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WAVELET TRANSFORM BASED NEURAL NETWORK ALGORITHM FOR DETECTION AND CHARACTERIZATION OF SEIZURE ACTIVITIES OF THE BRAIN

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ABSTRACT

In this paper, a wavelet-based neural network (WNN) classifier for recognizing EEG signals is implemented and tested for different sets EEG signals(healthy subjects, patients with epilepsy). First, the Discrete Wavelet Transform (DWT) with the Multi-Resolution Analysis (MRA) is applied to decompose EEG signal at resolution levels of the components of the EEG signal to extract the percentage distribution of energy features of the EEG signal at different resolution levels. Second, the neural network (NN) classifies these extracted features to identify the EEGs type according to the percentage distribution of energy features. The performance of the proposed algorithm has been evaluated using in total four EEG signals. The results showed that the proposed classifier has the ability of recognizing and classifying EEG signals with 99% efficiency.

KEYWORDS: Back Propagation, Classification, EEG, Epilepsy, Energy Distribution, Neural Network, Wavelet Transform

INTRODUCTION

Epilepsy is one of the World's most common neurological diseases. Affecting more than 40 million people worldwide. Epilepsy's symptom, seizures, can have a broad spectrum of debilitating *medical* and social consequences. Although antiepileptic drugs have helped to treat millions of patients, roughly a third of all patients are unresponsive to pharmacological intervention. An area of great interest is the development of devices that incorporate algorithms capable of detecting early onset of seizures or even predicting those hours before they occur. This lead time will allow for new types of interventional treatment. In the near future a patient's seizure may be detected and aborted before physical manifestations begin. Electroencephalogram (EEG) has established itself as an important means of identifying and analyzing epileptic seizure activity in humans. In most cases, identification of the epileptic EEG signal is done manually by skilled professionals, who are small in number. The diagnosis of an abnormal activity of the brain functionality is a vital issue. EEG signals involve a great deal of information about the function of the brain. But classification and evaluation of these signals are limited. Since there is no definite criterion evaluated by the experts, visual analysis of EEG is reviewed in time domain may be insufficient. Traditional method, the entire EEG is reviewed by a trained technician, is inefficient and time consuming. However, an automatic method for EEG analysis can provide an attractive alternative to visual analysis procedures, and offer several advantages over visual scoring.

Routine clinical diagnosis needs to analysis of EEG signals. Therefore, some automation and computer techniques have been used. Recent applications of the wavelet transform (WT) and neural network (NN) to engineering-medical problems can be found in several studies that refer primarily on the signal processing and classification in different medical area. WT applied for EEG signal analyses and WNN applied for classification of EEG signals is not a new concept. Discrete Wavelet Transform (DWT) with the Multi-Resolution Analysis (MRA) is applied to decompose EEG signal at resolution levels of the components of the EEG signal. The neural network(NN) classifies these extracted features to identify the EEGs type according to the percentage distribution of energy features[10].

Research Objective

The objective is to analyze the human normal and abnormal EEG signals using signal processing tools and classify them into different classes. To achieve this,

- Features are extracted based on area under the spectrum,
- Signals are classified with the help of Artificial Neural Network classifier.

Extracting the frequencies and amplitudes of an EEG is not enough to represent the characteristics of the signals. These methods not only made comparison of signals which have different bandwidths difficult, but also make comparison within subject groups difficult as these measures differ from person to person. In order to overcome these drawbacks, time frequency/scale based on wavelet transforms were proposed to analyze EEG data for detecting epileptic events. The major objective is to detect the interesting events from the EEG recordings automatically by using wavelet transform, especially epileptic events. We firstly use Daubechies(db4) wavelet to decompose an example with an epileptic seizure. The major changes of two different activities are found in the high level (high frequency band), however, only small energy changes in the low level(high frequency band). Comparing to the segment of the background activity with one of the epileptiform activity, it is clear that the energy of EEG is redistributed. Thereby, the selection of wavelet function lead to some differences if possible [8].

Traditional method, the entire EEG is reviewed by a trained technician, is inefficient and time-consuming. However, an automatic method for EEG analysis can provide an attractive alternative to visual analysis procedures, and offer several advantages over visual scoring. The automatic method cannot only result in considerable saving by highlighting likely areas of interest, but also make sure that nothing of importance is missed only allowing recordings to be reviewed much more quickly, meanwhile more patients can be treated in the time available. Some automatic methods have been proposed to detect epileptic seizures in EEG. Linear methods nonlinear methods, computational intelligence, Information theory. Although effective in identifying seizures, these methods can produce a high rate of false positives. Therefore, developing some new methods seems to be necessary for analysis of EEG signals with the epileptic seizures. An automatic method based on wavelet transform for the EEG analysis is developed. Some interest segments can be extracted and sent to an expert for review if an epileptic event occurs. Firstly, the clinical data and difference between the background activity and epileptiform activities based on wavelet decomposition are presented. Secondly wavelet analysis approach are addressed.

Statement of the Problem

Traditional method of analysis of the EEG is based on visually analyzing the EEG activity using strip charts. This is laborious and time consuming task which requires skilled interpreters, who by the nature of the task are prone subjective judgment and error. Furthermore, manual analysis of the temporal EEG trace often fails to detect and uncover subtle features within the EEG which may contain significant information. Hence many researchers are working to develop an automated tool which easily analysis the EEG signal and revel important information present in the signal.

Proposed Methodology

The proposed method uses DWT and ANN to classify the EEG signal for epilepsy detection. The clinical interest in (EEG) are; for example, sleep pattern analysis, cognitive tasks registration, seizure and epilepsy detection, and other states of the brain, both normal and patho-physiological. Epilepsy is the second most prevalent neurological disorder in humans after stroke. It is characterized by recurring seizures in which abnormal electrical activity in the brain causes altered perception or behavior. Well known causes of epilepsy may include: genetic disorders, traumatic brain injury, metabolic disturbances, alcohol or drug abuse, brain tumor, stroke, infection, and cortical malformations(sysplasia). The EEG signal contains a several spectral components. The amplitude of a human surface EEG signal is in the range of 10 to 100 µV. The frequency range of the EEG has fuzzy lower and upper limit, but the most important frequencies from the physiological viewpoint lie in the range of o.1 to 30 Hz. The standard EEG clinical bands are the delta(0.1) to 3.5Hz), theta(4 to 7.5Hz), alpha (8 to 13 Hz), and beta (14 to 30 Hz) bands(1). EEG signals with frequencies greater than 30 Hz are called gamma waves. The data consists of five groups, EEG signals both in normal subjects and epileptic patients. Each EEG segments sampled at a sampling rate of fs=3000Hz. Set a consisted of segments taken from surface EEG recordings that were obtained from three healthy volunteers using a standardized electrode placement. Set B only contained epileptic activity.

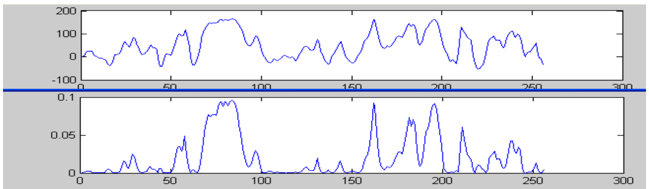

Figure 1: EEG Signal and its Energy

The object of wavelet analysis is to decompose signals into several frequency bands. Selection of appropriate wavelet and the number of decomposition levels are very important for the analysis of signals using DWT. The number of decomposition levels is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal are retained that correlate well with the frequencies necessary for classification of the signal are retained in the wavelet coefficients. Daubechies 4 (db4) is selected because its smoothing feature was suitable for detecting changes of the EEG signals. Daubechies wavelets are the most popular wavelets representing foundations of wavelet signal processing, and are used in numerous applications. The signals were decomposed into details D1-D5 and one final approximation A5.

Classification of EEG signals requires the use of pattern recognition techniques. Pattern recognition is a process of perceiving a pattern of a given object based on the knowledge already possessed [7]. So automated pattern recognition uses various artificial intelligence techniques like fuzzy logic (FL), artificial neural networks (ANN) and adaptive fuzzy logic (AFL) for the classification of disturbance signals. Recently, techniques based on probabilistic models like Hidden Markov models, Dynamic time wrapping, Dempster-Shafer theory of evidence are also proposed.

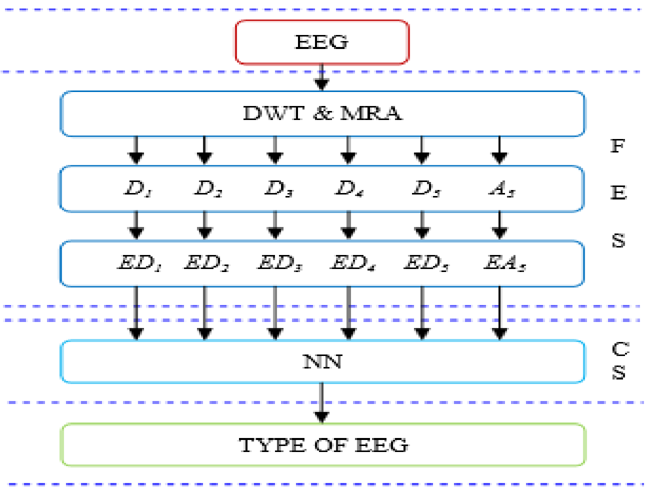

Figure 2: Block Diagram for Classification of EEG Signals

An algorithm block diagram for classification of EEG signals is presented on Figure 1. The algorithm structure is based on two stages: feature extraction stage (FES) and classification stage(CS). The input of the CS is a preprocessed signal. In this case, EEG signal in the time domain is transformed into the wavelet domain before applying as input to the (CS). Feature extraction is the key for pattern recognition. A feature extractor should reduce the pattern vector (i.e., the original waveform) to a lower dimension, which contains most of the useful information from the original vector. In this algorithm, after realizing the FES (preprocessing), using detail and approximation coefficients in each decomposition level obtained from WT and MRA, the CS (processing) is implemented by using neural network (NN). NN are good at tasks such as pattern-matching and classification.

In the classification stage, the proposed wavelet energy distribution features are applied as input to NN.NN is a powerful pattern recognition tool. It is defined as software algorithms that exist between input and output data, including nonlinear relationships. Feed-Forward Neural Network (FFNN) is used to classify different EEG signals. The basic unit of a NN is the neuron, which realizes a function of weighted summation. A FFNN structure can be considered as an algebraic operator, such as weighted summation and multiplication. So, it is possible to reconstruct a wide class of algorithms by using multiplier module.

Resources Used

- **Hardware Resources**

  High end computing system with required software

- **Software Resources**

  MATLAB R2010a

METHODOLOGY

Discreet Wavelet Transform and Multi Resolution Analysis

One drawback of the CWT is that the representation of the signal is often redundant, since a and b are continuous over R (the real number). The original signal can be completely reconstructed by a sample version of Wf(b,a). Typically, we sample Wf(b,a) i.e

A=2^{-m} and b= $n2^{-m}$ m,n εZ and Z is the set of positive integers.

DWTψf(m,n)=$\int_{-\infty}^{\infty} f(t)\psi m,n(t)dt$

Ψm,n(t)=$2^{-m}\psi(2^{m}\, t-n)$ is the dilated and translated version of the mother wavelet ψ(t).

The family of dilated mother wavelets of selected a and b constitute an orthonormal basis of

L^2(R). In addition, we sample Wf (b,a). in dyadic grid, this wavelet transform is also called dyadic-orthonormal wavelet transform. Due to the orthonormal properties, there is no information redundancy in the discrete wavelet transform[16]. In addition, with this choice of a and b, there exists the multiresolution analysis (MRA) algorithm, which decompose a signal into scales with different time and frequency resolution. MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies.

The fundamental concept involved in MRA is to find the average features and the details of the signal via scalar products with scaling signals and wavelets. In the PD signals we have seen, sharp spikes are observed when PD occurs. The spikes are typically of high frequency and we are able to discriminate the PD spikes with other noises through the decomposition of MRA into different levels.

The differences between different mother wavelet functions (e.g.Haar, Daubechies, Coiflets, Symlet, Biorthogonal and etc.) consist in how these scaling signals and the wavelets are defined. The choice of wavelet determines the final waveform shape; likewise, for Fourier transform, the decomposed waveforms are always sinusoid. To have a unique reconstructed signal from wavelet transform, we need to select the orthogonal wavelets to perform the transforms.

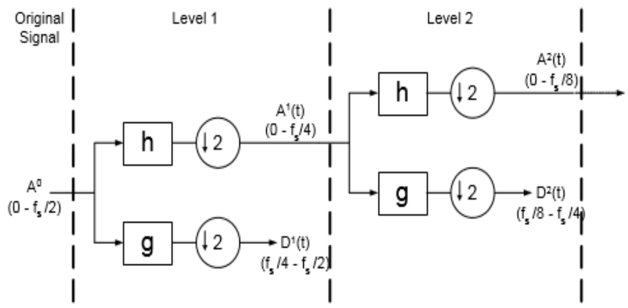

Figure 3: Multi-Resolution Wavelet Decomposition

Daubechies Wavelets

Ingrid Daubechies [Dau 92] developed the so-called compactly supported orthonormal wavelets, thus making discrete wavelet analysis practicable[28]. Daubechies' wavelets are also known as extemal phase wavelets due to the properties of their transfer function, since they produce a minimum delay filter. The wavelets of the Daubechies family are usually referred to as dbN, where N is the order, and db the "surname" of the wavelet. The db1 wavelet, as mentioned above, is the same as the Haarwavelet. Figure 4 shows on the top the db4 (middle) and db8 (right) wavelet functions.

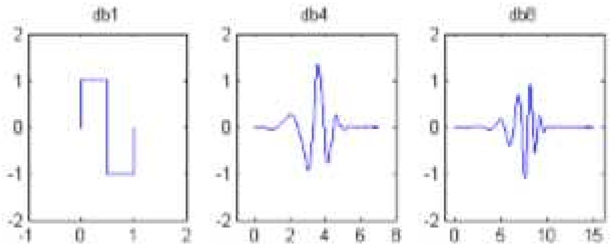

Figure 4: Daubechies Wavelet Function

Artificial Neural Network

Neural Networks (NN) are highly interconnected and simple processing units which is designed to model the way human brain performs a particular task. Each unit is called a neuron. It forms a weighted sum of its inputs and a constant term called bias is added. This sum is passed through a transfer function such as linear, sigmoid or hyperbolic tangent. In the construction of neural architecture, the choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems/ In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions.

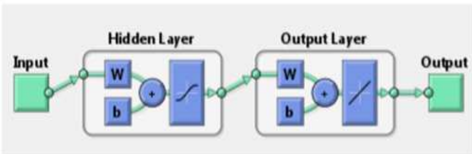

Figure 5: Neural Network

Architecture

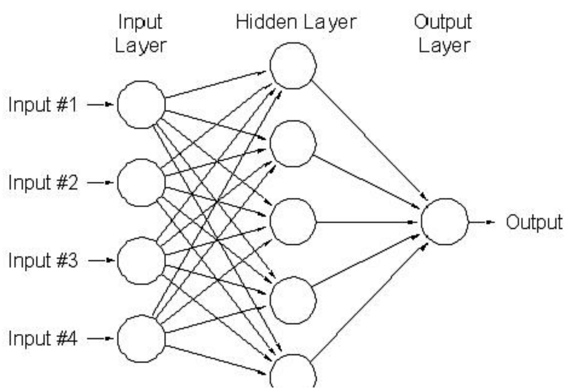

Figure 6: Simple Neuron Architecture

It is made up from an input, output and one or more hidden layers. Each node from input layer is connected to a node from hidden layer and every node from hidden layer is connected to a node in output layer. There is usually some weight associated with every connection. Input layer represents the raw information that is fed into the network. This part of network is never changing its values. Every single input to the network is duplicated and send down to the nodes in hidden layer. Hidden layer accepts data from the input layer. It uses input values and modifies them using some weight value, this new value is than send to the output layer but it will also be modified by some weight value, this new value is than send to the output layer but it will also be modified by some weight from connection between hidden and output layer. Output process information received from the hidden layer and produces an output. This output is than processed by activation function.

Back Propagation (BP) Algorithm

One of the most popular NN algorithm is back propagation algorithm. BP algorithm could be broken down to four main steps. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the necessary corrections. The algorithm can be decomposed in the following four steps:

- Feed-forward computation
- Back propagation to the output layer
- Back propagation to the hidden layer
- Weight updates

The algorithm is stopped when the value of the error function has become sufficiently small.

ENERGY DISTRIBUTION OF EEG SIGNALS AND CLASSIFICATION RESULTS

Using MRA and Db4 wavelet function the two sets of the EEG signals (A set of EEG signals of the healthy patient, and B set EEG signals of the epilepsy patient during the seizure) was performed according to the percentage energy distribution of decomposition levels.

Unlike the distribution of EEG signals of healthy subjects, the energy distribution of the signal of patients with epilepsy syndrome is obviously different

The percentage of energy distribution can be used for classification of EEG signals.

NN are highly interconnected simple processing units designed in a way to model how the human brain performs a particular task. Each of those units, also called neurons, forms a weighted sum of its inputs, to which a constant term called bias is added. This sum is then passed through a transfer function: linear, sigmoid or hyperbolic tangent. The choice of number of hidden layers and the number of neurons in each layer is one of the most critical problems in the construction of neural architecture. In order to find the optimal network architecture, several combinations should be evaluated. These combinations include networks with different number of hidden layers, different number of units in each layer and different types of transfer functions. The FFNN model was provided in Matlab.

Based on the feature extraction for training and testing data were constructed. The dimensions here describe different features resulting from the wavelet transform. Considering the classification performance of this method, this input vector is applied as the input to the WNN structure.

Simulation Output

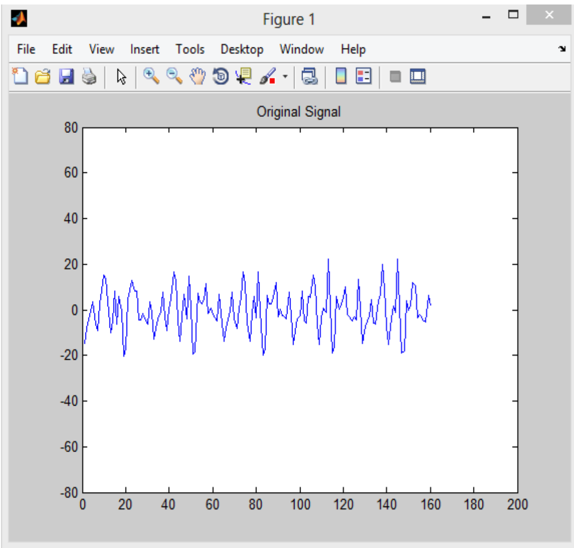

Figure 7: Output of Wavelet Transform

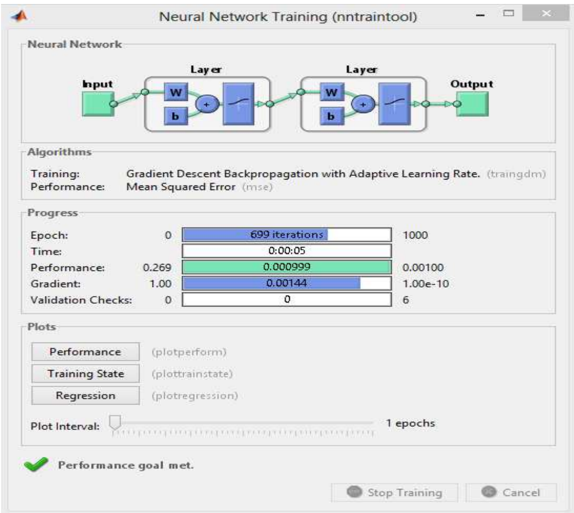

Figure 8: Neural Network Training Output

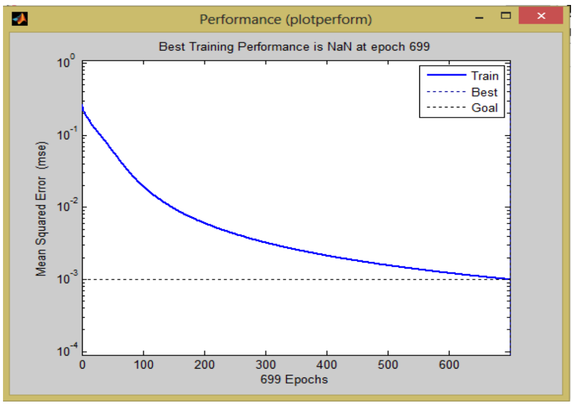

Figure 9: Performance Graph

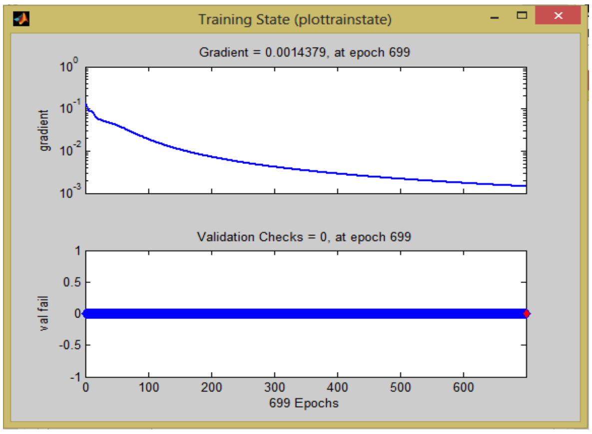

Figure 10: Training State Plot

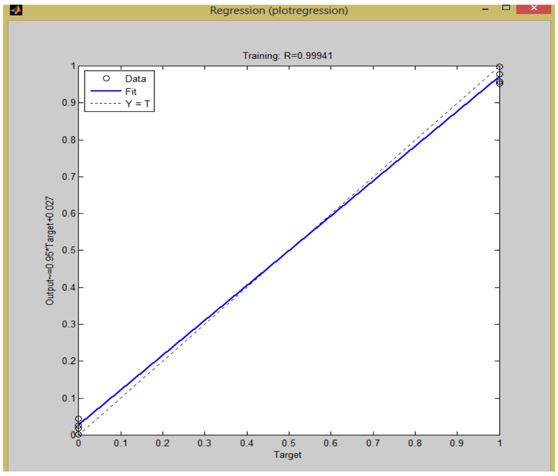

Figure 11: Plot of Regression

They were selected to obtain best performance, after several different experiments, such as the number of hidden layers, the size of the hidden layers, value of the moment constant and learning rate, and type of the activation functions.

The proposed method classifies normal and abnormal EEG signals efficiently with a regression of 99.9%

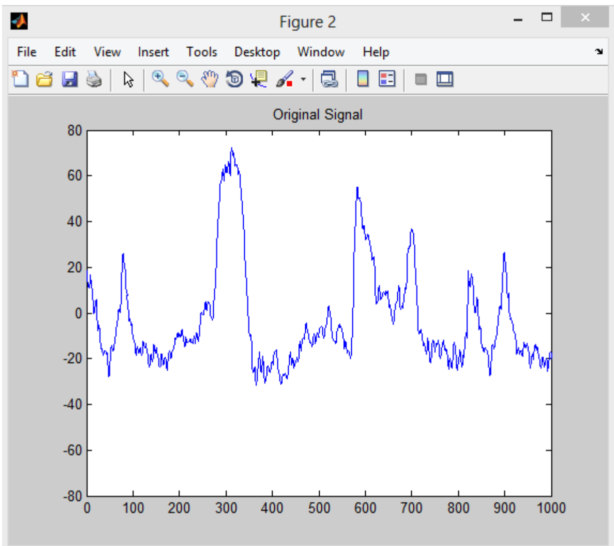

Figure 12: Input EEG Signal

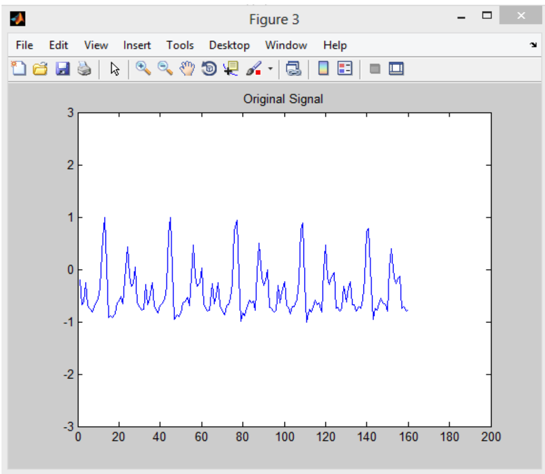

Figure 13: Output of Classifier

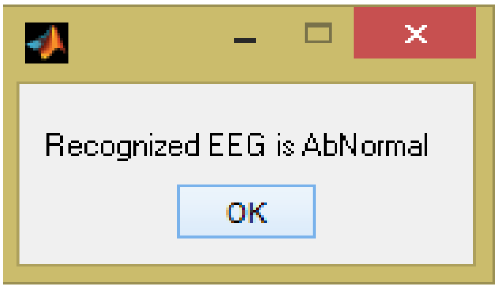

Figure 14: EEG Signal Recognition Output

CONCLUSIONS

Epileptic seizures are manifestations of epilepsy. The detection of epileptiform discharges in the EEG is an important component in the diagnosis of epilepsy. As EEG signals are non-stationary, the conventional method of frequency analysis is not highly successful in diagnostic classification. In this paper, an algorithm for classification of EEG signal based on WT has been proposed. DWT with the MRA is applied to decompose EEG signal at resolution levels of the components of the EEG signal and to extract the percentage distribution of energy features of the EEG signal at different resolution levels. The FFNN classifies these extracted features to identify the EEGs type according to the percentage distribution of energy features. The results showed that the proposed classifier has the ability of recognizing and classifying EEG signals with 99% efficiency. The most important advantage of the proposed method is the reduction of data size as well indicating and recognizing the main characteristics of signal. Furthermore, it can reduce memory space, shorten pre-processing needs, the network size and increase computation speed for the classification of an EEG signal.

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