Noise Elimination in Automatic Detection of Epileptic Seizures by wavelet Transform using Feature Selection Algorithm

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Abstract

One of the most important symptoms of epilepsy is convulsions, whose detailed analysis is performed by electroencephalography (EEG) signal. Electroencephalogram, as a clinical tool to illustrate the electrical activities of the brain accurately, provides an appropriate method for diagnosing epilepsy disorders, which plays an important role in identifying this disease, especially seizures. Seizures resulting from epilepsy may have negative physical, psychological, and social consequences such as loss of consciousness and sudden death. With timely and correct identification of epilepsy, its effect can be treated with medicine or surgery. In this thesis, a brief review of the methods of identifying epilepsy using EEG signal analysis along with the separation of epileptic signals from healthy and normal signals has been done. Methods based on EEG analysis, from non-linear methods of signal processing, provide much better results due to the properties of signal dynamics. Moreover, wavelet transformation can be used to extract signal features, innovative algorithms can be used to select their features, and neural networks can be used to classify signals. In this regard, in this research, the Kalman filter was used to remove the signal noise, and the wavelet transform was used to extract the characteristic of the EEG signal. By using the feature selection algorithm, the best features can be selected and then trained using a neural network so that the ability of these features in identifying the events in the EEG signal can be better displayed. Regarding the implementation of the algorithm of the data presented in this research and the simulation and training of the neural network, a complete analysis has been made, and the method of extracting the features of this data and the method of implementing the epileptic irregularity detection system has been explained. Finally, the simulation results are presented to confirm the performance of the studied algorithms, and general conclusions are made.

Keywords: Epileptic seizures, electroencephalogram (EEG) signal, wavelet transform, Kalman filter algorithm, neural noises.

1. Introduction

Human brain is comprised of cells like any other tissue. Of course brain cells are specific ones whose electric and chemical symptoms can tracked, recorded, and interpreted. A vast number of neural cells or neurons comprise human brain through which each neural cell consists of a cellular body with a diameter of several micrometers through which there exists an exon and a number of cluster branches called dendrites. The input messages are received by the cellular body and dendrites and then the cellular body sends out the output symptoms after integrating them. The exon distance transforms the output message from the cellular body to exon terminals and the exons transfer the data to other neural cells. The message that is created in the neural cell and moves throughout the exon is an electrical stroke, but the message transfer from a cell into another one is done through carrying molecules which go through a connection point called synopses. Each neural cell receives hundreds or thousands of messages from others and sends messages to hundreds or thousands of other neural cells .

The brain's electrical activities that can also be recorded from outside of the skull are among very sophisticated mysteries of the nature. The brain waves that were first observed and recorded in 1875 by Richard Gotten through the use of an electrode on naked skull and brain of a monkey and a rabbit reflect the severe and constantly changing activities of the brain. Human brain waves were first recorded by German Psychologist, Huns Berger in 1924. He was the very first person who investigated about Electroencephalography during epilepsy changes [1]. At first Burger encountered many criticisms but 5 years after the publication of his first paper in 1934 and when fire valve amplifier was utilized his findings were approved and Electroencephalography (EEG) was approved. The emergence of transistors and using them instead of amplifiers led into another revolution in EEG and currently computer is utilized in EEG [2]. In our era the most principal idea in investigating the cells' performance refers to understanding the electrical activities of the brain resulted from the biochemical interactions of the neurons and the very complicated connections between them. Currently EEG is the only means of understanding these activities. For the first time, Haar referred to wavelets. But in 1980, scholars such as Morlet, Grossman, Mallat and … explained wavelets and in 1988 Daubechies introduced its functions in different fields of mathematics and statistics. Artificial Neural Networks are driven from living neural networks. Each artificial neural network includes a series of pseudo-neurons connected through input and output routes. Of course, it should be noted that the relationship between the neurons is weighted. Artificial Neural Networks known as Neural Networks were first posed by MCClothes and Pich's in early 1940s using a simplified model of neurons. Neural Networks are used to implement complex functions in the fields such as pattern recognition, identity recognition, categorization, speech signal processing, image processing, and EEG signal analysis.

2. EEG Signal Analysis within the Field of Time

In this type of analysis, the original EEG signal is directly utilized without any transformation. Such transformations have lower calculation costs compared to other methods that require transformations like the one called Fourier. The analysis methods within the field of time are divided into several categories, some of which are known as: range analysis, distance analysis, … . In range analysis method some indexes such as mean, standard deviation, and change coefficients are used. In distance analysis method and due to its simplicity, EEG signal analysis is noticed regarding the practical function of it. The integrative energy includes the past energy data and in fact it is refers to a discrete integral of energy dominated by the time which is one of the most common characteristics utilized in classic detection of epileptic attacks. The mathematical equation for the discrete form integrative energy is as follows:

$$AE[n] = \frac{1}{10} \sum_{i=5(n-1)+1}^{5(n-1)+10} E[i] + AE[n-1] \tag{1}$$

3. EEG Signal Analysis Within Frequency Field

The classic EEG signal description could be calculated based on its frequency elements using distance analysis and analogue filtering or analysis based on self-correlation function. After the emergence of Fast Fourier

Algorithms (FFT) a great deal of changed happened in EEG analysis. The power calculation in four frequency ranges such as EEG signal band means: delta lower than 4 hertz (Θ), 4 to 8 hertz (α), 8 to 13 hertz (β), and more than 13 hertz can be profitable in detection of epileptic attacks. The equation to calculate the power is as follows:

$$P_i = \frac{1}{P_T}\sum_{k=f_i}^{f_2} X(K) \qquad (2)$$

Where, Pi represents power in i frequency band and i represents the representative of different bands in EEG. f1 and f2 are the high and low frequencies in each band. k represents the discrete frequency index. X(k) refers to signal spectrum and PT represents overall integral power of X(k).

4. The Disclosure of Spikes in EEG Using Wavelet Change

One of the most important diagnosis issues in epileptic patients is how to disclose spikes present in EEG which usually are resulted from sudden evacuation of neurons in a part of the brain. During some recent years, different methods such as pattern match, Fourier analysis, linear filters, domain isolation, AR methods and neural networks have been utilized to detect spikes within EEG. But the major problem in these methods is that sometimes spikes overlap each other. The detection of spikes using wavelet change is done through different methods. Since epileptic activities spikes have a higher frequency than EEG activities, we can isolate multiple precision analysis of this part from EEG activities.

Using an order 3 spline wavelet function along with a multiple precision method can isolate regular activities of frontal delta and sharp activities of EEG very well and show their different indexes. The transformation of continuous wavelet (CWT) on all times in f(t) signal multiplied in transformed versions and the indexed wavelet function can be expressed through the following mathematical equation:

$$WT_F(\partial,\tau) = \left(\frac{1}{\sqrt{\partial}}\right) = \int_{-\infty}^{+\infty} f(t) \cup * \left(\frac{t-r}{\partial}\right) dt \qquad (3)$$

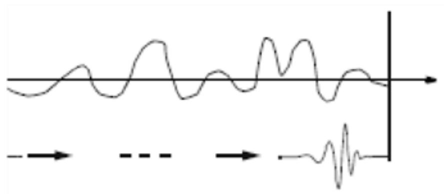


Fig. 1. The qualitative description of wavelet transformation

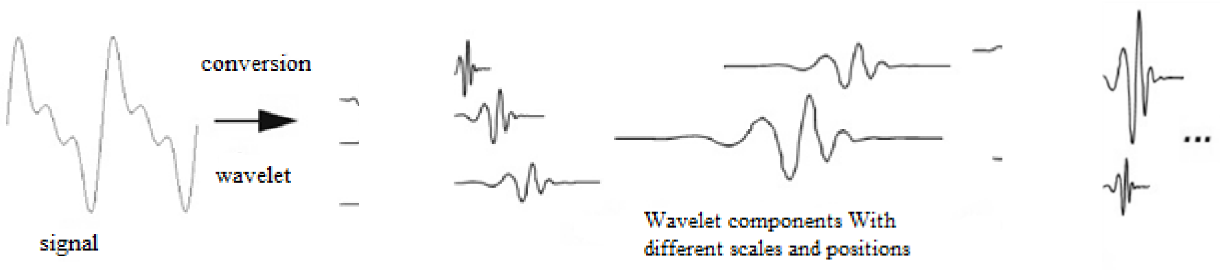


Fig. 2. The signal analysis on wavelet functions using different indexes

If integer representations of natural numbers are selected instead of the index and the continuous transformation in continuous wavelet transformation and in other words if there exists discreteness in indexes and transformation, the continuous wavelet transformation is changed into a discrete format. There exist several methods to implement discrete wavelet transformation (DWT). The most important and the most used DWT is known as binary wavelet transform as follows:

$$WT(2^j, k2^j) = dj(k) = \int 2^{\frac{-j}{2}} f(t)\varphi * (2^{-j}\,t - k)dt = < f(t), \varphi j.k(t) > \quad (4)$$

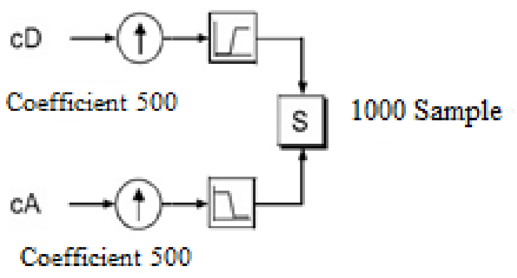


Fig. 3. Reverse binary discrete Wavelet transformation diagram block

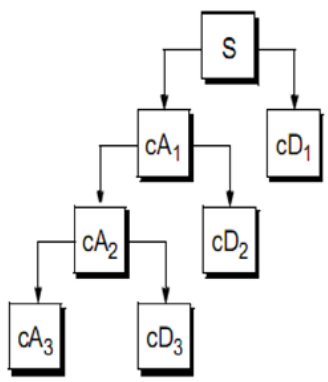


Fig. 4. The tree diagram for discrete wavelet analysis using a Mallat algorithm

5. Kalman Filter

Kalman filter is known as one of the classic tools in processing specific signals to process variable signals regarding time. The developed model of Kalman filter is widely used as a tool to model and predict nonlinear systems. Kalman filter in classic form is based on an estimation of a linear system in a recursive mode. The function for a linear system can be calculated using the two equations for processing and measuring as follows:

$$\begin{cases} X_{K+1} = F_{K,K+1}X_K + W_K \\ y_k = H_K X_K + V_K \end{cases} \quad (5)$$

Where, X represents system status vector, Y shows system output, W refers to the system's dynamic model noise, and V indicates measurement noise. Additionally, in all equations, the matrixes H and F model the system behavior. In this case, K index represents a stage through which the variable has been utilized.

6. The Suggested Algorithm

The input for this algorithm is comprised of one or several EEG signal channels and its output refers to the counterpart but filtered signal. Here, the intended signal is divided into 20000 items packages to avoid simulation of the very big amounts of the signals to result in blocking the RAM in the intended system.

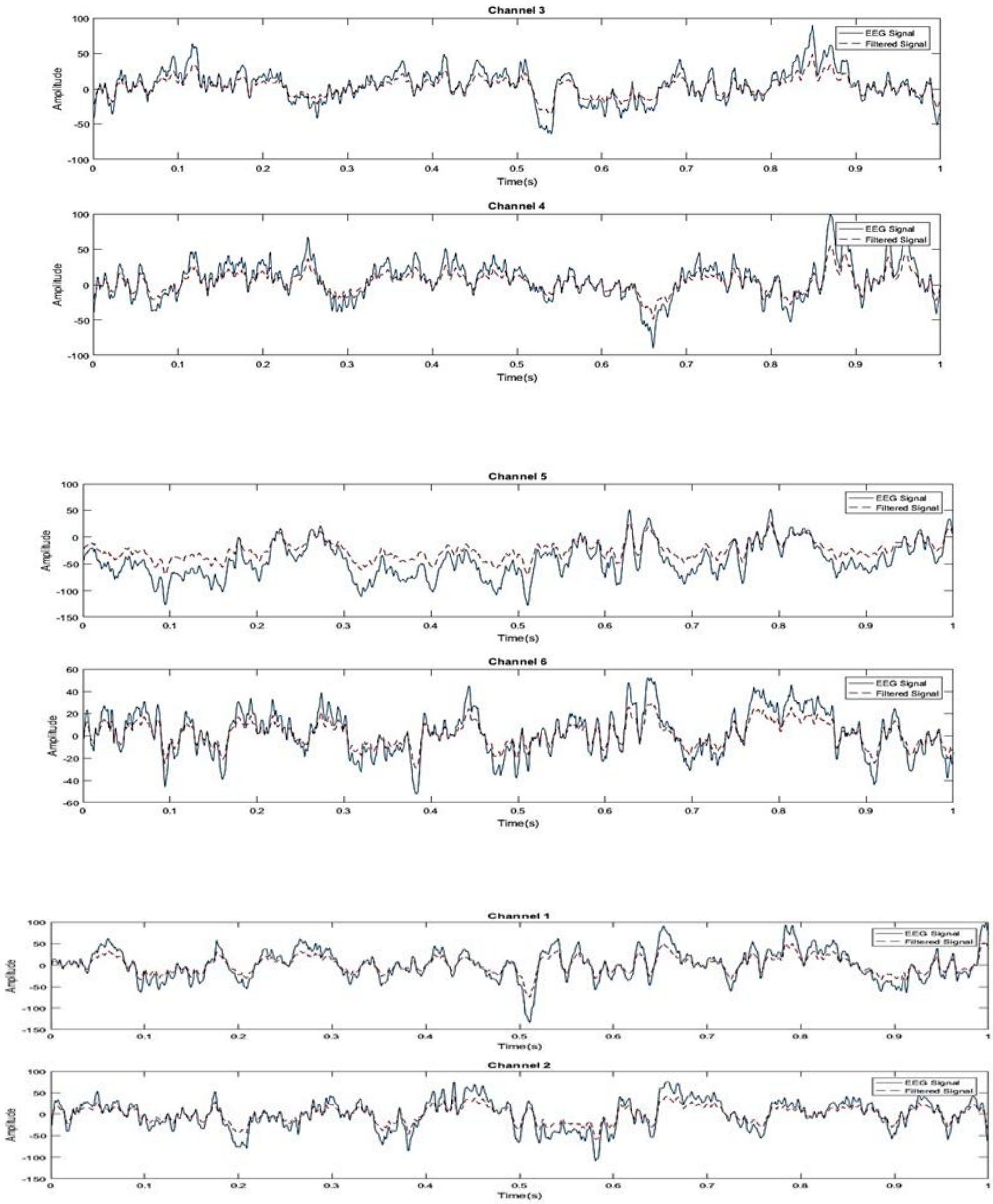


Fig. 5. Signal indicators before and after Kalman filter application

DWT-Feature Function

This function is coded to implement wavelet transformation method to extract the features sent with related data. The identification of the function using 4 inputs and 1 output has been done as follows:

1. It refers to the first signal input whose characteristics should be extracted.
2. It refers to the second input representing the size of the window through which the signal is cut and the processing is done on each window.
3. The third input refers to windows' movement in each stage.
4. The fourth input refers to the number of stages to apply wavelet transformation.
5. This program has only one output including a matrix containing the features.

This function is used in a wavelet transformation program.

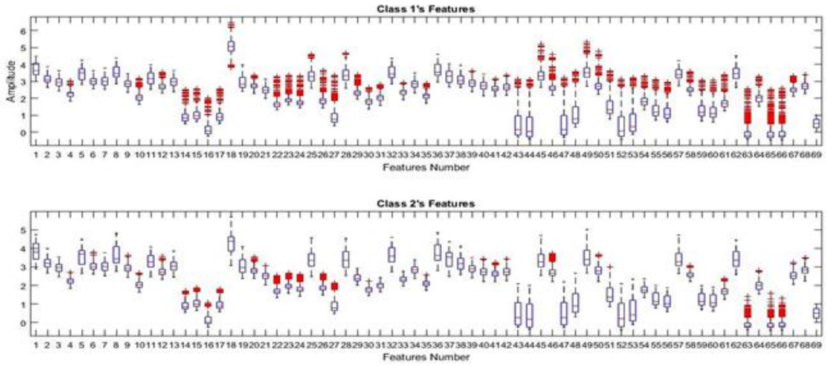


Fig. 6. Output features after wavelet transformation implementation

Concatenate Feature Data Function

This function is used to integrate the data generated up to now. The initial amount for the feature matrixes for the training data include Interictal and Preictal data and also the feature matrixes for test data in addition to the vector entailing the data throughout the whole windows of the data contain the cluster number of the data. Here number 1 cluster is considered for the data representing Interictal information.

UseANN function

This function is utilized to make benefit of the neural network as a predictor. The neural network used here is of Patternnnet type which applies Scaled conjugate gradient back propagation for training.

Neural Network Training

As it is apparent in this window, the number of inputs, outputs, layers, and neurons in every layer are predetermined. The program has ended in 122th repetition time and the reason to stop training is lack of enhancement in achieving a better result in 20 last repetitions. Meanwhile, the administration of all training stages lasts 4 seconds. Below you can see the graphs related to this type of neural network.

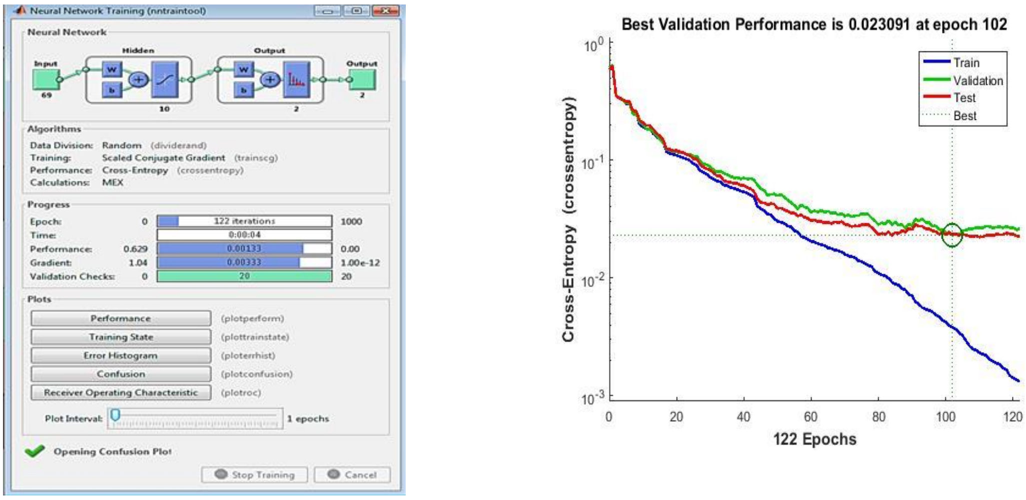
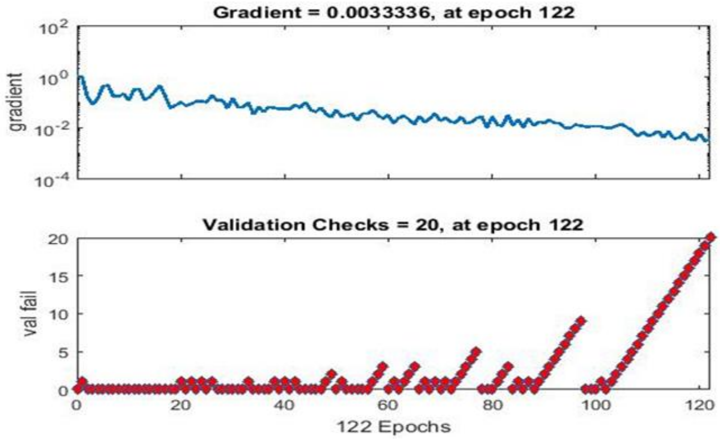
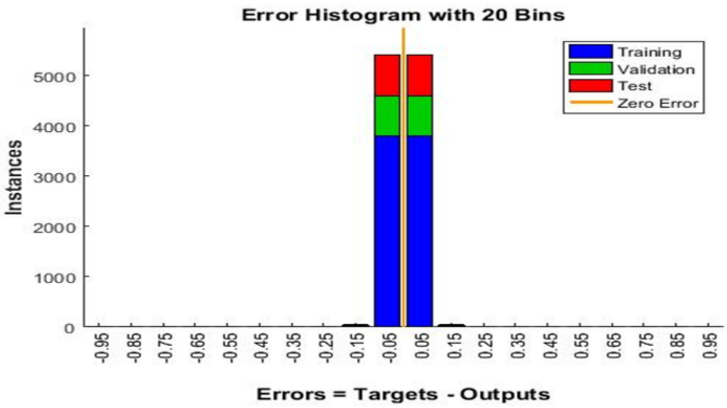


Fig. 7. Program efficiency graph in different stages of training for three data clusters including training, test, and validation .

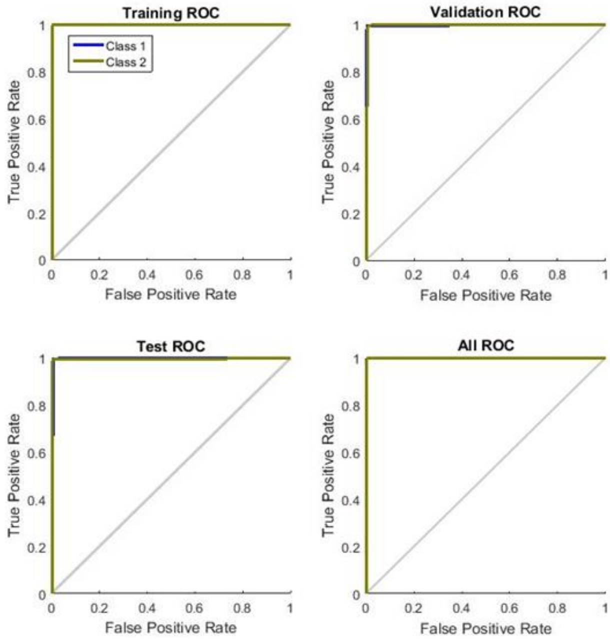


This graph entails two parts. In first section of this graph the gradient parameter throughout the training stages has been represented and in second part the number of training deviations on validation data throughout the training stages has been shown.



This graph indicates the scattered error amount. As it can be observed, the greatest amount of erroneous data has had an error or less than 0.05.

This graph entails four subsections as follows: 1) training data, 2) validation data, 3) test data, and 4) total data. In each part of the matrix, the confusion is calculated and drawn for every data cluster.



In this part, as the previous one, we have four graphs for four clusters. Regarding all four graphs, the area under the graph is almost equal to 1 which is considered as the best status. Thus, this graph represents the very great result of the proposed program.

Conclusion

In the present research, we have used a multiple stage method in order to cluster the data that predict the occurrence of epilepsy beforehand. These processes can be categorized into four stages. In primary stage, we have used Kalman filter to modify the signal regarding the presence of probable noises such as measurement noise or chaos noise and clearing them. To do so, Kalman filter indicates the values of predictions for any sample using the previous samples and modifies the amount of each sample when it is required. In the next stage, the wavelet transformation was utilized to extract signal features. The reason to use this transformation is the capability of this relationship to connect with the signal both in the field of time and the field of frequency. In this stage we have attributed 63 features signal for each channel and through the calculation of 16 current channels, 1008 features have been produced. In third processing stage, NCFS algorithm has been utilized to select superior features. In this algorithm SVM categorization using a Quadratic function has been applied for a low level categorization. After accomplishing this stage, only 69 features have been selected. In last stage, a neural network has been utilized to create a model and train it. Then, it could use the test data to test itself. The model chosen here for the neural network entails 3 layers whose middle layer contains 10 neurons. After the neural network is trained and tested itself and observed the test, the proposed integrated method would be able to predict epilepsy with a more than %99 occurrence probability precision.

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