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Seizure Detection using Wavelet Packet Analysis and Density Estimates of EEG Signals Using a Novel Wavelet.

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ABSTRACT

Wavelet packet analysis is an effectual means for the analysis of EEG signals for epileptic seizure detection. In this paper a new wavelet named as 'eegwav' which carries the likeness of an EEG wave pattern is used as the original wavelet. The statistical contents of the wavelet packets are analyzed to tell apart the seizure and seizure free EEG signal. The density estimate of the signal is also obtained using the mother wavelet 'eegwav'. The wavelet based density estimator utilized here is the histogram analysis using hard thresholding technique.

Keywords: EEG, Seizure, wavelet packets, density estimation.

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INTRODUCTION

Wavelet transform is a proficient mathematical tool which plays a vital role in signal processing and image processing [1]. Countless scientific and engineering applications use the principles of wavelet transform. It is definitely a cut above the Fourier transform since it provides the details of the time particulars at which various frequencies occur [2, 3]. Its significance has been realized and utilized in the field of Bio signal processing as well. Wavelet packet transforms which is also named as optimal Sub-band Tree Structuring provides supplementary information which is not made available in wavelet transform. EEG signal can be analyzed using wavelet packet transform for detecting epileptic seizure.

Density estimation using wavelet transform is a non parametric method. The histogram analysis is a very frequently used technique to obtain the density estimate. It gives valuable information the nature of the signal which can be used for classification. Wavelet thresholding is done to get the estimate. There are two types of thresholding techniques. They are hard thresholding and soft thresholding. Hard thresholding is used in this paper. Unlike soft thresholding method, hard thresholding fixes a definite value as the threshold. The density estimate of the wavelet coefficients of a normal EEG and Seizure EEG signals differ from each other and hence it can be used as a tool for classification.

A new mother wavelet named as 'eegwav' is formed which carries the morphological features of an EEG wave. The type of the wavelet is 'orthogonal wavelet with filter'. This wavelet is used in wavelet packet and density estimation analysis. Section 2 of this paper gives the details of the mother wavelet 'eegwav'. Section 3 deals with Wavelet packet Analysis. Section 4 explains the analysis of EEG using density estimation. Section 5 renders the concluding remarks of this work.

DETAILS OF THE NEW MOTHER WAVELET

The simple new mother wavelet resembling the EEG wave pattern is an 'orthogonal wavelet with filter'. The wavelet's is named as 'eegwav'. The following equation defines this wavelet.

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

The figure 1 shows the wavelet and the scaling function of this wavelet

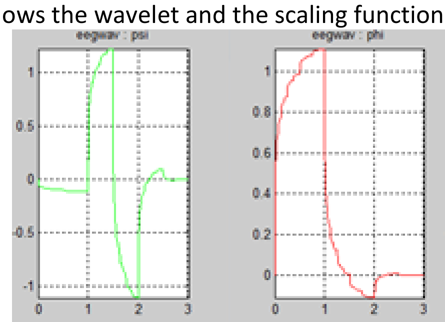

Figure 1: The wavelet and scaling function

This new wavelet can also be used in analyzing the EEG wave pattern by applying continuous and discrete wavelet transform. This novel wavelet is now used in analysis of EEG wave patterns using wavelet packet transform and density estimates.

WAVELET PACKET ANALYSIS OF EEG DATA FOR SEIZURE DETECTION

Wavelet packet transform is an extension of discrete wavelet transform. The input signal is discretised and passed to the Quadrature mirror filters which separate the frequency bands present signal. The decomposition is done in three levels which is sufficient for analysis of EEG signal [2]. The wavelet packet helps in bringing out the predominant frequency range which occurs during the occurrence of seizure and during the absence of seizure [3, 4]. The wavelet packet is expressed by the following expression after i iterations and its frequency is given by n which is the inverse of the scale function. The variable k is the time limit and x is the input signal [5].

$$w_{i,n} = w_{i,n}k(x), k \in z = 2^{-(\frac{i}{2})} w_n((2^{-i})x - k \quad \text{--------2}$$

The values of i and k are fixed and $w_{i,n}$ and the analysis is done as to how the signal fluctuates in the region of 2_i-k at the given scale 2_i for different frequencies for various permissible values of the final value of n.

The wavelet packet decomposition tree is given in detail figure 1. This figure shows three levels of decomposition. Each node in the tree denotes Approximations and Details at each level of decomposition. There is no loss of information in wavelet packet transform.

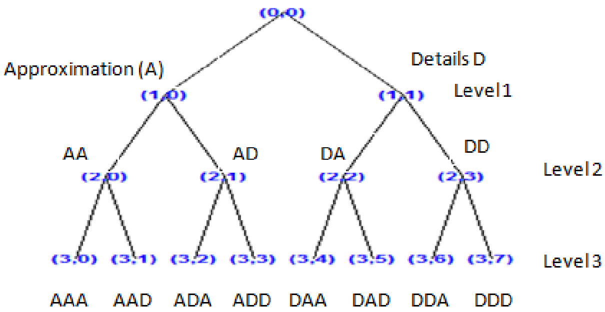

Figure 1: Wavelet packet decomposition tree

The 'eegwav' is used as the original wavelet for this analysis using wavelet packet analysis. This transform is applied to Normal and seizure EEG signals. The Shannon's entropy is used. In this method the log of the square of each sample is taken as given in equation number 3.

$$H(x) = -\sum x_i^2 \log(x_i)^2 \text{-------------- 3}$$

The wavelet packet coefficients at level three are displayed using the color code where the intensity of the color specifies the value of the wavelet coefficient present in each node. Figure 2 gives the result of color coefficient display when a normal EEG signal is analyzed and Figure 3 shows the result for a seizure EEG wave pattern.

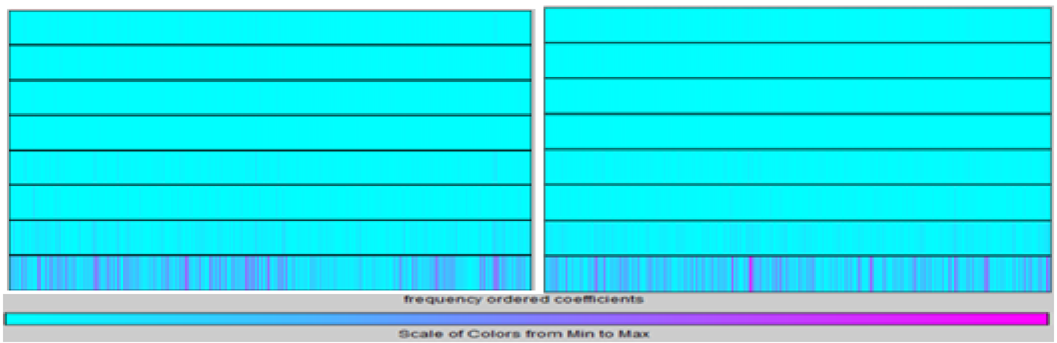

Figure 2: Wavelet packet analysis of normal EEG signals

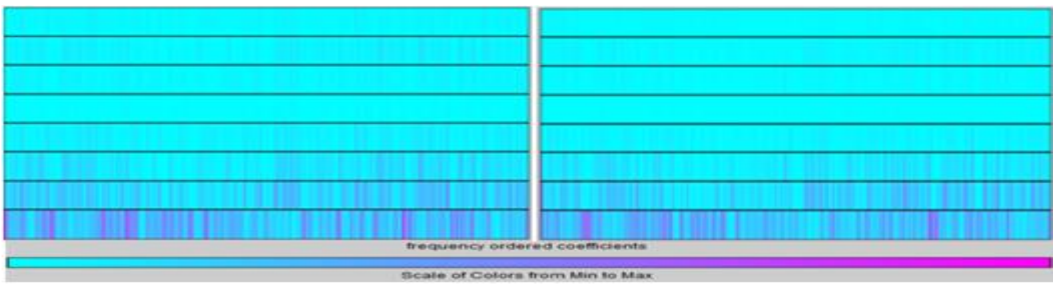

Figure 3: Wavelet packet analysis of seizure EEG signals

By comparing Figure 2 and Figure 3 it is clear that the frequency components for seizure EEG is seen in the first four terminal nodes and traces of color are also seen in the last three levels as well but for a normal EEG signal the frequency components are seen only in the first two nodes and traces of these color is seen in the third node. Hence by considering the color coefficient graph seizure and seizure free EEG signals can be effectively identified. The statistical analysis of these wavelet packet nodes can also be analyzed.

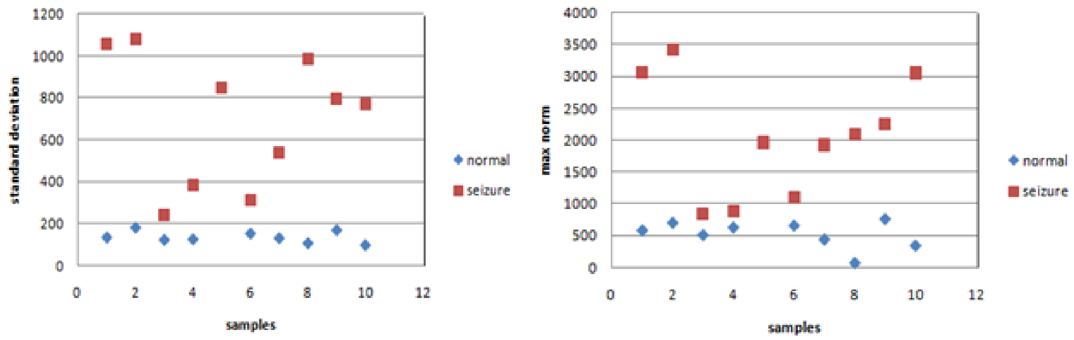

Figure 4: STD deviation and max norm of the wavelet packet coefficient at the first terminal node.

Figure 4 shows the standard deviation and maximum norm of normal and seizure EEG signals at one of the terminal node that is (3,0). The statistical details at the end nodes from (3, 4) to (3, 7) is very insignificant for normal EEG signal when compared to that of a seizure EEG signal.

ANALYSIS OF EEG USING WAVELET DENSITY ESTIMATION

Density estimation is a non parametric method for analysis of the time varying signal [8]. The density estimate provides the distribution of frequency components present in the frequency range of interest. The density estimate can be done by using several techniques and wavelet is the most widely utilized one. The essence of wavelet based density estimation is that the scaling of father wavelet is linearly combined with the mother wavelet as given in equation 4.

$$D(x) = \sum_{j_0,k} a_{j_0,k} \emptyset_{j,k}(x) + \sum_{j\geq j_0,k} d_{j,k} \Psi_{j,k}(x) \text{-------4}$$

Where $\emptyset$ and Ψ are the father and mother wavelets and a and d are the wavelet coefficients [9].

In this work density is estimated using histogram method. Hard thresholding of the wavelet coefficients is done to get the estimates since hard thresholding will vividly reveal the ‘peaks and jumps’ [10, 11]. The original wavelet employed here is the ‘eegwav’. The procedure for obtaining the estimate is that the input signal is converted into x data and y data. The x data is made into equally spaced bins. The corresponding y data is treated as a signal and discrete wavelet transform is performed on it. Then thresholding is done on the wavelet coefficients of the y data and the estimate is determined.

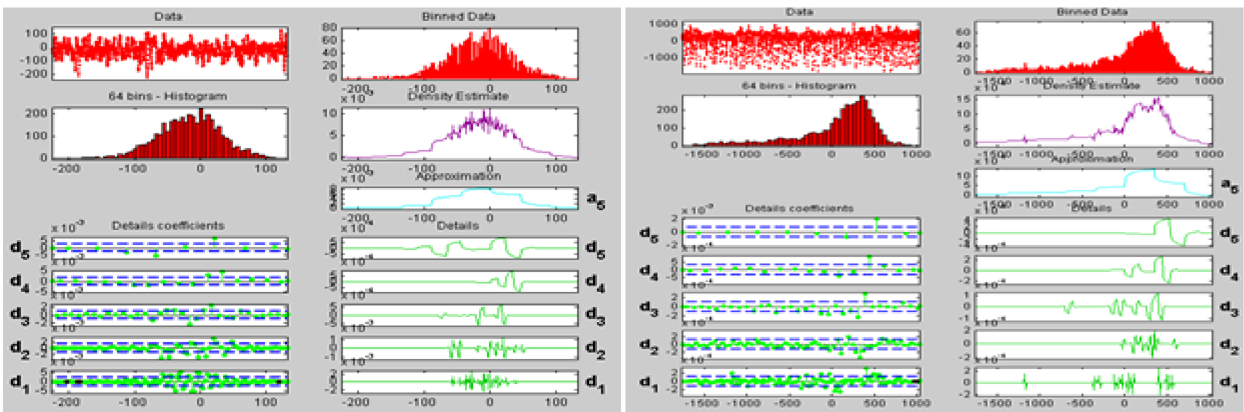

Figure 5: Wavelet based Density estimation for Normal and seizure EEG signals using eegwav

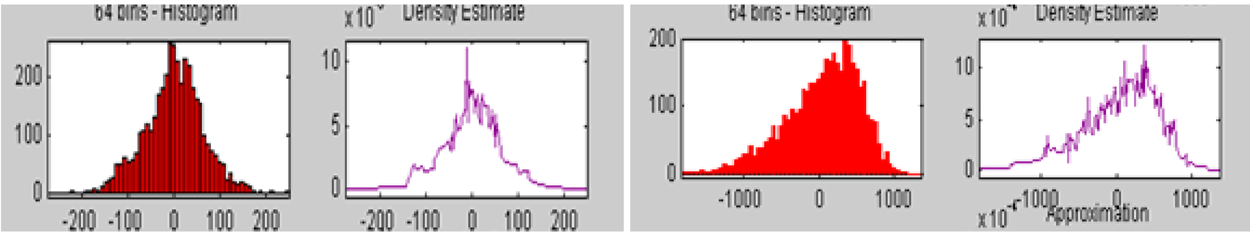

Figure 6: Histogram and density estimate of normal and seizure EEG signals

Figure 5 gives the details of the input signal and how it is converted into binned data. Wavelet coefficients are obtained and the density is estimated. Figure 6 shows two more samples of EEG signals. It is clearly seen from the figure that the frequency components of the normal EEG signal is distributed along a narrow range that is in terms of few hundreds. Whereas the Seizure EEG signal's frequency component distribution varies in terms of few thousands.

CONCLUSION

The wavelet packet transform has provided an efficient straight forward method for segregation of normal and seizure EEG signals. The color coefficient graph aid in effortless classification and detection of seizure from EEG signals. Likewise density estimation also proves to be an effective pointer for detection of epilepsy. This work ascertains the new wavelet eegwav can be effectively used for the analysis of EEG signals

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