Wavelet Analysis of Electrical Signals from Brain: The Electroencephalogram

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Abstract. The Electroencephalogram (EEG) is a measure of neural activity and is used to study cognitive processes, physiology, and complex brain dynamics. The analysis and processing of EEG data and to extract information from it, is a difficult task. The EEG signals are non-stationary signals. So, only transformation of these signals from time to frequency domain does not serve the purpose, it is required to know the time domain information too associated with the frequency domain information. Wavelet transform is one such tool being used recently for such analysis of non-stationary signals like EEG. In this paper, wavelet packet decomposition of EEG signals is presented. Feature extraction from EEG signal is also introduced in this paper.

Keywords: Electroencephalogram (EEG), Wavelet transform (WT), Wavelet Packet decomposition (WPD).

1 Introduction

Richard Canton, an English physician, discovered electrical currents in the brain in 1875. German psychiatrist Hans Berger[11], in 1929, first recorded these currents, and named them as Electroencephalogram (EEG) [3]. EEG is the electrical signal due to electrical activity of neurons in human brain. The EEG signals are very helpful in studying the physiological, psychological aspects and complex dynamics of brain. The electrical activity of brain changes during different conditions like sleep, awake-state, coma, eye open, eye closed, corresponding to different physical activities of body and different physiological & psychological disorders. From EEG, different distinct patterns can be identified corresponding to these conditions, but even a trained and experienced neurologist is sometimes incapable of identifying all patterns corresponding to all conditions. With the advancement in computing technology, the processing and analysis of these signals have opened new avenues for researchers to use EEG signals for automated diagnosis, brain computer interface, brain controlled prosthesis and understanding complex brain dynamics. This type of analysis and processing of bio-signals had came into use since 1960's; this paved the way for providing means towards accurate and precise diagnosis by physicians [2]. Time domain analysis is always very difficult for feature extraction and classification [1]. So frequency domain approaches, such as Fourier Transform and Fast Fourier

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Transform etc., are used for analysis and processing of EEG signals. But in case of these transforms, only frequency domain information is provided by the transformed domain, which is insufficient information for processing of non-stationary signals like EEG. So wavelet transform is used for analysis and processing of non-stationary signals. In this paper, wavelet analysis is presented for EEG signals, which are non-stationary in nature. The features can be extracted from the coefficients of decomposition; by calculating some statistical and non statistical properties for each node of decomposition.

2 Wavelet Transforms

This section provides a primer on wavelet transforms. Mathematical transforms are applied to signals to extract further information and that too in forms amenable for further processing. Often signals intended to be processed are in time-domain, but in order to process them and extract some information of interest, the frequency domain transformation is required. Mathematical transforms translate the information of signals into different representations. For example, the Fourier Transform provides the information about how many frequency components are there in a signal but cannot provide information about at which time these frequencies occur, because time and frequency is viewed independently. To solve this problem, the Short Term Fourier Transform (STFT) introduced the idea of windows through which different parts of a signal are viewed. For a given window in time, the frequencies can be viewed. However Heisenberg's Uncertainty Principle states that, as the resolution of the signal improves in the time-domain, by zooming on different sections, the frequency domain resolution gets worse. Ideally, a method of multi-resolution is needed, which allows certain parts of the signal to be resolved well in time, and other parts to be resolved well in frequency. This multi-resolution is the basis of wavelet transforms. It provides the time frequency representation. A wavelet is a little part of a wave, a wave that is only non-zero in a small region. In wavelet analysis, rather than examining the entire signal through the same window, different parts of the wave are viewed through different sized windows. High frequency parts of the signal use a small window to give good time resolution while low frequency parts use a big window to get good frequency information. Hence, Wavelet transform is capable of providing the time and frequency information simultaneously.

Continuous as well as discrete forms of wavelet transforms are available. The continuous wavelet transform was developed as an alternative approach to the Short Time Fourier Transform (STFT), to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function and the transform is computed separately for different segments of the time domain signal.

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*\left(\frac{t-\tau}{s}\right) dt$$

As seen in the above equation, the transformed signal is a function of two variables, τ and s, the translation and scale parameters, respectively. Ψ is the transforming function, and it is called the mother wavelet. The continuous wavelet transform is computed by changing the scale of the analysis window, shifting/translating the window in time, multiplying by the signal, and integrating over all times. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales. The signal is passed through a series of high pass filters to analyze the high frequencies, and then it is passed through a series of low pass filters to analyze the low frequencies. The resolution of the signal, which is a measure of the amount of detailed information in the signal, is changed by the filtering operations, and the scale is changed by up-sampling and down-sampling operations.

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k].h[n-k]$$

The sequence is denoted by x[n], where n is an integer. The procedure starts with passing this signal sequence through a half band digital lowpass filter with impulse response h[n]. Filtering a signal corresponds to the mathematical operation of convolution of the signal with the impulse response of the filter. The convolution operation in discrete time operates in this manner: a half band lowpass filter removes all frequencies that are above half of the highest frequency in the signal. The wavelet decomposition corresponds to passing of a signal through filters successively and designating the divided signal into detailed coefficients and approximate coefficients. At every level of decomposition, the data is filtered and then the approximation and detailed coefficients are produced from this filtered data. The same process is followed for further levels of decomposition. Suppose we have a signal S, after the decomposition we get A_1 approximation coefficient and D_1 Detailed coefficient. If we do the decomposition of the A_1 then we get AA_2 and DA_2 as the approximation and detailed coefficients of A_1. The same procedure is followed for D_1 and so on. In this way, a decomposition tree can be obtained for any number of decomposition levels, as shown in Fig.1.

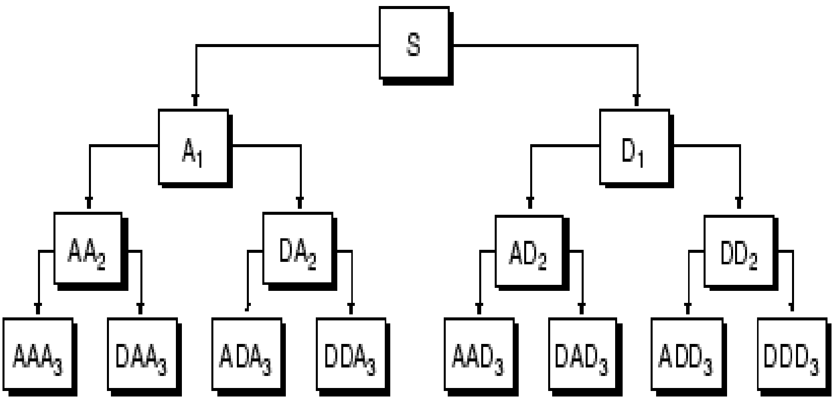
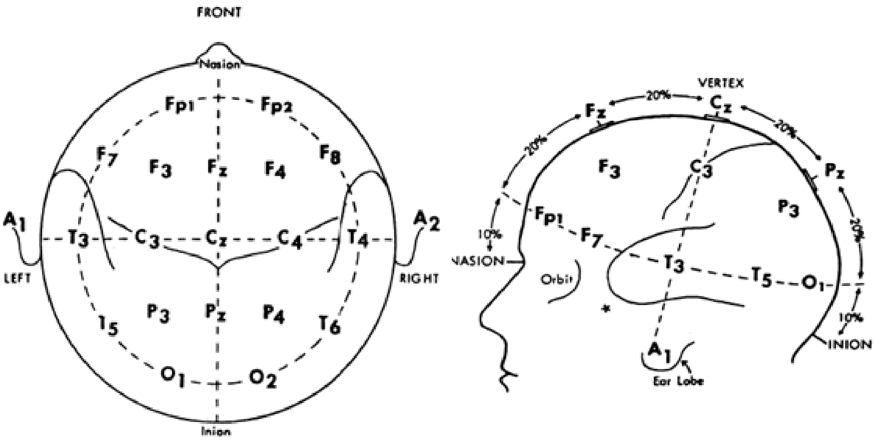


Fig. 1. The Wavelet Decomposition tree

3 Electroencephalogram Data

EEG is usually recorded according to the international 10-20 electrode placement system [4] shown in Fig.2. The 10-20 system was developed to standardize the collection of EEG and facilitate the comparison of studies performed in different parts of the world. When only a few channels of EEG are collected, the electrodes are placed at a subset of the sites. Fig.3 shows plot of EEG data from a normal subject and Fig.4 shows EEG recordings from a patient in ictal state. This data is taken from the source as given in [5]. Two sets of data are used, one from healthy subjects with eyes open and another for patients in ictal state, meaning thereby that the patient is under seizure during the recording of data. These two data sets are used in the subsequent section to demonstrate wavelet decomposition EEG of signals.



(a) (b)

Fig. 2. 10/20 International system of electrode placement. (a) Top view (b) Left side view.

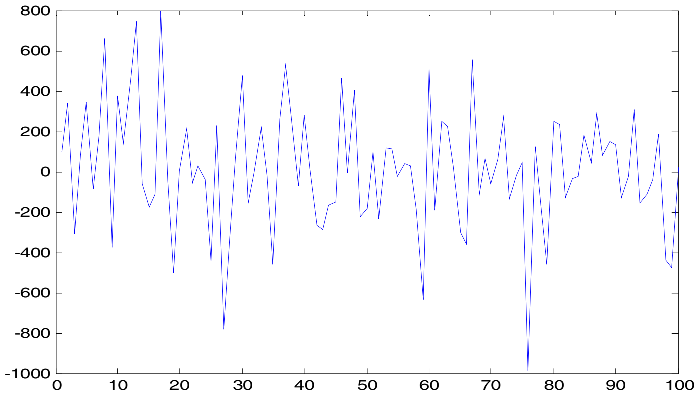


Fig. 3. EEG Signal from a normal subject

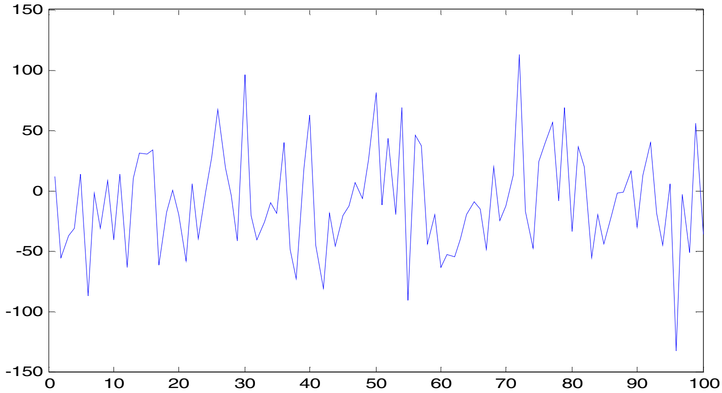


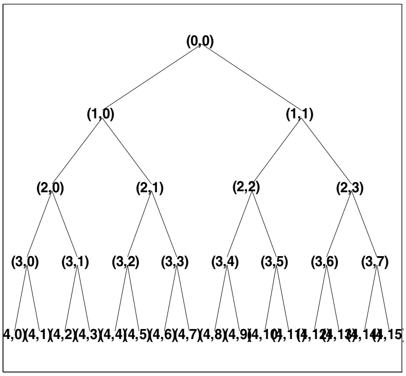
Fig. 4. EEG Signal from a patient in ictal state

4 Wavelet Decomposition of EEG

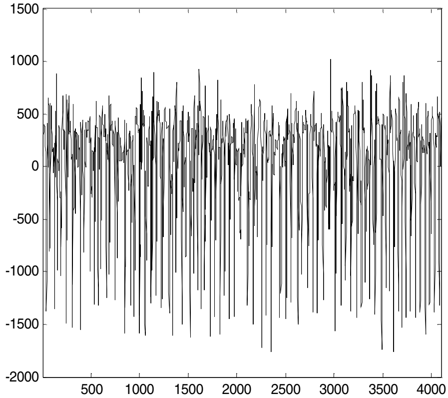
Feature extraction and classification of the signals are required for both diagnostic and brain computer interface purposes. However, Feature extraction always suffers from critical problems in time domain analysis [1]. The main purpose of feature extraction, is to extract salient characteristics from digitized data collected from the data acquisition phase [6] follows classification based on the extracted features [7, 8]. The features of the signal are derived from its linear expansion coefficients; the most common linear expansion method used is Fourier transform [10]. Fourier transform is suitable only for stationary signals. However, EEG signals are characterized as non-stationary signals; so, if processed with Fourier transform, would not yield the best result. Hence, for such non-stationary signals, a time–frequency representation is required, in order to derive meaningful features [9]. So wavelet transforms are one of such good choices to process these kind of signals. There are family of wavelet transforms which can be used for different purposes here Wavelet packet decomposition of EEG signals is demonstrated in subsequent section.

Wavelet Packet Decomposition of EEG Signals Wavelet packet analysis is used for extracting features of non-stationary signals, and is appropriate for extracting features from EEG signals which are non stationary in nature. Wavelet packet analysis is a generalized form of the DWT, wherein a signal is split into approximation and detailed coefficients. The approximation is again split into a second-level approximation and detailed coefficients, and the process is repeated. There are n + 1 possible ways to encode the signal for the n-level decomposition. The signal is passed through a series of low-pass and high-pass filters called quadrature mirror-filters.

In wavelet packet analysis, the approximation as well as detailed coefficients can be split like complete binary tree structure. A 4th level decomposition of an EEG signal from a normal subject is demonstrated in this paper. In Fig.5(a), the decomposition tree for a 4th level decomposition and in Fig.5(b), the data at node first of the 4th level of decomposition is shown. The features can be extracted from the coefficients of decomposition; by calculating some statistical and non statistical properties for each node of decomposition.



(a)



(b)

Fig. 5. (a) Wavelet packet analysis decomposition tree up to 4th level decomposition (b) Data at node (4, 1)

5 Conclusions and Future Directions

Wavelet packet decomposition using Matlab with wavelet and bioinformatics tool box, is carried out. A 4th level decomposition using wavelet packet decomposition is demonstrated. The displayed data in Fig 5(b) are the data corresponding to the coefficient at node 1st of 4th level decomposition. For n-level decomposition, we have 2^n coefficients, we can generate characteristic features from these coefficients for the purpose of classification. For both diagnostic and brain computer interface we need an efficient and accurate strategy of classification of EEG signals. So this kind of decomposition may be used for extraction of features for different kinds of classifier systems. Further we can try and compare the efficiency of the classification system for different types of wavelet transforms and can find out the best wavelet transform this purpose.

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