Analysis of Epileptic Events Using Wavelet Packets

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Abstract: *Many studies have focused on the nonlinear analysis of electroencephalography mainly for the characterization of epileptic brain states. The spatial and temporal dynamics of the epileptogenic process is still not clear completely especially the most challenging aspects of epileptology which is the anticipation of the seizure. Despite all the efforts we still don't know how and when and why the seizure occurs. However actual studies bring strong evidence that the interictal-ictal state transition is not an abrupt phenomena. Findings also indicate that it is possible to detect a preseizure phase. We will study the patients admitted to the epilepsy monitoring unit for the purpose of recording their seizures. These patients have their EEG signal recorded 24 hours a day for several days until they have enough number of seizures to determine eligibility for seizure surgery. Thus, preictal, ictal, and post ictal electroencephalography recordings are available on such patients for analysis. We propose to use wavelet analysis in order to investigate a case study of the electroencephalography signal and determine the localization of the seizure and its characteristics.*

Keywords: *Epilepsy analysis, wavelet, spike detection.*

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1. Introduction

Epileptic seizures are manifestation of epilepsy. The ElectroencEphaloGraphy (EEG) recorded signal presents the electrical activity of the brain cortex; it provides information about the area of abnormal neural tissues responsible for the initiation of epileptic seizure. The field of seizure prediction in which engineering technologies are used to decode brain signals and search for precursors of impending epileptic seizures, holds great promise to elucidate the dynamical mechanisms underlying the disorder, as well as to enable implantable devices to intervene in time to treat epilepsy [2, 10, 7, 3].

In order to analyze the EEG signal we suggest the wavelet analysis which reduces the signal into fewer coefficients compared to the classical fourier analysis. Epileptiform transients are spikes, slow waves, polyspikes and sharp waves. The spike is the most important characteristic on epilepsy electrical recordings, it is a transient clearly distinguished from EEG background activity with pointed peaks whose duration goes from 70 to 120ms.

Multiresolution analysis is a powerful concept that has proven to be very efficient whenever a signal is dominated by transient behavior or discontinuities like epileptic events. This analysis is based on a function called wavelet which is a short oscillating waveform that persists for only few cycles. Certain wavelets have a finite duration and non-zero values over a small time period. This property gives a compact support for the detection of transient signals location as spike location.

The multi-resolution analysis uses a pair of functions: the scaling function $\varphi(t)$, to represent the signal's high frequencies and the wavelet function $\psi(t)$ to represent the smooth components. The wavelet analysis will be conducted using the pyramid algorithm that reduces the number of operations to the $N \log2N$ order. The electroencephalography applications use the wavelet transform to reduce the amount of information to process long-term EEG recordings. The proposal is to represent the discrete signal derived from the EEG by using wavelet packet decomposition, which is a wavelet that presents more oscillations than a regular wavelet but still with finite duration. The wavelet packet decomposition has location (position), scale (duration), and oscillatory (frequency) characteristics and is called a time-frequency waveform.

The aim of the paper is to apply wavelet packet property, time-frequency waveforms to characterize spikes on EcoG segments. We use the pyramid algorithm to be able to get on-line processing. The paper is organized in three sections. Material and methods, results, and discussion.

2. Materials and Methods

The data concerns a case of epilepsy, methods are used after an introduction to wavelet and packet transforms and finally the detection algorithm is defined, and applied on the case study.

2.1. Data Collection

The data used in this study is obtained from a young patient aged 13 years at the neurophysiology unit of the American University Hospital of Beirut. The EcoG segments were acquired by placing a grid of 20 electrodes according to the 10-20 system over the 4 lobes of the cortex, as shown in Figure 1. The EEG starts with the patient awake and the background consists of posterior moderate reactive 10Hz alpha activity with higher amplitude on the right side. Anterior low voltage beta activity and central alpha range mu rhythms were seen. Drowsiness results in diffuse slowing of the background. It has been seen in wakefulness and drowsiness that there were 1-2s episodes of generalized 3Hz spike slow wave activity, as shown in Figure 2.

Among all the electrode signals we have chosen the signals obtained from the FP1-F3 electrodes and the F3-C3 electrodes located on the frontal left lobe of the brain. The parameters to be extracted from the analysis of those signals will help us to localize and describe the kind of spike wave involved in this form of epilepsy.

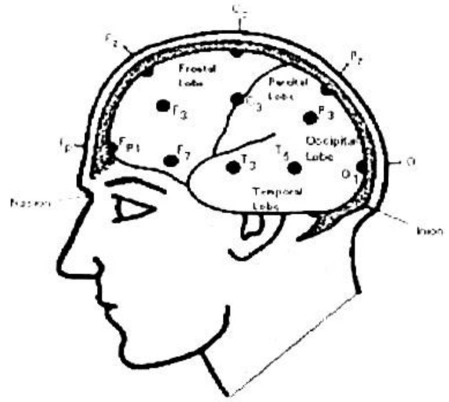

Figure 1. Electrodes positioning.

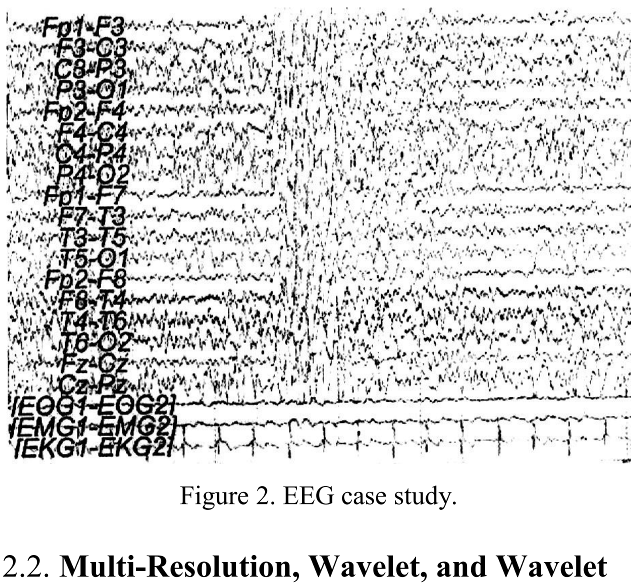

Figure 2. EEG case study.

2.2. Multi-Resolution, Wavelet, and Wavelet Packet Transforms

The multi-resolution framework software is implemented on a Pentium IV personal computer in MATLAB [12, 13]. The study has been conducted based on the results given according to the paper [8]. It shows after applying multi-resolution analysis based on wavelet transform and using different functions to extract spike waveforms from the multi-channel EcoG signals, that the function biorthogonal eight-order decomposition and sixth-order reconstruction is the one giving the highest precision in detecting spikes among B-spline biorthogonal wavelet, daubechies, non-orthogonal mexican hat functions.

The spike waveform could be detected because of its short duration high amplitude and high energy. Thus the designated method will be the wavelet transform. It can detect signals with singularities and edges such as the spike waveform in an EEG signal [5]. It is based on a pair of functions one, $\psi(t)$ acting as a filter of high frequencies corresponding to the detailed parts of the signal and another, $\varphi(t)$ acting as filter for low frequencies or smooth parts of the signal. The two shapes can be translated and scaled to produce wavelets at different locations (positions) and on different scales (duration), to get a multiresolution decomposition. The equation used for the wavelet transform is:

$$(W\psi\, f)(a,b)=\sqrt{1/a}\int f(t)\ \psi a,b((t-b)/a)\ dt \qquad (1)$$

where $f(t)$ is the EEG signal, and $\psi a,b$ is one of the basic functions orthonormal, non-orthonormal, or biorthogonal. Any wavelet can be decomposed into a direct sum of closed subspaces Wj [ ]. The sequence $\{Wn(x)\}$ is defined as:

- $W0(x) = \varphi(x)$, $\varphi(x)$ act as the scale or the duration function.
- $W1(x) =\psi(x)$, $\psi(x)$ act as the wavelet function.
- $W2n(x) = \sqrt{2}\ \sum h(k)*\ Wn(2x-k)$ for k=0….2n-1, $h(k)$ is the scale filter.
- $W2n+1(x)= \sqrt{2}\ \sum g(k)*\ Wn(2x-k)$ for k=0….2n-1, $g(k)$ is the wavelet filter.

we use the scaling function $\varphi(x)$ that verifies the following properties:

$$\varphi(0)=1 \qquad (2)$$

and $$\varphi(0)*\ \varphi(x) = 2^{1/2}\sum_k h_k * \varphi(2x-k)$$

(3)

$$\psi(x)=2^{1/2}\sum_k g_k * \varphi(\text{٢}x-k) \text{ with}$$

$$\sum_{n\in z} h_{n-2k}\, h_{n-2l} = \delta_{k-l} \qquad (4)$$

and $$\sum_{n\in z} h_n = \sqrt{2}\ ,\ g_k = (-1)^k * h_{1-k}$$

(5)

with these two sequences $W2n(x)$ characterizing the scaling function and $W2n+1(x)$ characterizing the wavelet function, we introduce a family of functions called wavelet packet which is a generalization of the orthogonal wavelet $\psi(k)$ and is used to improve the performance of wavelets for time-frequency localization.

The wavelet packet used after j iterations and frequency n (1/scale) is

$$Wj,n= (Wj,n,k(x),k€Z)= 2^{-j/2} W_n((2^{-j})*x-k) \quad (6)$$

where k is the time localization.

The formula can be computed by the fast pyramid algorithm [1] that halves the data each time reducing the computations of each iteration. The wavelet packet transform's structure is based upon a binary tree [4, 6], as shown in Figure 3, each node representing the application of a quadrature mirror filter pair to the signal *f(n)* as the digitized EEG samples. Different decompositions can be created, each level corresponding to a different frequency band in the original signal.

It was shown [11, 14] that wavelet packet functions are able to localize a segment of the signal duration depicting the locally oscillatory signals as the transient spikes in the EEG signal.

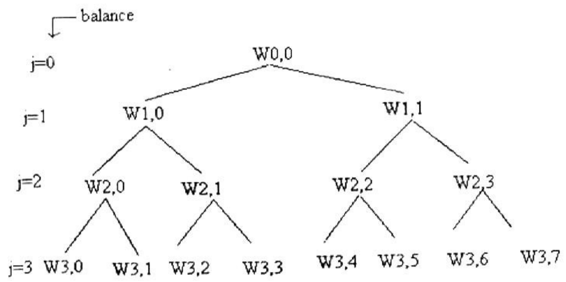

Figure 3. Wavelet packet binary tree.

The simulation corresponding to the wavelet packets consist of the decomposition of the signal into detailed coefficients vector using the wavelet filter *G* and approximation coefficients vector using the scale filter *H* given in equation 2.

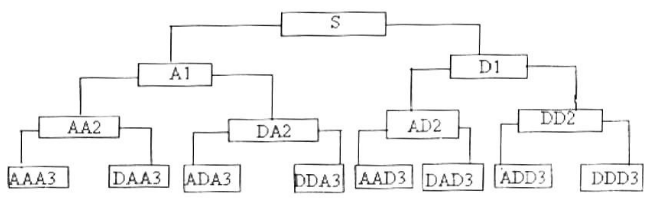

Figure 4. Detailed and approximation nodes.

where S is a sequence of vectors containing the detailed and approximated coefficients for a frequency n of the signal.

After the decomposition into approximate and detailed vectors, the shannon entropy is used $E(s) =-\sum s^2 \log s^2$ that will explicit the energy variations in order to depict the spike signal. The entropy is a good indicator because it satisfies the property that it is statistically null when there are non-epileptic events and has a sensible deviation from zero for a sharp signal as the spike.

The nodes to be chosen as representative of the signal are those satisfying the following equation:

$$Max\ Entropy\ (di,n*dj,k) \quad (7)$$

where i, j are the resolution index and n, k are the position of the binary tree node (frequency of the signal) and *di,n* or *dj,k* are the detailed and approximated coefficients in each node.

The reconstruction is conducted from the nodes retained using the following equation:

$$dj,n(k)=H*dj+1,2n(k)+G*dj+1,2n+1(k) \quad (8)$$

2.3. **Detection Algorithm**

To detect the spike into an EEG reconstructed signal we have first chosen to define a representative index of the spike given by the formula:

$$I=di,n*dj,k \quad (9)$$

(6)

This operator depends on time-scale plane and by multiplying the wavelet coefficients the detection algorithm is more sensitive to signal variation concerning duration, increments, and decrements of the signal.

3. Results

Results are presented according to the EEG signal FP1-F3, the signal which is d0,0 at the level 0, position 0 first node of the binary tree is divided into segments of 15s corresponding to 106 samples/s. The samples amplitude varies from -50 microVolts up to 50 microVolts.

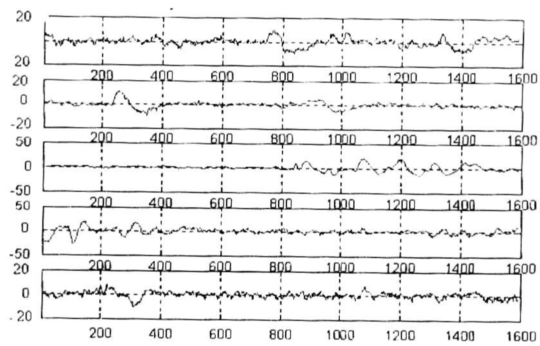

Figure 5. The four 15s segments of the FP1-F3 signal.

From analyzing those segments using the criteria max of I among nodes on epileptic events and non-epileptic events of the generalized wave where spikes are difficult to predict, we concluded that the criteria for the spike detection is that the index detection I must satisfy the following property: The spike is the signal that has the max index among all the nodes indexes I verifying ($I*I > 10^4$).

Tables 1 represents the third segment of the EEG signals decomposed according to biorthogonal wavelet function up to the 4th level showing the approximate nodes entropy and the detailed nodes entropy. The max entropy was found at nodes $d_{4,0}$; $d_{3,0}$; $d_{4,1}$. Figures 6, 7, and 8, show the selected signal reconstructed from the retained nodes.

Table 1. Approximation and detailed coefficients nodes after decomposition of the third EEG segment.

Approximation Coefficient Nodes	|Entropy|
$d_{4,0}$	|-1.1603e+009|
$d_{3,0}$	|-5.6697e+008|
$d_{2,0}$	|-2.5982e+800|
$d_{1,0}$	|-1.1595e+008|
$d_{4,2}$	|-1.7900e+005|
Detailed Coefficient Nodes	**|Entropy|**
$d_{4,1}$	|-8.3893e+006|
$d_{3,1}$	|-6.9476e+005|
$d_{4,3}$	|-6.7796e+005|
$d_{2,1}$	|-1.2963e+005|
$d_{3,3}$	|-1.2097e+005|

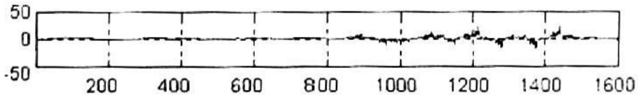

Figure 6. Signal reconstruction from the iteration 4, position 0 node $d_{4,0}$.

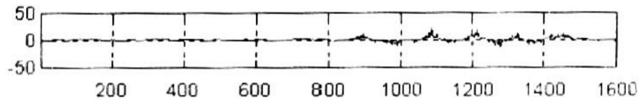

Figure 7. Signal reconstruction from the iteration 4, position 0 node $d_{3,0}$.

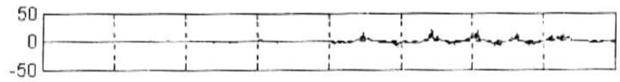

Figure 8. Signal reconstruction from the iteration 4, position 0 node $d_{4,1}$.

We apply the criteria for the spike detection by representing the different compositions of the squared index I according to Figures 9, 10, 11, the spike will be detected and all other events has been removed, and the precise time position of the spike is the one corresponding to the nodes $d_{4,0}$, $d_{4,1}$ at time t_1=10.19s, t_2=11.4s, t_3=11.99s.

Because the EEG consists of generalized bursts of 3Hz slow wave, we have detected 3 spikes /s.

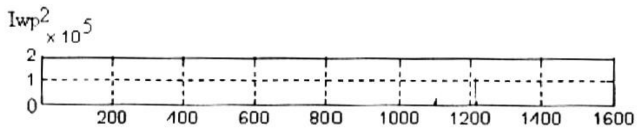

Figure 9. Wavelet packet index spike detection for nodes $d_{4,0}$ and $d_{3,0}$.

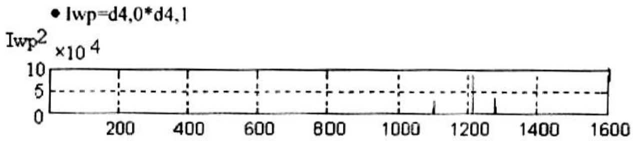

Figure 10. Wavelet packet index spike detection for nodes $d_{4,0}$ and $d_{4,1}$.

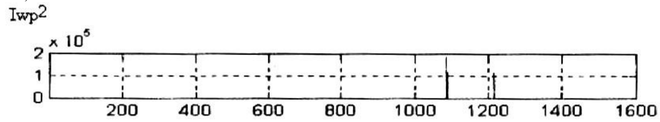

Figure 11. Wavelet packet index spike detection for nodes $d_{3,0}$ and $d_{4,1}$.

4. Conclusion

The developed algorithm based on wavelet packet transform showed a high potentiality for the characterization of epileptic events (spikes) extracting duration, timing, amplitude and energy of the spike. The wavelet packet transform is an adaptive tree-structure filter bank where each node is filtering out different frequency bands. We have studied another type of epileptic events that are the generalized waves and we came to the conclusion that for generalized waves where spikes are not recognizable and distinguished easily from the general form of the epileptic signal the criteria of (max I) is not sufficient, we find a new criteria for generalized waves spikes detection that is more efficient.

These results need a more exhaustive study of the algorithm performance concerning true or false detection of other epileptic events according to the new criteria of detection (The spike is the signal that has the max index among all the nodes indexes I verifying ($I*I > 10^4$).

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