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DETECTING CLINICALLY RELEVANT EEG ANOMALIES USING DISCRETE WAVELET TRANSFORMS

P. JAHANKHANI[1], K. REVETT[2], V. KODOGIANNIS[1]
[1]Mechatronics Group, [2]Artificial Intelligent and Multimedia
School of Computer Science
University of Westminster
London HA1 3TP
UNITED KINGDOM

Abstract: - An EEG is a recording of the electrical signals produced by activity within the brain. A variety of cognitive and pathologies yield specific EEG signatures, which are diagnostic of the condition. As a clinical EEG may contain non-stationary signals, we have employed a Daubechies wavelet to automatically detect embedded signals that vary both in their frequency and magnitude from a clinical EEG dataset. The experimental results indicate that our system is able to identify anomalous signals embedded in a standard EEG data-stream that have frequencies within the range of 0.5-30 Hz.

Key-Words: - Electroencephalogram (EEG) Signal, Time-Frequency Analysis, Wavelet Transform

1 Introduction

The human brain is obviously a complex system and exhibits rich spatiotemporal dynamics. Among the non-invasive techniques for probing human brain dynamics, electroencephalography (EEG) provides a direct measure of cortical activity with millisecond temporal resolution. EEG is a record of the electrical potentials generated by the cerebral cortex nerve cells. There are two different types of EEG depending on where the signal is taken in the head: scalp or intracranial. For scalp EEG, the focus of this research, small metal discs, also known as electrodes, are placed on the scalp with good mechanical and electrical contact. Intracranial EEG (EcoG) is obtained by special electrodes implanted in the brain during surgery. In order to provide an accurate detection of the voltage of the brain neuron current, the electrodes are of low impedance (<5 kΩ) [1]. The changes in the voltage difference between electrodes are sensed and amplified before being transmitted to a computer program to display the tracing of the voltage potential recordings. The recorded EEG provides a continuous graphic exhibition of the spatial distribution of the changing voltage fields over time. EEG signals involve a great deal of information about the function of the brain. But classification and evaluation of these signals are limited. Since there is no definite criterion evaluated by the experts, visual analysis of EEG signals in time domain may be insufficient. Routine clinical diagnosis needs to analysis of EEG signals. Therefore, some automation and computer techniques have been used for this aim. These signals are not deterministic and they have no special formation like electrocardiogram (ECG) signals. Because of this, in the analysis of EEG signals, statistical and parametric analysis methods are used (such as time–frequency analysis, self relation, crosswise relation, wavelet transform). They also provide the determination of the time of frequency rhythm analysis of periodic EEG signals. Since their statistical properties are dependent on time and space, EEG signals are treated as complex signals. But these signals may be decomposed into typical sample periods analytically. Furthermore, if the temporal characteristics of EEG signals are taken into consideration, it will be seen that they are not stable [2-3].

Spectral analysis of the EEG signals is performed using the short-time Fourier transform (STFT), in which the signal is divided into small sequential or overlapping data frames and fast Fourier transform (FFT) applied to each one. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands–delta (< 4 Hz), theta (4-8 Hz), alpha (8-13 Hz) and beta (13-30 Hz). The output of successive STFTs can provide a time–frequency representation of the signal. To accomplish this, the signal is truncated into short data frames by multiplying it by a window so that the modified signal is zero outside the data frame. In order to analyse the whole signal, the window is translated in time and then reapplied to the signal [4]. Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric power spectrum estimation methods such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution. But, since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals [5].

A powerful method was proposed in the late 1980s to perform time-scale analysis of signals: the wavelet transforms (WT). This method provides a unified framework for different techniques that have been developed for various applications [6]. Since the WT is appropriate for analysis of non-stationary signals and this represents a major advantage over spectral analysis, it is well suited to locating transient events, which may occur during epileptic seizures. Wavelet's feature extraction and representation properties can be used to analyze various transient events in biological signals. Adeli et al. [3] gave an overview of the discrete wavelet transform (DWT) developed for recognizing and quantifying spikes, sharp waves and spike-waves. They used wavelet transform to analyze and characterize epileptiform discharges in the form of 3-Hz spike and wave complex in patients with absence seizure. Through wavelet decomposition of the EEG records, transient features are accurately captured and localized in both time and frequency context. The capability of this mathematical microscope to analyze different scales of neural rhythms is shown to be a powerful tool for investigating small-scale oscillations of the brain signals. The Discrete Wavelet Transform (DWT) is a versatile signal processing tool that finds many engineering and scientific applications. One area in which the DWT has been particularly successful is the epileptic seizure detection because it captures transient features and localizes them in both time and frequency content accurately. DWT analyzes the signal at different frequency bands, with different resolutions by decomposing the signal into a coarse approximation and detail information. DWT employs two sets of functions called scaling functions and wavelet functions, which are associated with low-pass and high-pass filters, respectively. The decomposition of the signal into the different frequency bands is simply obtained by successive high-pass and low-pass filtering of the time domain signal. Detailed derivations related to wavelet transform are given in [7]. Selection of suitable wavelet and the number of levels of decomposition is very important in analysis of signals using DWT. The typical way is to visually inspect the data first, and if the data are kind of discontinuous, Haar or other sharp wavelet functions are applied; otherwise a smoother wavelet can be employed. Usually, tests are performed with different types of wavelets and the one, which gives maximum efficiency, is selected for the particular application. The number of levels of decomposition is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlates well with the frequencies required for classification of the signal are retained in the wavelet coefficients. A better understanding of the dynamics of the human brain through EEG analysis can be obtained through further analysis of such EEG records. Numerous other techniques from the theory of signal analysis have been used to obtain representations and extract the features of interest for classification purposes. Neural networks and statistical pattern recognition methods have been applied to EEG analysis. In this study WT is applied to EEG experimental data obtained at the Clinical Neurophysiology of Great Ormond Street Hospital for Children Trust, London, UK. The time frequency characteristics of spontaneous brain rhythms have been investigated and the results using WT.

2 EEG data acquisition and representation

The data for this experiment were obtained at the Clinical Neurophysiology of Great Ormond Street Hospital for Children Trust, London, where 45 Ag/AgC1 electrodes were applied, based on a modified version of the International 10-10 system, on a 24yr old female adult volunteer. The stimulus of duration is 20 ms have been presented at regular intervals of 1/sec, and stimulus between 6-10 Secs into the recording. Continuous EEG data for this experiment was recorded using 'SYNAMPS' amplifiers set to amplify at x12500 with a band pass of 0.05-200HZ and a sampling rate of 500HZ. Epochs of -50 to 600ms were constructed offline using Neuroscience 4.2 software. Example of EEG recordings from a normal subject is shown in Figure 1.

2.1 Implementation of wavelet Coefficients

To analyse EEG signal in time for its frequency content we used DWT. Daubechies wavelet of order 3 was investigated for the analysis of EEG signals. Daubechies wavelet is known for its orthogonality property and efficient filter implementation [8, 9].

Fig 2 shows the Daubechies order 3 wavelet approximation and details sampled at 500Hz (0.002 ms epoch per second).

Our preliminary study [10] analysed a similar EEG dataset consisting of a series of embedded pulses (via cutaneous tapping at a frequency of approximately 1 Hz). We were able to identify the embedded signals, but assumed they occurred at a fixed frequency. In order to increase the general applicability of our system, in this study we investigated how our detection system detects embedded signals at variable frequencies. Further, since we are working with clinical EEG datasets, we restrict the frequency range to those found in a clinical setting: 0.5 – 30 Hz. In order to increase the inherent variability of the dataset, we up/down-sampled the dataset in order to increase the frequency range of the embedded signals. Table 1 presents frequencies and periods corresponding to different levels of decomposition for Daubechies order 3wavelet with a sampling frequency of 500 HZ and with centre frequency 0.8.

Level of Decomposition (i)	Scale (2^i)	Frequency (Hz)DB3	Period (S) DB3
0	1	400	0.0025
1	2	200	0.0050
2	4	100	0.0100
3	8	50	0.0200
4	16	25	0.0400
5	32	1250	0.0800
6	64	6.25	0.1600
7	128	3.125	0.3200
8	256	1.5626	0.6400
9	512	0.7813	1.2800

3. RESULTS

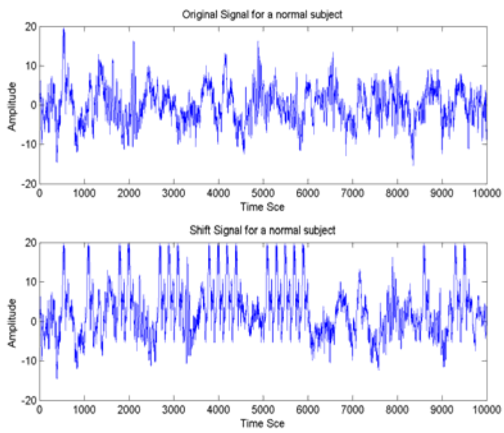


Figure 1: Normal and shifted (top and bottom panel respectively) child EEG Record used in this study. The x-axis corresponds to time (approximately 10 minutes in this data sample) and the y-axis signal intensity

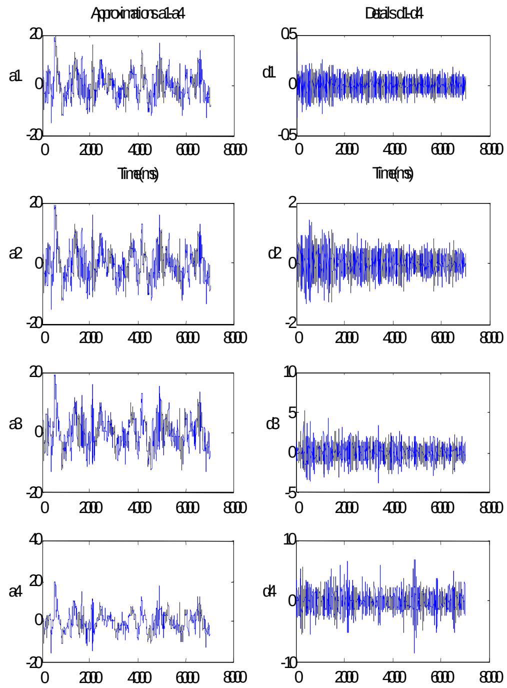
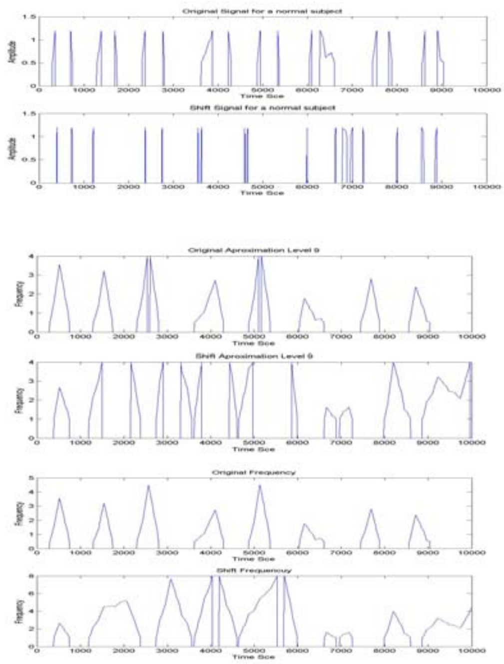


Figure 2: Daubechies order 3 wavelet transform of EEG record of a normal subject. The approximation data is presented in the left column and the detail components are displayed in the right column, at increasing spectral resolution. The x-axis corresponds to time and the y-axis signal magnitude



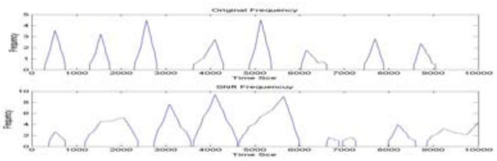


Figure 3: Illustrates the signal extraction algorithm we employed in this study. The bottom panel Normal and shifted frequency (top and bottom panel respectively) was generated by filtering out the signal with values outside of the specified frequency range (0.5 – 30 Hz) band filtering

4 CONCLUSIONS

In this paper, we present the results of a preliminary study that autonomously extracts an embedded signal, occurring at 1 Hz from a single channel EEG recording in a clinical setting. The embedded signal entailed a somatosensory stimulus, occurring at approximately 1 Hz embedded in a typical EEG acquired in a controlled setting from a collection of 5-7 year old children. The embedded signal was extracted using a Daubechy DWT level 9 and band-passed filtered. The resulting signal extraction algorithm was able to detect the embedded signal with 100% sensitivity (see Figure 3 above). In our future work in, we will investigate the automated detection of additional phenomena that frequently appear in clinical EEG recordings which are either background signals such as eyeblinks and related phenomena that require removal from the dataset in order to reduce artefact levels. In addition, our system will be adapted to be able to automatically detect relevant neurophy-siological conditions that have an EEG signature such as petite mals, cortical spreading depression, migraine aura and other related phenomena.

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