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Time Frequency Analysis of Epileptic Seizure in EEG

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Abstract: *Biomedical related research requires lots of mathematical and engineering techniques to analyze data. Among the subfields, electrophysiological research plays the core role. In this paper, several tools are examined in electroencephalogram and these are the most common tools used to diagnose our physiological activities since neural responses carry information. Because biomedical signals are usually non stationary, Fourier transform is not suitable to apply here. Besides, traditional signals are analyzed in frequency domain, separately from time domain, such that extraordinary conditions are hard to be observed. To solve such problem, time-frequency analysis and wavelet transform provide both time and frequency information simultaneously.*

The theoretical background of both time-frequency analysis and wavelet transform methods, including what properties they have, their common types, and how to operate them will be discussed over here. Secondly, we would briefly introduce common physiological tool EEG. Where they can be applied, what they are targeting, and what analysis methods can be used, and how they perform will be described.

The paper is organized as follows. The first section gives an introduction. In the second section briefly wavelets and energy computation from wavelet coefficients will be introduced, while in the third section analysis of epileptic EEG will be discussed. The last two sections include data, methodology, application to EEG and results.

1. INTRODUCTION

Doctors have been using Ultrasound, MRI, ECG, EEG, EMG for the diagnose and treatment of various disease.

Epilepsy is one of the most prevalent neurological disorders in human being. EEG signals exhibit several patterns of rhythmic or periodic activity in different frequency bands, any deviation from the normal pattern can be identified by time-frequency analysis. Hence for the prediction and diagnose of epileptic seizures time frequency analysis of EEG Spectrum can be done using Wavelet Transform[1].

2. ELECTROENCEPHALOGRAM (EEG)

The EEG was originally developed as a method for investigating mental processes. Clinical applications soon became visible, most notably in epilepsy, and it was only with the introduction of ERP recordings that EEG correlates of sensory and cognitive processes finally became popular. The first recordings of brain electrical activity were reported by Caton in 1875 in exposed brains of rabbits and monkeys, but it was not until 1929 that Hans Berger (Berger, 1929) reported the first measurement of brain electrical activity in humans. EEG visual patterns were correlated with functions, dysfunctions and diseases of the central nervous system, then emerging as one of the most important diagnostically tools of neurophysiology. The electroencephalogram (EEG) can be roughly denied as the mean electrical activity of the brain in different sites of the head. More specially, it is the sum of the extracellular current Flows of a large group of neurons. EEG recordings are achieved by placing electrodes of high conductivity (impedance < 5000) in different locations of the head. Measures of the electric potentials can be recorded between pairs of active electrodes (bipolar recordings) or with respect to a supposed passive electrode called reference (monopolarrecordings). These measures are mainly performed on the surface of the head (scalpEEG) or by using special electrodes placed in the brain after a surgical operation (intracranial EEG).

3. INTRODUCTION TO BRAIN OSCILLATIONS

Berger (1929) already mentioned the presence of what he called alpha and beta oscillations. The study of different types of rhythmicities of the brain and their relation with different pathologies and functions keep the attention of researchers since the beginning . Brain oscillations were divided in frequency bands that have been related with different brain states, functions or pathologies.

Alpha rhythms (7.5-12.5Hz): They appear spontaneously in normal adults during wakefulness, under relaxation and mental inactivity conditions. They are best seen with eyes closed and most pronounced in occipital locations

Beta rhythms (12.5-30Hz): They are best denied in central and frontal locations, they have less amplitude than alpha waves and they are enhanced upon expectancy states or tension. They are traditionally subdivided in 1 and 2 oscillations.

Theta rhythms (3.5-7.5Hz): They are enhanced during sleep and they play an important role in infancy and childhood. In the awake adult, high theta activity is considered abnormal and it is related with differentbrain disorders.

Delta rhythms (0.5-3.5Hz): They are characteristic of deep sleep stages. Furthermore, delta oscillations with certain specific morphologies, localizations and rhythmicities are correlated with different pathologies.

Gamma rhythms (30-60Hz): Previously not of major interest with regard to the surface EEG, they gained popularity after the cellular level experiments of Gray and Singer (1989) and Gray et al. (1989) showing their relation with linking of stimulus features into a common perceptual information(binding theory).

4. EPILEPSY

One important application of the EEG is to the study of epilepsy. The appearance of abrupt high amplitude peaks (spikes), abnormal rhythmicities, “slowing" of the recording and several other paroxysms are a general landmark of it, helping to identify, classify and localize the seizures. Epilepsy is a disorder of the normal brain function that affects about 1% of the population, characterized by an excessive and uncontrolled activity of either a part or the whole central nervous system. Historically ,the EEG has been them ostusefultoolfor its evaluation, now complemented with the advances in imaging techniques, especially the ones achieved by the MRI. Given that ictal recordings (i.e. recordings during a seizure) were rarely obtained, EEG analysis of epileptic patients usually relied on interictal findings. In those interictal EEGs, seizures are usually activated with photostimulation, hyperventilation and other methods. However, one disadvantage of these stimulation techniques is that provoked seizures do not necessarily have the same behavior as the spontaneous ones. The introduction of long term Video-EEG recordings has been an important milestone providing not only the possibility to analyze ictal events, but also contributing with valuable information in those candidates evaluated for epilepsy surgery. In this setting and following strict protocols, seizures are elicited by gradually reducing anti-epileptic drug [1-3].

5. WAVELET TRANSFORM IN EEG

The Fourier transform (FT) has been the traditional method applied to the analysis of time series signals for decades. Fourier coefficients are determined by the entire signal support and frequencies are not localized in time, since the infinite basis functions are used in FT. Consequently, Fourier analysis provides only globally time-averaged information, whereas it lacks any local behavior within the signal. Hence, it is suitable for extracting frequency information from stationary signals.

EEG signals like many biomedical signals are non-stationary, and Fourier transform does not give an effective analysis for such signals. For non-stationary signals one method to partly overcome this difficulty is the usage of short-time Fourier transform, STFT (the windowed Fourier transform) in which the signal is multiplied by a sliding window of limited extent, considering the signal as quasi-stationary for such a short period. In essence, STFT extracts several frames of the signal to be analyzed with a window that moves with time. If the time window is sufficiently narrow, each frame extracted can be viewed as stationary so that Fourier transform can be used. With the window moving along the time axis, the relation between the variance of frequency and time can be identified. However the compromise between the temporal and frequency resolution, established by the window size, is the same for all frequencies.

The wavelet transformation is well-suited to representing various aspects of EEG signals such as trends, discontinuities, and repeated patterns where other signal processing approaches fail. Wavelet is an effective time/frequency analysis tool for analyzing transient signals. In the wavelet transform (WT) case, WT employs a windowing technique with variable-size windows. Wavelets are mathematical functions that cut up data into different frequency components, and then study each component with a resolution matched to its scale. They have advantages over traditional Fourier methods in analyzing physical situations where the signal contains discontinuities and sharp spikes. The fundamental idea behind wavelets is to analyze according to scale.

Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. Approximation using superposition of functions has existed since the early 1800's; Joseph Fourier discovered that he could superpose sines and cosines to represent other functions. However, in wavelet analysis, the scale used to look at data has a special role. Wavelet algorithms process data at different scales or resolutions. If we look at a signal with a large window, we can notice gross features, and if we look at a signal with a small window, we can catch small features. This makes wavelets interesting and useful

Wavelets have been traced all the way back to Alfred Haar in 1910; however, the starting point of their modern history coincides with two publications in the 1980s by Mallat (Mallat, 1989) and Ingrid Daubechies (Daubechies, 1990). S. Mallat identified the important concept of multiresolution analysis which is the corner stone of modern wavelet theory, while Ingrid Daubechies constructed the first orthogonal wavelet bases that were compactly supported.

In 2009 Magosso *et al* wavelet methods have been applied to EEG data obtained from epileptic patients suffering from drug resistance temporal lobe seizures acquired at Bellaria Hospital (Bologna)[8]. In this particular paper Magosso *et al* analyzed whether the energy distribution of the EEG is altered among the different scales of the wavelet representation and exhibit distinct patterns of energy redistribution. In the present work we exploit the same for our data obtained at Kocaeli University's Medical Hospital in Turkey to characterize the epileptic attack in quantitative terms and to obtain indications concerning the genesis of the seizure propagates among adjacent regions of the brain. We have obtained similar results for digitally recorded video EEG recordings for epileptic patients as Magosso *et al*. We have shown that energy distribution of the EEG has altered among the different scales of wavelet representation at seizure onset and during the seizure.

The wavelet is a quickly vanishing oscillation function localized both in frequency and time. In both continuous and discrete forms of wavelet analysis, the signal is decomposed into scaled and translated versions $(\psi_{a,b}(t))$ of a single function $\psi(t)$ called mother wavelet:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\Psi(\frac{t-b}{a}) \tag{1}$$

where a and b are the scale and translation parameters, respectively, with $a,b \in \Re$ and $a \neq 0$. If a signal $f(t)$ is a square integrable function of time, i.e. $f \in L^2(\Re)$ (the space of finite energy signals), then the continuous wavelet transform (CWT) of the signal is defined as

$$W(a,b) = C_{a,b} = \int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{|a|}}\psi^*\left(\frac{t-b}{a}\right)dt = \langle f, \psi_{a,b} \rangle \tag{2}$$

where <.,.> means the inner product and the symbol '*' means complex conjugate. The factor $1/\sqrt{|a|}$ is used to normalize the energy so that it stays at the same level for different values of a and b. The wavelet function $\psi_{a,b}(t)$ becomes narrower when a is increased and displaced in time when b is varied. Therefore, a is called the scaling parameter which captures the local frequency content and b is called the translation parameter which localizes the wavelet basis function at time $t = b$ and its neighborhood. CWT at every possible scale a and translation b provides a redundant representation of the signal; hence CWT requires a heavy burden of computations compared to the DWT. DWT provides sufficient information both for analysis and synthesis of the original signal, with a significant reduction in the computation time. The filters of different cutoff frequencies can be 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 it is passed through a series of low pass filters to analyze the low frequencies (Addison, 2002)[1,5].

The discrete wavelet transform (DWT) is obtained by discretizing the parameters a and b. We may choose $a = 2^{-j}$, $b = k2^{-j}$ with $j,k \in$Z. By substituting this in (1) we get

$$\Psi_{j,k}(t) = 2^{j/2}\Psi(2^j t - k). \tag{3}$$

Energy Computation

When the family $\{\Psi_{j,k}(t) = 2^{j/2}\Psi(2^j t - k)\}$ is an *orthonormal* basis in $L^2(\Re)$, the concept of energy is linked with the usual notions derived from the Fourier theory, and the sum of the square of the coefficients of the series is the energy of the function, *i.e.* the energy series associated with coefficients series is given by

$$E_{j,k} = |d_{j,k}|^2 \tag{4}$$

and the over all energy at resolution j is

$$E_j = \sum_{k=0}^{2^{M-j}-1} |d_{j,k}|^2 \tag{5}$$

The total energy associated with entire signal can be obtained as

$$E_{tot} = \sum_{j=1}^{M} \sum_{k=0}^{2^{M-j}-1} |d_{j,k}|^2 . \tag{6}$$

Grouping and spreading-out energy coefficients

In this method the original signal will be divided into non-overlapping temporal windows of fixed length $L = 2^J T_s$. Here 2^J is the number of signal samples falling within the window, and an atom of energy within each window at every resolution level j will be computed. Two different cases have to be considered:

Case a) J > j: In this case, at each scale j $(j = 1,\ldots,M)$, the assigned window contains 2^{J-j} energy coefficients. The atom of energy within the window n $(n = 0,1,\ldots,N_W - 1)$ can be computed by grouping all the energy coefficients falling within the window:

$$\hat{E}_{j,n} = \sum_k E_{j,k} \tag{7}$$

$$\begin{cases} 0 \le k \le 2^{J-j-1} - 1, & n = 0, \\ (2n-1)2^{J-j-1} \le k \le (2n+1)2^{J-j-1} - 1, & n = 1,\ldots,2^{M-J} - 1. \end{cases}$$

Center point of the corresponding time window will be set according to (Eq.7). So the first window will be centered on 0, and half of the coefficients contained in it are null. Thus for each scale a series of N_W energy atoms uniformly time distributed with a time resolution $\Delta t_J = 2^J T_S$.

Case b) $j > J$: This means that coefficients at some scale have a time resolution lower than L. In other words there is a scale j^* within the decomposition $(1 < j^* < M)$ such that $j^* = J$. In this case again Eq.13 can be used for each scale $j < J$ as before to group energy coefficients within a window. At scale $j^* = J$ no processing is required for energy coefficients, because they have the desired time resolution. However for coefficients at scale $j > J$ we use

$$\hat{E}_{j,n} = \frac{E_{j,k}}{2^{j-J}} \qquad k = \text{round}\left(\frac{n}{2^{j-J}}\right), \qquad n = 0,\ldots,2^{M-J}-1, \tag{8}$$

where the function round (x) rounds x to the nearest integer.

Therefore the total energy within a time window n can be obtained by

$$\hat{E}_{tot,n} = \sum_{j=1}^{M} \hat{E}_{j,n}, \tag{9}$$

and the relative energy associated with the resolution j in the time window n can be obtained by

$$\hat{\rho}_{j,n} = \frac{\hat{E}_{j,n}}{\hat{E}_{tot,n}}. \tag{10}$$

Energy coefficients as computed by Eq. (10) have a different localization and density over the temporal axis, depending on the scale: at scale j, the coefficients are placed at instants $k2^j T_s$,

$k = 0,\ldots,2^{M-j}-1$ Thus, to study and to compare the temporal evolution of energy at different scales, it is necessary to recover for the halved time resolution at each scale due to the down-sampling operation. In the following, two methods which allow uniformly time distributed atoms of energy to be obtained across all scales will be intoduced. In the last section these methods will be applied to the analysis of the EEG data.

6. METHODOLOGY

In this research paper we have used data of 30 epileptic patients suffering from temporal lobe seizures at Medical School's Hospital of Kocaeli University. Data were recorded by the neurology laboratory of the hospital by using International 10-20 recording system (see Fig. 1) using digital EEG recording device. The scalp EEG recording is used since most hospitals have limited or no usage of intracerebral EEG recordings. Using scalp EEG recordings we get the same major modifications of frequency and of energy distribution as intracerebral EEG recording. The signals were sampled at 200 Hz and stored on a 32–64 channel computerized video-EEG system. Each patient has been hospitalized for EEG video monitoring for several hours, and seizures in their EEG have been detected visually. The data were cut into small pieces containing a few minutes before and after the seizures. The multiresolution wavelet analysis was applied to all channels using the Daubechies order 4 wavelet (Db4). Each EEG signal was decomposed into seven resolution levels, in order to consider all frequency bands which are commonly considered in the analysis of EEG signals[7,8,12].

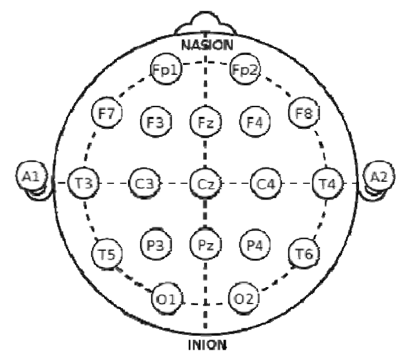


Fig. 1: International 10-20 EEG recording system

Fig. 2 shows the 7 level decomposition of T6–O2 channel from one patient, with seizure activity starting at t = 115 s. The signal (s), the seven levels of details (D1–D7) and the residual approximation (A7) are shown in the Fig. . The approximation and detail records are reconstructed from the scaling coefficients and wavelet coefficients, respectively. The original signal is the superimposition of details D1–D7 and approximation A7.

Fig. 3 shows the power spectral density (PSD) of the details and approximation estimated with the Welch's method. The frequency components captured by details move from the high frequencies towards the low frequencies as scale increases from 1 to 7 (35 – 100 Hz at scale 1 vs. 0.75–1.5 Hz at scale 7), whereas approximation A7 contains all the residual lower frequency information (<0.75 Hz) of the signal for our data. From Fig. 3 the spectra clearly indicate the frequency content captured by each detail and the approximation[9-12].

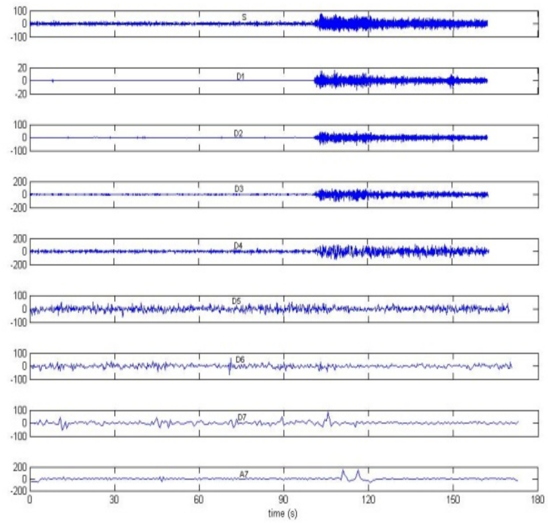


Fig. 2: T6-O2 channel of the signal (*s*) and Wavelet Decomposition of it using Db4.

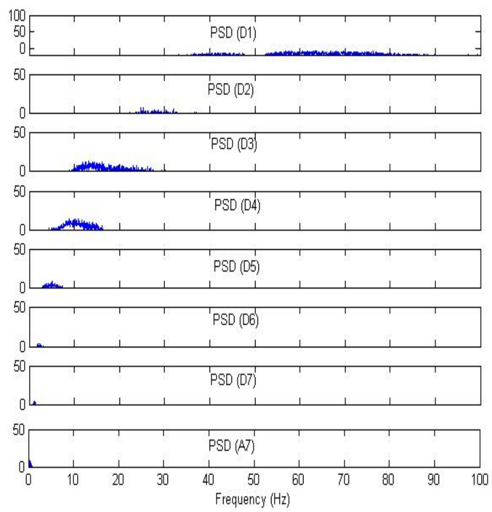


Fig. 3: Power spectrum density (PSD) of the details and approximation.

An important aspect in the analysis of EEGs during epilepsy is the energy redistribution among the different details; this redistribution may indicate changes in the characteristics of EEG signals which, in turn, may represent specific events in the course of seizure. In order to characterize the temporal evolution of the energy redistribution of EEG signals, the signal was divided into moving average windows each with a duration $L = 2^J Ts$ (where Ts is the sample time) and the energy of all details were computed within each window. In particular, all energy atoms at the same resolution level, contained within the same window, were summed up to have energy at that particular level (Eq. (9)).

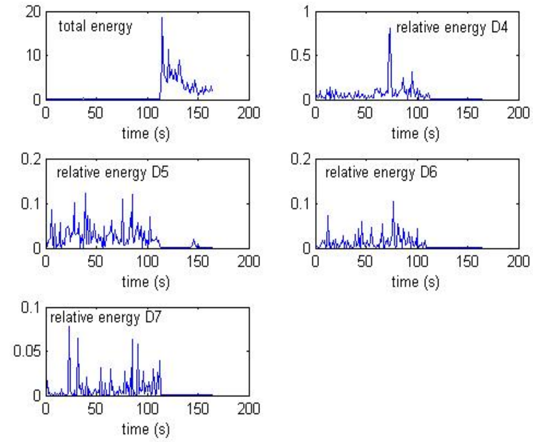
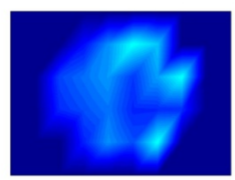
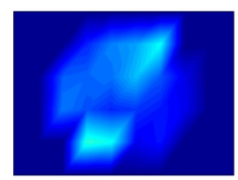
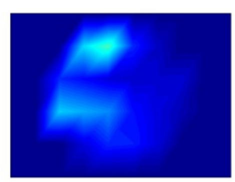
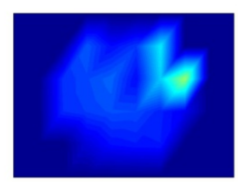


Fig. 4: Total energy of the signal (*s*) and the relative energies contained in each detail D4-D7.

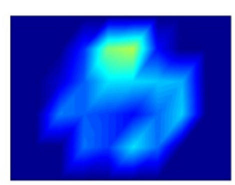
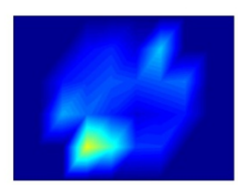
In Fig. 5 below snapshots of the relative energy distribution in all EEG channels for a patient with temporal lobe epilepsy just before seizure (t=65s), at seizure beginning (t=105s), and during several seconds of seizure with reference to detail 4 can be seen. Different colors indicate different relative energy; dark blue for colored pictures (light grey for black/white pictures) show values close to zero, while dark red (light grey) shows higher values.

65s **70s**

75s **80s**

85s **90s**

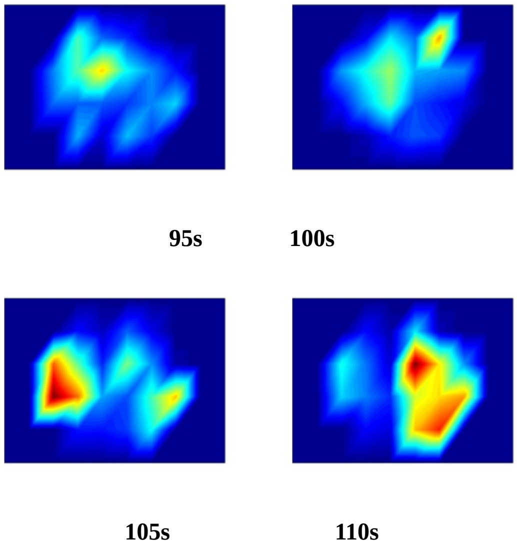


Fig. 5: Snapshots of the relative energy distribution in all EEG channels for a patient with temporal lobe epilepsy

7. CONCLUSION

These results show that EEG Patients exhibit a rearrangement of relative energy among the different frequency band just before and during the seizure. Particularly for patients with temporal lobe epilepsy These results show that EEG recordings of epileptic our analysis confirms this result. However this relocation of the energy is not the same at all channels.

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