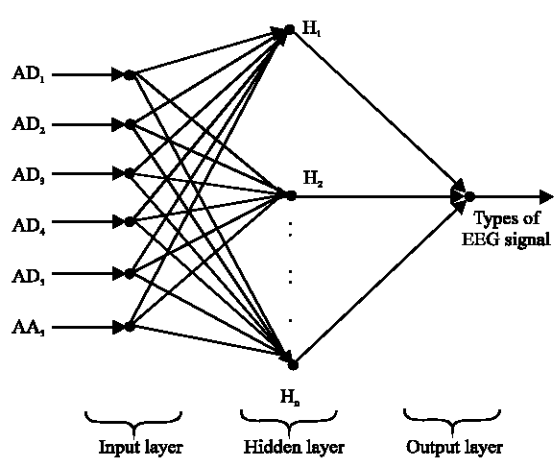

Fig. 7: Neural network structure

$\Delta W_{(n)}$ = The differences in Weight between the n and (n-1) iteration
μ = The constant

Mean square error define as:

$$MSE = \frac{1}{N}\sum_{n=1}^{N}\left(O_{(n)}-T(n)\right)^2 \tag{8}$$

Where:
$O_{(n)}$ = The Observed value at time n
$T_{(n)}$ = The Target value
N = The total No. of observations

Feed forward backpropagation consist of 3 layers input layer, hidden layer and output layer. The input layers consist of 16 neurons and the output layer consist of 2 neurons for two class.

RESULTS AND DISCUSSION

The system was implemented on data consisting of 160 normal signals and 160 abnormal signals to be the total data 320 signals. These data were divided into two groups 160 signals were used for training and 160 others were used for testing. The features used in this study are able to distinguish the differences between signals that leads to a good classification of signals. Table 2 and 3 show features from two state. The neural network used in the proposed system uses these features to train the network and store it in a database. The proposed system is able to recognize abnormalities in the brain with accuracy of 95.6%. The proposed method DWT has been

Table 2: Features from normal data

Waves	MAV	STD	Band power	DMM
Person 1				
Gama	15.3892	23.9472	338.8799	90.2246
Beta	1.4271	2.7885	5.5939	48.0289
Alpha	3.3371	5.4263	18.5103	24.0826
Theta	8.3026	13.5773	118.2330	63.0913
Person 2				
Gama	9.88570	15.6159	146.2839	65.2501
Beta	1.8845	3.0141	5.5126	12.9547
Alpha	3.1618	5.1361	16.2336	22.4028
Theta	9.6321	15.2636	140.9620	58.1858

Table 3: Features from abnormal data

Waves	MAV	STD	Band power	DMM
Person 1				
Gama	26.6838	43.9265	1.2110e+03	198.6287
Beta	4.9156	8.2489	43.8814	47.1178
Alpha	14.0104	22.4938	305.1952	101.3371
Theta	33.0120	53.5926	1.7499e+03	226.5111
Person 2				
Gama	24.6349	39.6423	966.1854	171.4911
Beta	4.5649	7.4534	34.6722	46.0947
Alpha	13.6079	21.8349	288.8075	81.6828
Theta	31.0639	50.2234	1.5227e+03	207.5775

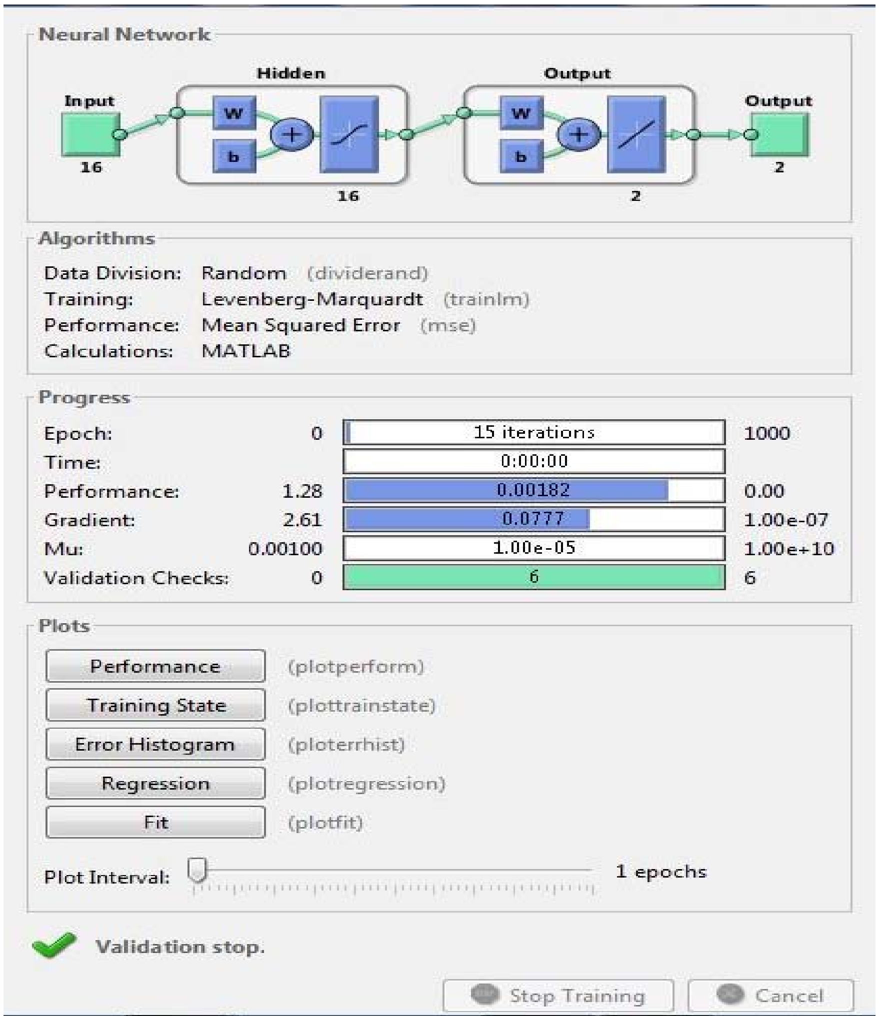

Fig. 8: Neural network training

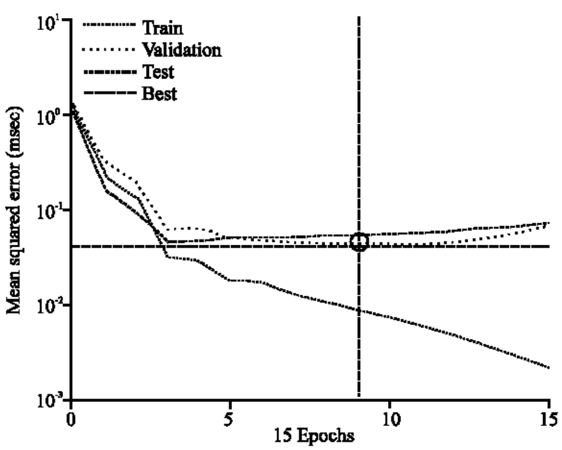

Fig. 9: Training performance (Best validation performance is 0.041047 at Epoch 9)

a practical and useful method for analyzing brain signals and extract the brain rhythms and then extract the features. Six features were extracted from each rhythm. These features were trained and categorized by feed forward backpropagation. The network receives 16 features used as input to ANN. The network consists of the input layer, hidden layer and output layer, consisting of 16 neurons for the input layer and 2 neurons for the output layer (Fig. 8 and 9).

CONCLUSION

The most common way to record neural activity of the brain is EEG recording system. EEG signals are complex signals and contain information about brain functions and neurological turmoils. EEG also plays an important role in detection of stroke, epilepsy, meningitis and brain tumors. Diagnosis of brain signals by encephalographers are very difficult, tedious and requires specialized technicians, this leads to long period of diagnosis and costly expenses. So, brain abnormalities must be detected automatically to provide effort, time and cost reduction. The artificial neural network is able to distinguish and classify brain signals with high accuracy. DWT is applied to analyze the signal and extract the brain rhythms gives a high accuracy of the neural network to classify the signals. The proposed features give high accuracy and efficiency in distinguishing between different situations and detect abnormality in brain.

RECOMMENDATIONS

Therefore, use of DWT with feed forward backpropagation in medical applications gives good results with high accuracy. The proposed system achieved a good accuracy of 95.6%.

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