Epilepsy Disorder Detection from EEG Signal

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Abstract: In this novel paper we propose a technique of detecting epilepsy disorder from Electroencephalogram (EEG) signals using discrete wavelet transform (DWT) and neural network. EEG signal is a technique for identifying neurological disorders. There are various neurological disorders like Epilepsy, brain cancer, etc. Epilepsy is one of the common neurological disorders and EEG is one of the ways of identifying and analyzing epileptic seizure activity in human brain. In the most cases, the skilled professionals identification of the epileptic EEG signal is manually. In this paper, we proposed the automatic detection process of identifying that the patients carrying epilepsy disorder or not. To make the process for automatic detection, we used wavelet transform for feature extraction and to generate statistical parameters from the decomposed wavelet coefficients. A feed-forward neural network (ANN) algorithm is used for the classification to make the automatic detection process. This paper also provides epilepsy disorder with great accuracy and Average specificity of 99.19%, sensitivity of 91.29% and selectivity of 91.14% are obtained

Keywords: Electroencephalogram (EEG), Discrete wavelet transform (DWT), artificial neural network (ANN), epilepsy, seizure.

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1 Introduction

EEG involves recording and analysis of electrical signals generated by the brain. It is an important clinical tool for diagnosing and monitoring of neurological disorders related to epilepsy. Epilepsy is characterized by sudden recurrent and transient disturbances of mental functions and/or movement of the body that results from excessive discharging of groups of brain cells. Epileptic EEG from the scalp is characterized by high-amplitude and synchronized periodic waveforms [1]. In between seizures, spikes and sharp waves are typically observed. The detection and classification of these activities by visual screening of the recorded EEG is a complex and time consuming operation and requires highly skilled doctors, who are in great demand. This translates to longer diagnosis time, increase in medical expenditure and consequent delay in necessary treatment. In many cases, epilepsy can be controlled purely by medication. In some other cases, surgical removal of the epileptic part of the brain may be carried out. Newer methods where parts of the brain are electrically stimulated to avoid the onset of seizure are being developed. Automatic detection of seizures forms an integral part of such methods. Therefore there exists a strong need to automate this process.

Most of the work in automatic EEG processing falls into two broad categories—seizure detection and seizure prediction. Artificial neural networks for the automatic detection of epileptic form events in EEG signals and compared back-propagation multi-layer perceptron, radial basis function network trained by a hybrid method and a support vector method as candidate classifier tools [1].

A fractal dimension algorithm was used in EEG analysis [7]. An association rule approach has been used for the classification of EEG signals [8], and the auto-SLEX method has been used for preseizure detection of epilepsy in EEG [9]. An overview of the application of signal processing methodologies based on the theory of non-linear dynamics and chaos theory to the problem of seizure prediction is presented [10] .The modern techniques applied to EEG for seizure detection[11-13]. The relative phase clustering index (rPCI) to predict epileptic seizure through EEG signals [14]. Litt and co-workers [15] have presented a scheme for quantifying seizure precursors and coupling these measures to brain stimulation for aborting seizures. Sensitivity as high as 90.47% [16] has also been achieved by him in predicting seizures. Reeves and Taylor [17] have used genetic algorithm to choose training sets for neural networks employing radial basis function, to obtain good generalization performance. His networks were trained to solve the XOR problem.

For the purpose of this research, we define the term “the diagnosis of epilepsy” as the determination of whether a person is epileptic or non-epileptic [6]. In majority of the cases, the onset of the seizures cannot be predicted in a short period, a continuous recording of the EEG is required to detect epilepsy. The approach of using automatic seizure recognition/detection algorithms would still require the recording of clinical seizures. Therefore, very long continuous EEG recording, preferably with synchronized video for several days or weeks, are needed to capture the seizures.

In this paper we proposed the observation that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands: delta (δ) (< 4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–13 Hz) and beta (β) (13–30 Hz).

2. Methodology

The wavelet transform (WT) introduces a useful representation of a function in the time-frequency domain [18- 21]. Basically, a wavelet is a function $\psi \in L^2(R)$ with a zero average

$$\int_{-\infty}^{\infty} \psi(t)dt = 0$$

The Continuous Wavelet Transformation (CWT) of a signal $x(t)$ is defined as

$$CWT_{\psi} x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt$$

where $\psi(t)$ is called the mother wavelet, the asterisk denotes complex conjugate, while *a* and *b* (*a*, *b* $\in R$) are scaling (dilation and translation) parameters, respectively. The scale parameter *a* determines the oscillatory frequency and the length of the wavelet, and the translation parameter *b* determines its shifting position. The application of WT in engineering areas usually requires the discrete WT (DWT). The DWT is defined by using discrete values of the scaling parameter *a* and the translation parameter *b* . To do so, set $a = a_0^m$ and $b = nb_0 a_0^m$, then we get $\psi_{m,n}(t) = a_0^{-m/2}\psi(a_0^{-m}t - nb_0)$, where *m*, *n* $\in Z$, and *m* is indicating frequency localization and *n* is indicating time localization. Generally, we can choose $a_0 = 2$ and $b_0 = 1$. This choice will define a dyadic-orthonormal WT and provide the basis for multi-resolution analysis (MRA). In MRA, any time series $x(t)$ can be completely decomposed in terms of approximations, provided by scaling functions $\phi_m(t)$ (also called father wavelet) and the details, provided by the wavelets $\psi_m(t)$. The scaling function is associated with the low-pass filters (LPF), and the wavelet function is associated with the high-pass filters (HPF). The decomposition procedure starts by passing a signal through these filters. The approximations are the low-frequency components of the time series and the details are the high-frequency components. The signal is passed through a HPF and a LPF. Then, the outputs from both filters are decimated by 2 to obtain the detail coefficients and the approximation

coefficients at level 1 (A1 and D1). The approximation coefficients are then sent to the second stage to repeat the procedure. Finally, the signal is decomposed at the expected level.
According to Parseval's theorem, the energy of the distorted signal can be partitioned at different resolution levels. Mathematically this can be presented as:

$$ED_i = \sum_{j=1}^{n} \left|D_{ij}\right|^2, i = 1,2..l$$

$$EA_l = \sum_{j=1}^{n} \left|A_{lj}\right|^2$$

Where $i = 1,2..l$ the wavelet decomposition level from level 1 to level l. *is* n is the number of the coefficients of detail or approximate at each decomposition level. ED_i is the energy of the detail at decomposition level *i* and EA_l is the energy of the approximate at decomposition level *l*.

3. Back Propagation Network

The back propagation algorithm is a feed forward neural network architecture. In this architecture, nodes are partitioned into layers numbered 0 to n, where the layer number indicates the distance of a node from the input nodes. The lowermost layer is the input layer numbered as layer 0, and the topmost layer is the output layer numbered as layer n. Back propagation addresses networks for which n > 2, containing "Hidden layers" numbered 1 to n- 1. Hidden nodes do not directly receive inputs from nor send outputs to the external environment. For convenience of presentation, we will assume that n = 2 in describing the back propagation algorithm, implying that there is only one hidden layer, as shown in figure. The algorithm can be extended easily to cases when n >2. The presentation of the algorithm also assumes that the network is strictly feed forward, i.e., only nodes in adjacent layers are directly connected; this assumption can also be done away with. Input layer nodes merely transmit input values to the hidden layer nodes, and do not perform any computation. The number of input nodes equals the dimensionality of input patterns, and the number of nodes in the output layer is dictated by the problem under consideration. For instance, if the task is to approximate a function mapping p-dimensional input vectors to q-dimensional output vectors, the network contains p input nodes and q output nodes. An additional "dummy" input node with constant input (= 1) is also often used so that the bias or threshold term can be treated just like other weights in the network. The number of nodes in the hidden layer is up to the discretion of the network designer and generally depends on problem complexity. Each hidden node and output node applies a sigmoid function to its net input [22].

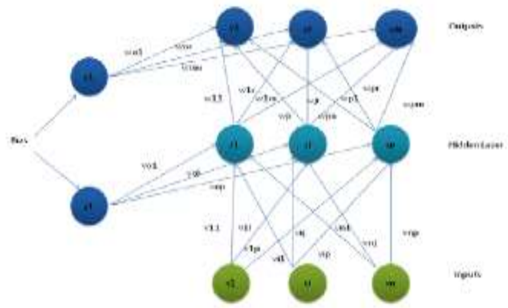

Figure 1. Architecture of Backpropogation

3.1. Back Propagation Algorithm

1. Initialize instances i=1.
2. Supply the input components for the ith instance to the input of the neural network and make a forward pass and compute the outputs.
3. Compute the error vector E_i at the output layer by taking the component wise difference of the target vector and the computed output vector $E_{ij} = T_{ij} - O_{ij}, \forall j$, where denotes the jth components of the ith vector, target vector and output vector respectively.
4. Repeat steps 2 and 3 for i=1to n

5. Determine root mean square(RMS) value of error, denotes by ERROR, whose jth component is given by $(ERROR)_j = \left[\sum_{i=1}^{n} E_{ij}^{\ 2} \Big/ n \right]^{1/2}$
6. Back –propagate the error from the RMS value of error components of the last layer to the preceeding layers and adapt the weights of the network layerwise starting with the last layer.
7. Repeat steps 2-6 until $\sum_{\forall j} (ERROR)_j^{\ 2}$ is sufficiently small.

4. Proposed Model

The proposed model is consisting of following modules is presented in the flowchart in Figure 2. Two sets of EEG data [16] of normal and epileptic subjects from 18 subjects is used. 10 subjects normal and epileptic EEG data is used for training and remaining was used for testing. The depth electrodes are placed symmetrically into the hippocampus formations and strip electrodes are placed onto the lateral and basal regions of the neocortex. The epileptic EEG segments are selected from all the recording sites exhibiting ictal activity[34].

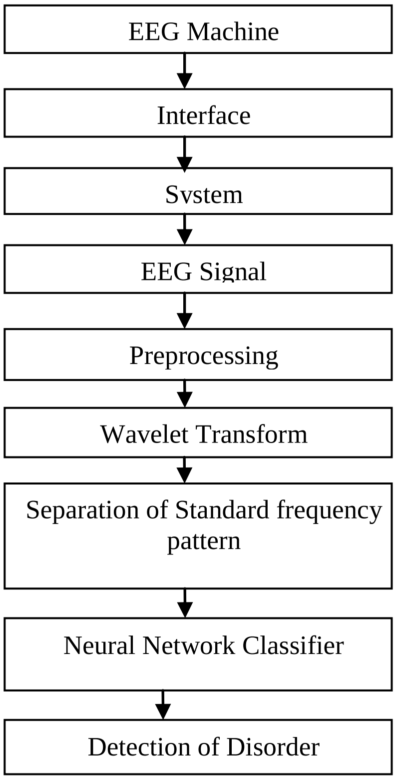

Figure 2: Proposed Model for Epileptic Disorder Detection

5. Experiment and Simulation Result

EEG Signals are obtained from the hospitals as shown below. These signals are in .eeg format which are not supported by the MATLAB software and converted EEG signal in .eeg format to .xls format for processing in MATLAB software.

The performance is evaluated in terms of the three parameters i.e., Sensitivity (**SE**), Specificity (**SP**) and Overall Accuracy (**OA**) is defined as:

$$SE = \frac{TN_{CP}}{TN_{AP}} \times 100$$

Where **TNCP** depicts the total number of correctly detected positive patterns and TNAP represents the total number of actual positive patterns. A positive pattern indicates a detected seizure

$$SP(\%) = \frac{TN_{CN}}{TN_{AN}} \times 100$$

Where **TNCN** represents the total number of correctly detected negative patterns and **TNAN** represents the total number of actual negative patterns. A negative pattern indicates a detected nonseizure.

$$OA(\%) = \frac{TN_{CDP}}{TN_{APP}} \times 100$$

Where **TNCDP** represents the total number of correctly detected patterns and **TNAPP** represents the total number of applied patterns. A pattern indicates both seizure and nonseizure. From 10 patients, a total of 40 datasets were selected, with 20 ictal(epileptic seizures) and 20 interictal(non epileptic) data, for testing. The Performance Evaluation Parameters were calculated and the results obtained as follows:

Overall Accuracy (OA) = 99.19%

Sensitivity (SE) = 91.19%

Specificity (SP) = 91.14%

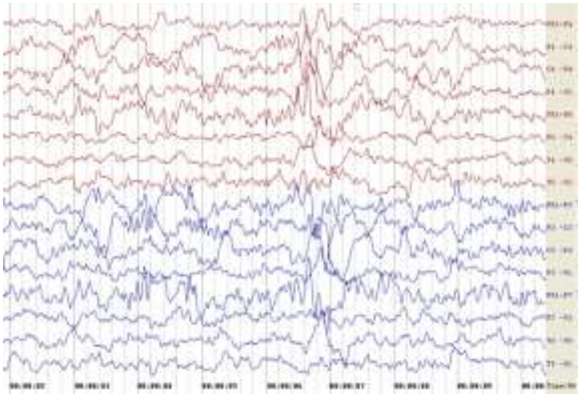

Figure 3 : Recoded EEG Signal

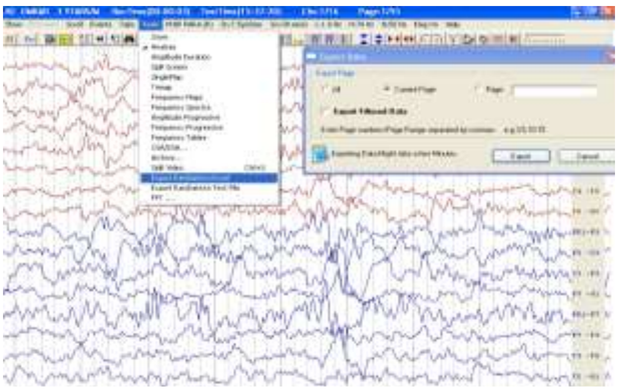

Figure 4: Original EEG Signal in .eeg Format to Excel format

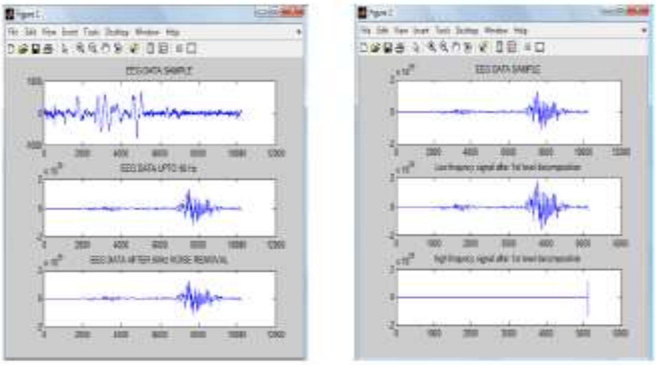

Figure 5:First Level decomposition of signal

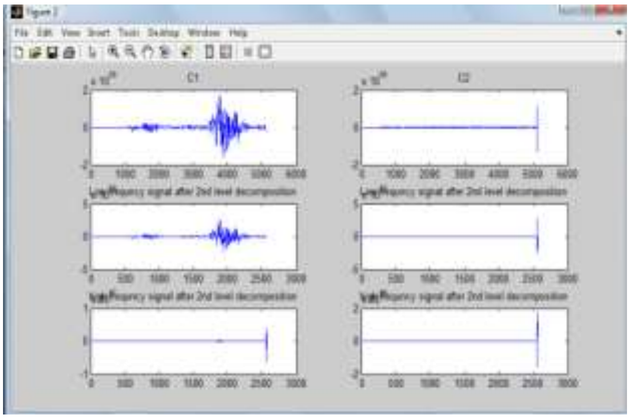

Figure 6: Second level Decomposition

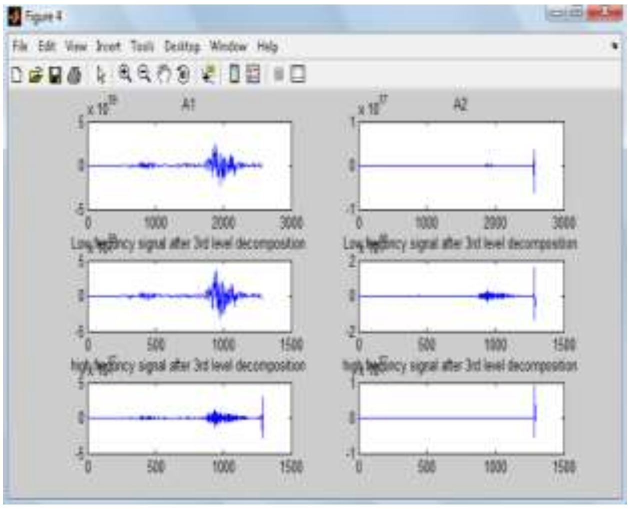

Figure 7: Third Level Decomposition

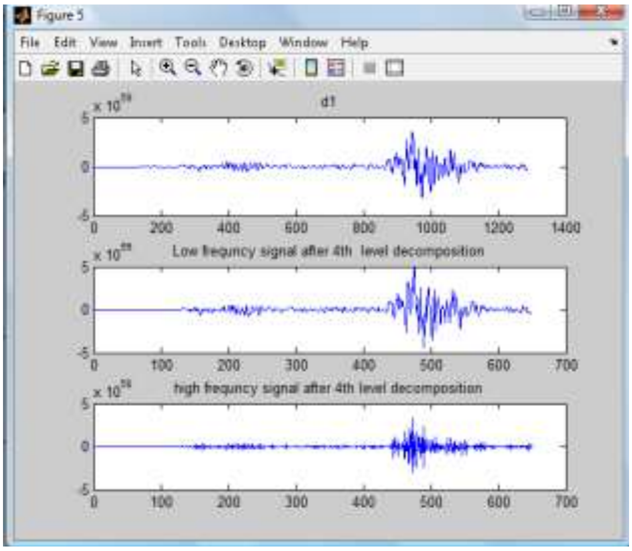

Figure 8 :fourth level Decomposition

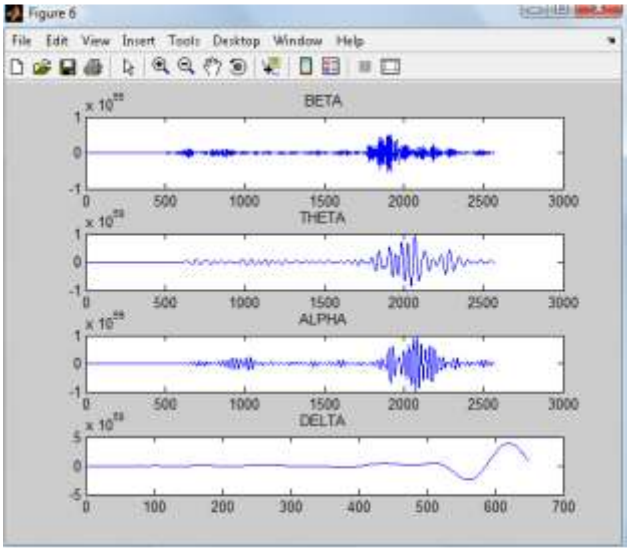

Figure 9: Separation of frequency band form EEG signal

6. Conclusions

Epilepsy is a common neurological disorder not a disease which is not contagious, fainting disorder and cause mental illness. Epileptic person has a tendency to have recurrent seizures which produces non linear dynamic system. This paper proposes a technique of detecting epilepsy disorder using discrete wavelet transform and the back propagation algorithm for classification using MATLAB software. These experiments provide experimental verification that the use of this tool can be used for detection of epilepsy within few seconds.

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