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Epileptic seizure detection using EEG signals by means of stationary wavelet transforms

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ABSTRACT

Wavelet transform provides a fine means of classifying seizure EEG signals from the normal EEG signals. Stationary wavelet transform (SWT) is used to further improve the performance of discrete wavelet transform. EEG signal prediction and classification can be bolstered up by applying SWT. In this work the residues obtained from denoising the signal using SWT is considered. Its arithmetical factors like standard deviation mean and median absolute deviation, maximum norm and histogram are considered and analyzed. It can be vividly seen that the seizure EEG signal parameters are higher than the normal EEG wave pattern. The original wavelet used here is a novel wavelet named as eegwav which has a resemblance with the EEG wave pattern.

Keywords: Seizure detection, EEG signal, Stationary Wavelet transform, Neural networks.

1. INTRODUCTION

Epileptic seizure detection has received more significance since more than a percent of world's population is affected by epilepsy and most of them are found in developing countries [1]. 14 in 1000 people in India have epilepsy and mainly more percentage of patients is found in rural areas [2]. Epileptic seizure occurs more rampantly in differently abled people like those who have Down syndrome, autism and cerebral palsy [3]. The universally used scheme for diagnosing the seizure is through careful study of EEG data taken over a long duration of time. The doctors have to go through huge number of EEG data sheets to analyze EEG for detection of seizure. Hence automatic seizure detection is gaining grounds and numerous studies have been carried out for the same.

The application of Stationary Wavelet transform on EEG signals analyzed in this paper. Statistical details of the signals which can segregate the normal and abnormal EEG signal are obtained. Since the seizure EEG signals have distinct morphological characters and marked rhythemisity its parameters are different from that of the normal ones.

The SWT characteristics study is done using a novel mother wavelet which has the likeness of EEG signal. Classification of normal and seizure EEG signals through CWT, DWT, density estimation and wavelet packet analysis have been carried out successfully using this novel wavelet "eegwav" [4].

The specifics of the novel wavelet are given in section 2. The detail of stationary wavelet transform is given in section 3.Prediction using Backpropagation gradient descent method is explained in section 4. The conclusion to this paper is given in section 5.

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2. NOVEL WAVELET "EEGWAV"

The mother wavelet eegwav depicts a cycle of the EEG wave consisting of spike and valley pattern [5]. This eegwav is simple to construct and is used as the original wavelet for analyzing EEG signals for effective classification. The EEG signal samples are obtained from the data base provided by Epilepsy Centre, University of Bonn, Germany [6]. The expression for eegwav is given in equation (1). This original wavelet and its scaling function is seen in figure 1. This wavelet is used to obtain the stationary wavelet transform.

$$\text{eegwav} = [1 + e^{-2},\ 1.5 + e^{-2},\ 1.5 - e^{-2},\ 1 + e^{-2}] \qquad (1)$$

3. STATIONARY WAVELET TRANSFORM

Stationary wavelet transform is also called as redundant wavelet transforms or undecimated wavelet transform. The keydissimilarity between DWT and SWT is that the decimation is not done in SWT. The input signal is given to high pass and low pass filter which segregates the approximated and detailed information. In DWT the filtered output has half the length of the input signal whereas in SWT the filtered output has the same length as that of the input signal. The filteredsignal thus has the coefficients of DWT which is decimated at all the chosen interval value of and rest of the sampling

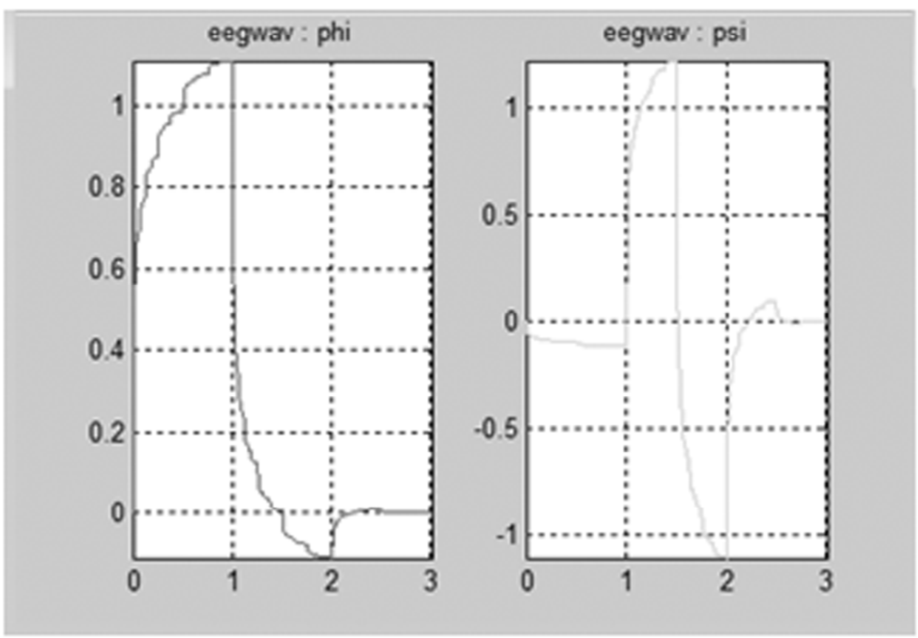

Figure 1: Mother wavelet "eegwav"

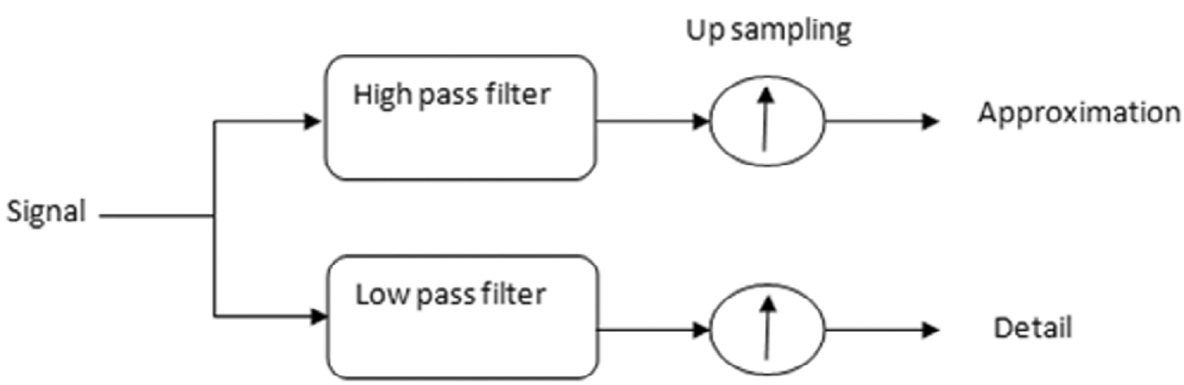

Figure 2: Representation of Stationary Wavelet Transform

instants are padded with zeros. Hence it is also named as decimate discrete wavelet transform. Figure 2 shows a simplified representation of SWT. The major application of stationary wavelet transform is denoising.

The EEG signal is given as the input signal and it is passed through high pass and low pass filters. The approximation and details are obtained. Five levels of decomposition are done. Five details and one approximation are available. Thresholding is done only for the detail coefficients. The high frequency components of the signal are segregated from that of the low frequency component. The approximated data along with signals and the thresholded data from the details are available as denoised signal. The remaining high frequency components of the signal are set apart as residue. The residue can give valuable information regarding the nature of the signal. Figure 3 shows the original EEG signals, the denoised and residue signals of normal and seizure EEG signals.

The residue is analyzed using histogram [8], cumulative histogram [9], autocorrelation, FFT and statistical parameters such as mean, median, mode, standard deviation, median absolute deviation, mean absolute deviation, maximum norm etc [10]. Figure 4 illustrates the statistical analysis of the residues of normal and seizure affected signals. The parameters of seizure affected signals are comparatively higher than normal signals.

The analysis of histogram for the residues clearly specifies the diversity between seizure EEG and seizure free EEG signals. The range of histogram for a seizure EEG signal is vast when compared with that of the seizure free EEG signal. This indicates the presence of wide range of frequencies present in seizure EEG signals.

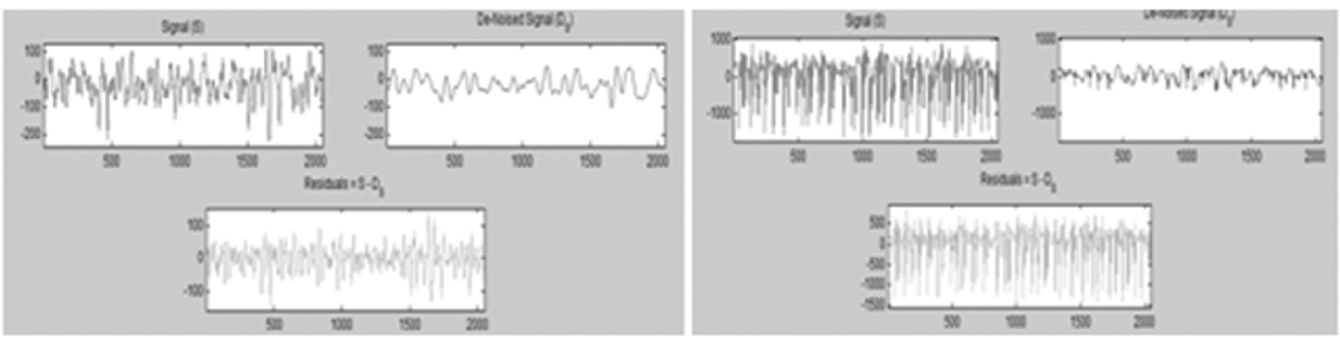

Figure 3: EEG signal, Denoised signal and the residue of normal and seizure EEG signals

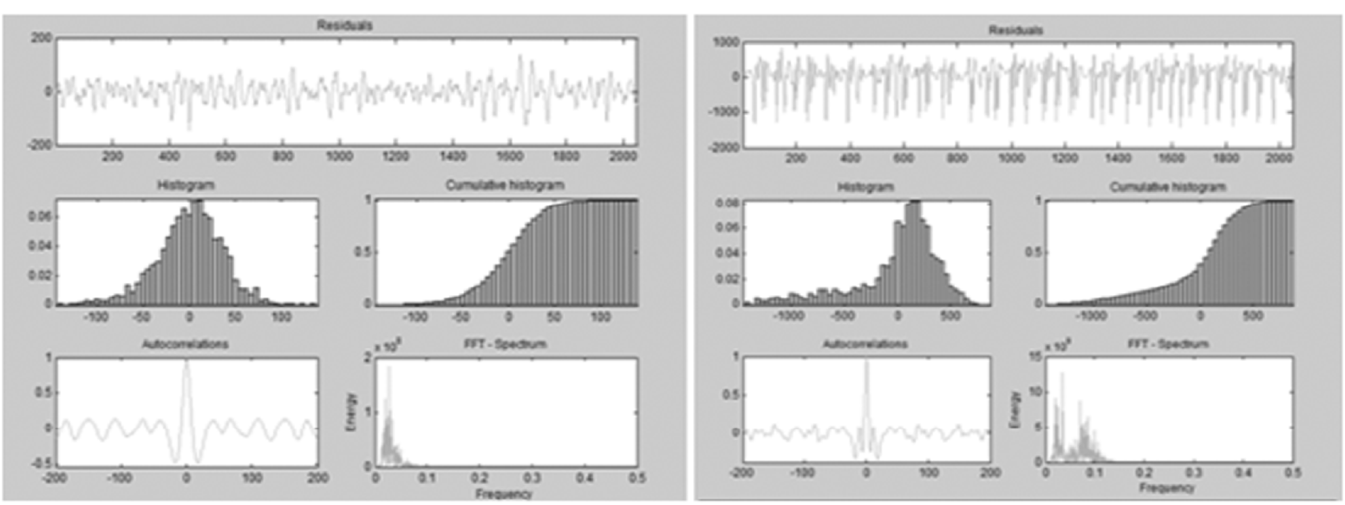

Figure 4: Analysis of residue of normal and seizure EEG signals

4. PREDICTION OF SEIZURE USING SWT FEATURES OF EEG SIGNALS USING NEURAL NETWORK

A simple Backpropagation algorithm as shown in figure 5 with a single layer is employed to predict whether the given test signal belongs to the seizure class of EEG or not. The Backpropagation algorithm is a widely used one because of its efficiency in solving classification problems [11], [12]. The gradient descent Backpropagation enumerates the gradient of the cost function by considering the weights of the neural network. The updation of weights is done in such a manner that the cost function is reduced to the minimum. Since the target is specified it is a supervised learning.

The activation function applied here is logarithmic sigmoidal function. It is illustrated in figure 6 [13]. This function achieves better result when correlation is superior. The output of this function ranges from 0 to 1. A four dimensional data set is given as input to the network. The features of the residue that are fed as inputs are Standard deviation, Median deviation, Maximum Norm and Range of the signal. The targets of the network are assigned as 1 for seizure signal and 0 for normal signals.

The Backpropagation network is trained. The performance curves are plotted. Over fitting has not occurred since the test curve does not rise appreciably before the validation curve rises as shown in figure 7.

The regression plot in figure 8 gives the relationship of the output to that of the target. The network is trained repeatedly by adjusting the training parameters as long as the output closely matches the target. The regression is plotted for training, testing, validation and combination of all the above said parameters.

The prediction capability was tested by feeding four new sample data out of which the first two are normal EEG SWT residue parameters and the next two belong to seizure class of signal. The network has predicted the data correctly. The first row indicates seizure class and second row indicates normal signal. It is thus seen from the results given in figure 9 that the first two samples have 1 in the second row indicating

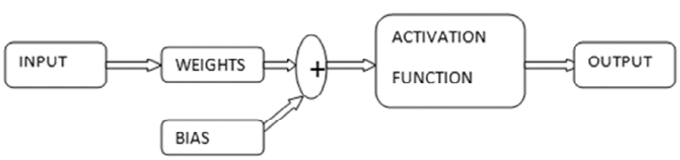

Figure 5: Block Diagram of Neural Network

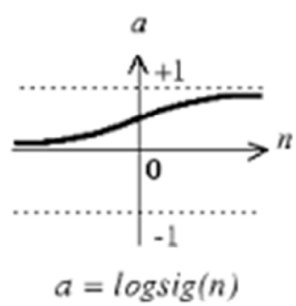

Figure 6: Logarithmic Sigmoidal Function

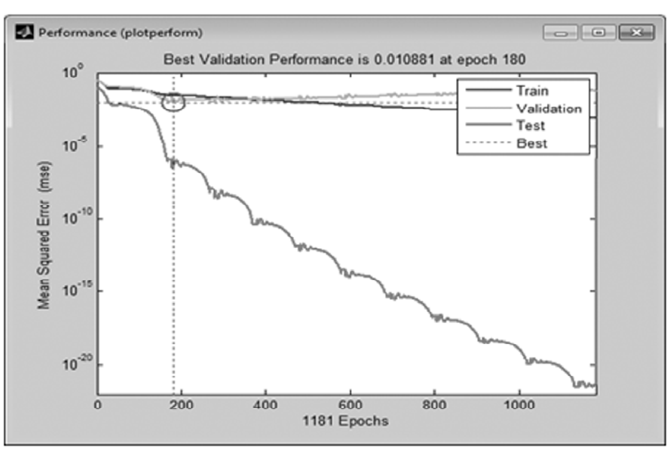

Figure 7: Performance plot

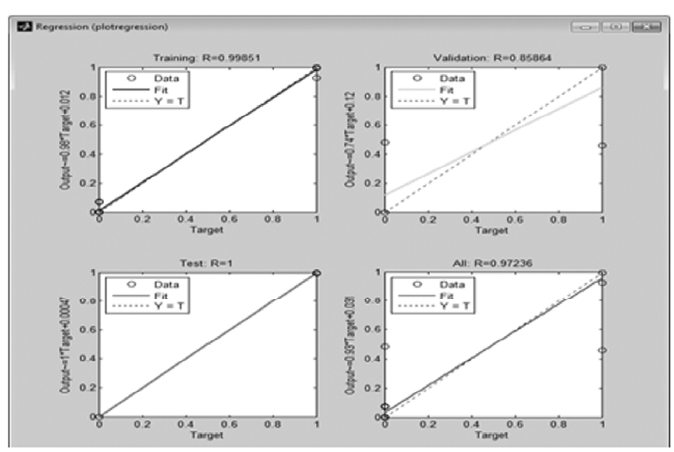

Figure 8: Regression plot

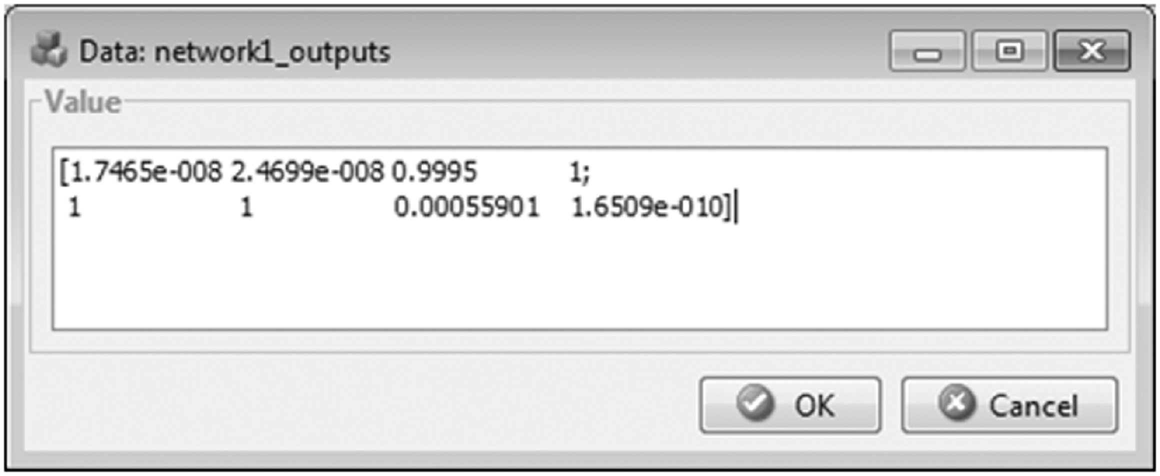

Figure 9: Result of prediction for new set of data

that it is a normal signal and the next two samples have approximately 1 in first row which notably indicates that it belongs to the seizure class of EEG signals.

5. CONCLUSION

Thus the features obtained from the residues using Short time wavelet transform denoising provides appreciable result for marking the difference between normal and seizure EEG signals. Prediction of data has been also successfully carried out using gradient descent Backpropagation algorithm of Neural Network. This technique proves to be more efficient and accurate. It also enables several number of data predictions simultaneously.

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