First evidences for interpreting EEG reading through wavelet transform

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Abstract: - The study proposes a new method for the interpretation of EEG signal, whose reading and understanding are, today, dependent on the expertise of neurologists and electroencephalographers. The aim of this work is to perform an advanced signal processing by means of multiresolution wavelet transform.

Key-Words: - Signal processing, EEG interpretation, Wavelet Transform, multiresolution analysis.

1 Introduction

The study of neurological pathologies is performed by means of electroencephalographical methodology (EEG) that supplies aspecific and not elective indications, except for some Eegraphics readings typical of epilepsy. Sometime diagnosis is dependent on the expertise of the neurologists and electroencephalographers. Therefore, in order to specify the diagnosis the patient is obliged to undergo a TAC or a RMN and sometimes also the SPECT.

Such an instrumental investigation further represents a verification for operating a differential diagnosis. Although the experience of the EEG reader could also allow a diagnosis for pathologies unlike the epilepsy, the doubt is left until a complete typical sintomatologic check-up is closed.

The epilectiphorm bioelectrical activities (e.g., tip wave, spike wave, complex sharp wave, slow wave), in agreement with the EEG International Federation Society, are of undisputed evaluation. In fact, tips can occur isolated or in conjunction with slow waves and showing several parameters recognized as standard in terms of amplitude and duration. Obviously, it is quite difficult to study these graphical-elements during an EEG readings because of the aspects sometimes similar and overlapped to some activities generated by artifacts. The employment of the modern technology (i.e., digital filters, software and neural networks) concurs to reduce the presence of such artifacts which alter the background of cerebral bioelectrical activity. Our method proposes an alternative approach, based on wavelet transform (WT), concurring to interpret prefixed spiked difasic potentials (usually expression of pathology) showed by the EEG.

It is based both on the contemporary study of two symmetrical hemispheric areas and on the possibility to verify, in real time, the presence of pathological graphical-elements. Moreover, the method will allow, with reference to the next investigation, not only the study of contra-lateral correspondence and its evolution but and also peculiar features involving signal polarity , which

can be used as index of the existence of pathology. Starting from this last consideration, in order to operate a soft de-noising and signal processing, a method was developed based on wavelet transform.

In the last years a strong impulse was made for the interpretation of EEG signal. It was based on many methodologies: neural networks and filtering systems based on the STFT, FT, WT, etc. However, the tendency is to investigate on the eventual presence of spike, noise reduction and presence or not of artifacts, by analyzing the EEG signal of predetermined bipolar derivation.

The clinical electroencephalographer correlates central nervous system functions as well as dysfunctions and diseases with certain patterns of the electroencephalogram (EEG) on empirical basis. The range of EEG interpretations can be much widened and mis-interpretations avoided when the underlying elementary processes are also considered [1].

The EEG , as the continuous "roar" or "noise" of the brain, contains a fairly wide frequency spectrum, but it is not simply a hodgepodge of frequencies. The frequency range of the EEG has a fuzzy lower and upper limit. There are ultra-slow and ultra-fast frequency components that play no significant role in the clinical EEG (with exception for the forensic problems). For these reasons, the frequency–response curve of an EEG apparatus concentrates on the clinically relevant frequency range, which is also the most important from the psychophysiological viewpoint. This range lies between 0.1/s (or cps or HZ) and 100/s and, in a more restricted sense, between 0.2/s and 70/s. In the normal adult, the slow ranges (0.3-7/s) and the very fast range (above 30(s) are sparsely represented; medium (8-13/s) and fast (14-30/s) ranges predominate.

These frequencies are broken down into the following bands or ranges:

Delta below 3.5/s (usually 0.1-3.5/s)
Theta 4-7.5/s
Alpha 8-13/s
Beta above 13/s (usually 14-40/s but unlimited in the upper range) or more recently;
Beta 14-30/s and
Gamma above 30/s (unlimited in upper range).

The sequence of these Greek letters is not logical and can be understood only in the historical view [2].

Alpha rhythm is the classical EEG correlate for a state of relaxed wakefulness best obtained with the eyes closed. A degree of higher alertness attenuates or suppresses the alpha rhythm, which is then supplanted by "desynchronized" low voltage fast activity.

The earliest stage of drowsiness is characterized by "alpha dropout".

The trains of alpha waves become less and less continuous, and the last alpha fragments finally give way to a low voltage pattern of mixed slow (mostly theta range) and fast frequencies. This type of alpha dropout is a hallmark of a normal adult EEG. In adult with some organic cerebral problems and in old age, a posterior alpha rhythm of normal appearance may be replaced by activity in theta and delta range. [2].

2 Materials and methods

50 healthy subjects were examined of age ranged from 16 to 70 years. To everybody a basic EEG was executed by means of 10/20 system for a time of approximately 30 minutes, with a time constant of 0.3 and 5mm of amplitude equivalent to 7 μV. In order to reduce eventual artifacts due to the extra cerebral origin as well as to carry out a soft-denoising, a LP 15.0 Hz and HP 1.60 Hz as well as Notch algorithm were used to filter the EEG signal. The sampling rate was 256 Hz, whereas the amplitude was set to 7 mm/50microVolt.

Moreover, for the original signal decomposition (time-frequency dominion) into more elementary ones the wavelet transform has been applied.

Periods of epochs of 8192 points = 33 seconds = 2^{13} were randomly examined from posterior derivations C3O1, C4O2 and T3O1, T4O2 (because in such areas the Alpha activity in condition of psycho-sensorial quiet is well represented). The choice of such derivations has been done because the EEG Alpha signal is predominant in such areas.

The traditional method used to analyze the time series EEG signals has been Fourier transform. It, however, can not capture the transient features in EEGs and time-frequency information is not readily in the transformed Fourier coefficients. For that reason the Fourier transform presents a limitation to the detection of abnormal brain activity.

In the present work, the interpretation of EEG readings is based on timing variable windows and multiresolution wavelet analysis.

Finally a cluster analysis [3] was performed to put in evidence the relationship between the cases and variables, starting from the wavelet coefficients derived from EEG signal.

The wavelet analysis and the multivariate statistical analysis were performed by using Matlab

5.3, The MathWorks, Inc, Natick, Mass and SPSS ver. 10.2.

3 Mathematical background

3.1 General remarks

The word wavelet is used in mathematics to denote a kind of orthonormal bases in L^2 with remarkable approximation properties.

Wavelets allow to simplify the description of a complicated function in terms of small number of coefficients. Often there are less coefficients necessary than in the classical Fourier analysis. Wavelets are adapted to local properties of functions to a larger extent than the Fourier basis. The adaptation is done automatically in view of the existence of a second degree of freedom: the localization in time (or space, if multivariate functions are considered).

The vertical axis in the next graphs denotes always the level, i.e., the partition of the time axis into finer and finer resolutions. The advantage of this "multiresolution analysis" is that we can see immediately local properties of data and thereby influence our further analysis. There were attempts in the past to modify the Fourier analysis by partitioning the time domain into pieces and applying different Fourier expansions on different pieces. But the partitioning is always subjective. Wavelets provide an elegant and mathematically consistent realization of this intuitive idea [4].

In summary, wavelets offer a frequency/time representation of data that allows us time (respectively, space) adaptive filtering, reconstruction and smoothing.

Recall that a mother wavelet ψ is a function of zero h-th moment (e.g. see [5], [6], [7], [8])

$$\int_{-\infty}^{+\infty} x^h \psi(x)dx = 0, \quad h \in \mathbf{N}. \qquad (1)$$

From this definition, it follows that, if ψ is a wavelet whose all moments are zero, also the function $\psi_{ik}(x) := 2^{j/2}\psi(2^jx - k)$ is a wavelet.

Now consider a wavelet ψ and a function φ such that $\{\{\varphi_{j_0k}\}, \{\psi_{jk}\}, k \in \mathbf{Z}, j = 0, 1, 2,...\}$ is a complete orthonormal system. In this case, a given signal $s(t)$, decomposed by wavelet (i.e., CWT) is represented in the following detail function coefficients

$$d_{jk} = \int_{-\infty}^{+\infty} s(\tau) \cdot \frac{1}{\sqrt{2^j}}\psi\left(\frac{\tau - k}{2^j}\right)d\tau \qquad (2)$$

and in the approximating scaling coefficients as follows

$$a_{j_0k} = \int_{-\infty}^{+\infty} s(\tau) \cdot \varphi(\tau - k)d\tau \qquad (3)$$

Note that, for any j, d_{jk} can be regarded, as a function of k. Consequently, if the signal $s(t)$ is a smooth function, then the relative details are zero, since, as said before, a wavelet has zero moments (for a detailed argumentation see [5]).

The sequence of spaces $\{V_j, j \in Z\}$, generated by φ is called a multiresolution analysis (*MRA*) of $L^2(R)$ if it satisfies the following properties

$$V_j \subset V_{j+1}, j \in Z \text{ and } \bigcup_{j \geq 0}V_j \text{ is dense in } L^2(R).$$

It follows that if $\{V_j, j \in Z\}$, is a *MRA* of $L^2(R)$, we say that the function φ generates a *MRA* of $L^2(R)$, and we call φ the father wavelet.

Besides, based on Parseval theorem, for any $s \in L^2(R)$, it follows that

$$s(t) = \sum_k a_{j_0k}\varphi_{j_0k}(t) + \sum_{j=j_0}^{j_1}\sum_k d_{jk}\psi_{jk}(t) \qquad (4)$$

The relation (4) is called a multiresolution expansion of s. This means that any $s \in L^2(R)$ can be represented as a series (convergent in $L^2(R)$), where a_k and d_{jk} are some coefficients, and $\{\psi_{jk}\}, k \in Z$, is a basis for W_j, where we define

$$W_j = V_{j+1} - V_j, j \in Z.$$

In (1) $\{\psi_{jk}(t)\}$ is a general basis for W_j. The space W_j is called resolution level of multiresolution analysis. In the following, by abuse of notation, we frequently write "resolution level j" or simply "level j". We employ these words mostly to designate not the space W_j itself, but rather the coefficients d_{jk} and the function ψ_{jk} "on the level j".

4 Results

As general remark the results depicted below are referred to C3O1 and C4O2 derivations.

CASE # 1: *Male Patient 49-year-old (Fig. 1).*
- **Anamnesis:** Headache and anxiety.
- **EEG:** post rolandic alpha activity at 11 Hz concentrated on two controlateral areas, bilateral, synchronous, symmetrical and reactive, with rapid activity localized on right side.
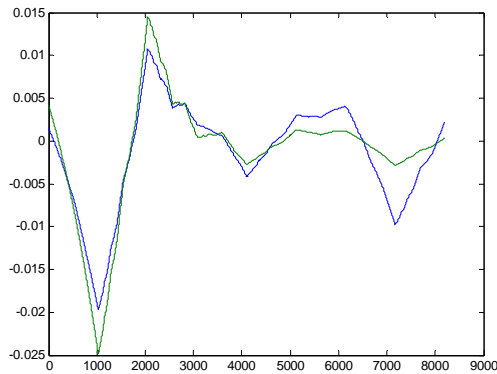
- **Comment:** normal activity.

Fig. 1 Case #1, Comparison of wavelet coefficients at level $j = 12$

CASE # 2: *Male patient 30-year-old (Fig. 2).*
- **Anamnesis:** healthy.
- **EEG:** Posterior 11 Hz alpha rhythm in two controlateral examined area, normal voltage, bilateral, symmetrical, synchronous, reactive.
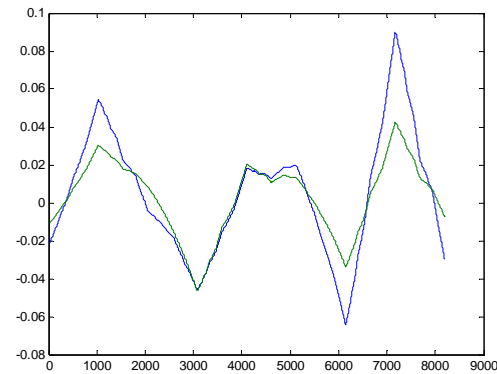- **Comment:** normal activity.

Fig. 2 Case # 2, Comparison of wavelet coefficients at level $j = 12$.

CASE # 3: *Female patient 37-year-old (Fig. 3).*
- **Anamnesis:** lipotimic events.
- **EEG:** post rolandic alpha activity at 10 Hz in two controlateral examined areas, not stable at 9-11 Hz, bilateral, synchronous, symmetrical sufficiently and reactive.
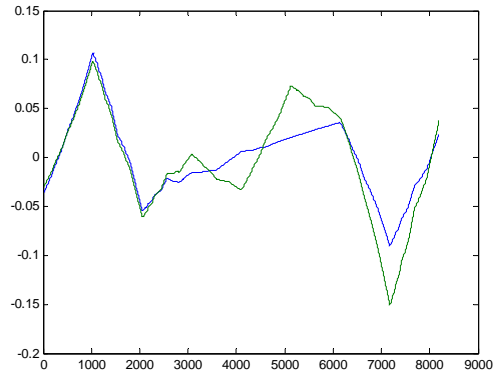- **Comment:** normal activity.

Fig. 3 Case # 3, Comparison of wavelet coefficients at level $j = 12$

CASE # 4: *Male Patient 27-year-old (Fig. 4).*
- **Anamnesis:** Headache and anxiety.
- **EEG:** post rolandic alpha activity at 11 Hz concentrated on two controlateral areas, bilateral, synchronous, symmetrical and reactive, with rapid activity localized on the right side.
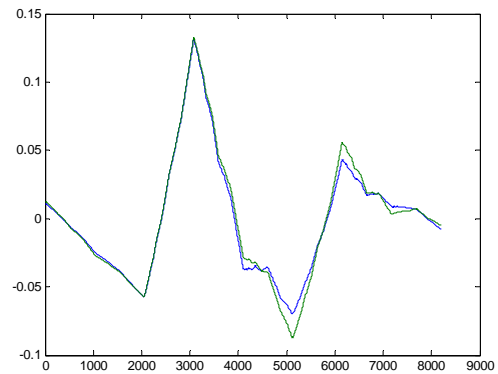- **Comment:** normal activity.

Fig.4 Case # 4, Comparison of wavelet coefficients at level $j = 12$

CASE # 5: *Female patient 68-year-old (Fig. 5)*
- **Anamnesis:** generalized anxiety.
- **EEG:** post rolandic alpha activity at 10 Hz concentrated on two controlateral areas, not stable at 9-11 Hz, bilateral synchronous, symmetrical sufficiently and reactive.
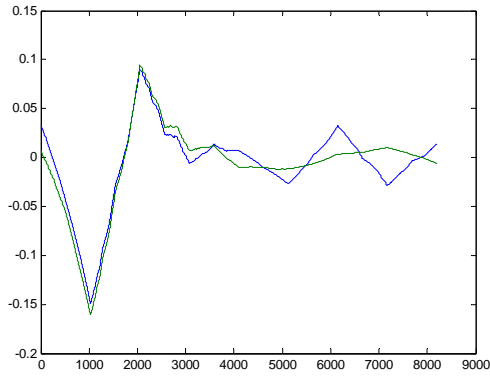- **Comment:** normal activity.

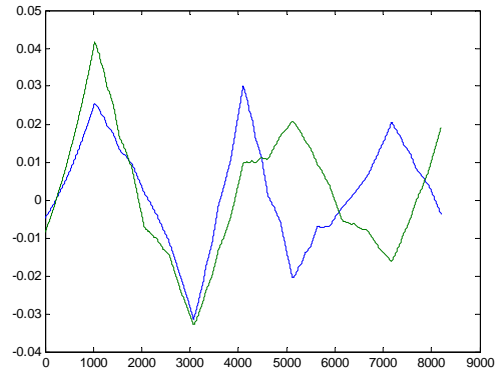Fig. 5 Case # 5, Comparison of wavelet coefficients at level $j = 12$

Fig. 7 Case # 7, Comparison of wavelet coefficients at level $j = 12$

CASE # 6: *Male patient 17-year-old (Fig. 6)*
- **Anamnesis:** healthy.
- **EEG:** Posterior 10-12 Hz alpha rhythm in two controlateral examined area, normal voltage, bilateral, symmetrical, synchronous, reactive.
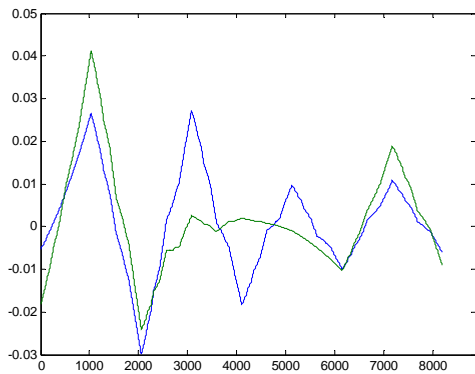- **Comment:** normal activity.

CASE # 8: *Female patient 30-year-old (Fig. 8)*
- **Anamnesis:** generalized anxiety.
- **EEG:** post rolandic alpha activity at 10 Hz in two controlateral examined area, not stable at 9-11 Hz, bilateral synchronous, symmetrical sufficiently and reactive.
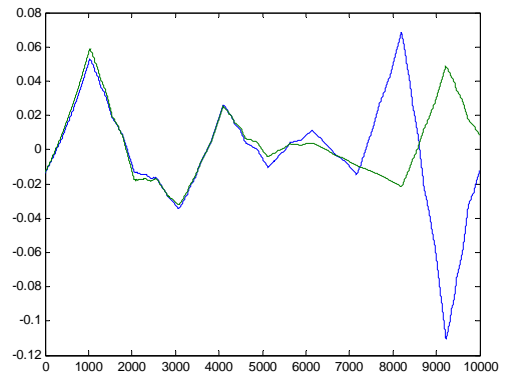- **Comment:** normal activity.

Fig.6 Case # 6, Comparison of wavelet coefficients at level $j = 12$

Fig. 8 Case # 8, Comparison of wavelet coefficients at level $j = 12$

CASE # 7: *Female patient 30-year-old (Fig. 7).*
- **Anamnesis:** Pain crisis.
- **EEG:** post rolandic alpha activity at 9-10 Hz in two controlateral examined area, not constant, bilateral, synchronous, symmetrical sufficiently and reactive with rapid activity localized on the right side.
- **Comment:** normal activity.

The figures below show the WT comparison of two EEG signals belonging to the same derivation (i.e., C3O1 of case #1) and shifted of 2 s.
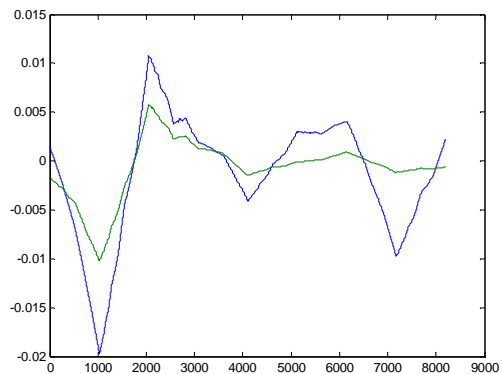

Fig. 9 Comparison of two WT response applied to shifted signals of case # 1, at level $j = 12$

Finally, a statistical multivariate analysis was performed based on detail coefficients constituting the decomposition curve.

Several statistical parameters were calculated such as minimum (min) and maximum (max) recurrence showed by data and the corresponding mean, standard deviation (std) as well as skewness (skew), kurtosis (kurt) and entropy.

The result of cluster analysis is depicted in Fig. 19. Note the existence of two main groups formed by the case number 2, 4, 8 and 1, 5 respectively.

The case number 6, witch represents the youngest subject, is associated to the 1st group even if it is evident that his *physiological* position is influenced by the presence of slow brain activity background depending to the young age (i.e., 17 years old).

In fact, the successive cluster analysis computed on all the variables, confirmed the presence of a straight relationship between the kurtoses and age (see Fig. 20).
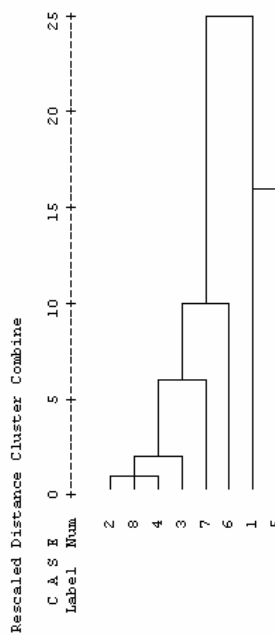

Fig. 19 Cluster analysis of cases. Dendrogram using Average Linkage (Within Group)

5 Comments

As a general comment we can observe that the graphical representation, reported in the previous paragraph, shows the following features:

    A. Signals are well synchronized in time that means a normal bioelectrical brain activity;

    B. In terms of energetic content (i.e., cerebral activity) it is observed a minimum prevalence of one cerebral area with respect to the other one;

    C. It is evident an high correlation index between the vectors representing the wavelet transform coefficients of two cerebral areas;

    D. Uncorrelated shape concentrated in the range of the higher frequencies, probably due to the presence of noise.

Furthermore it is evident a low correlation of WT curves when shifted signals are compared. It demonstrates both the importance of comparing signals belonging to the same time space and the reliability of wavelet analysis, demonstrated by minor correlation (see Fig. 9) in the lower and higher frequency range with reference to Fig. 8.

The correlation between the content of brain energy, with reference to the left cerebral hemisphere, and the age of the subjects is an important demonstration of how good is the application of WT to EEG signals for obtaining information concerning neuro-physiological aspects.

Finally, note the reliability of WT regarding the case number 6. The relative graphical representation shows the presence of slow brain activity background depending to the young age (i.e., 17 years old). This means that WT is able to represent some physiological aspects also in such cases where the information is localized on the lowest frequencies of EEG.

6 Conclusions

In the present work a study was performed by comparing the EEG signals of two symmetrical cerebral areas.

The various scales of resolution level in which the EEG signal was decomposed by means of wavelet transform, if compared with the standard EEG method, have confirmed the cerebral condition of subjects defined as *normal*. In particular, it was evident by comparing the curves at level j=12 obtained through wavelet decomposition. The simple inspection of the EEG series is not always sufficient for extracting the information of cerebral activity, above all when such an information needs "quantitative" data to fix, for instance, the limit between *normality* and *abnormality*. The automatized analysis by means of advanced instruments well designed for complex signal processing should take the place of the visual interpretation of EEG readings. Our method appears to be valid on that. In fact, it seems immediately interpretable as well as it provides by means of specific mathematical applications the

energetic level associated to each decomposition level. In future, based on the study of a wider sample, we are confident to estimate quantitatively the Eegraphs elements with reference to pathologies already standardized through clinical aspects and/or typical EEG traces consolidated in the arc of the last 50 years.

The proposed signal processing methodology should be useful to reach differential diagnoses when, for instance, problems such as convulsions due to paroxysmal disturbs with or without loss of conscience are involved. Nowadays, it can be obtained exclusively on clinical basis even if it appears of difficult resolution in the case of children. In fact, such a synthomatology is diagnosed as epilepsy: simple faints with or without hypossic-clonic convulsions, nocturnal headache, terrors, mioclonous during the sleep, arhythmical cardiac and tic.

From a legal-medicine point of view, the employment of such a methodology should allow us a faster evaluation and interpretation of the Eegraphic readings of subjects showing a commotive post-traumatical cranial. In fact, in such subjects, an eventual alteration, performed by means of proposed method, should supply information on the eventual damage by deeper and sophisticated analysis. Besides it could be useful for revealing the residual energetic level in the cases where are involved children or adult affected by ipotyroidism or poisoned by barbiturate.

In order to eliminate the uncertainty regarding residual cerebral activity, a further practical application in legal medicine should be the death ascertation. Nowadays, when particular legal conditions concur, it is performed by means of neurological instrumental methodology. A particular interest is showed for the diagnosis of post-traumatical epilepsy, often uncertain and incorrectly trusted to data obtained by anamnesis.

From a clinical point of view such a method can also help us for interpreting the necessity to suspend the therapy on epileptic subject, based not only on what the patient reports (i.e., absence of crisis for more one year) but on a response based on neural activity with reference to its energetic contents.

An other important goal is to design an advanced computational model for monitoring brain signals in order to eliminate the difficult task of visually analyzing hours of EEG readings. In fact the WT has the characteristic of compressing the response in the time dominion. So it will be possible to analyze automatically EEG long term series by decreasing the chances for human error.

The major feature of the proposed method resides in the immediate comparison, less susceptible to suggestion, between healthy and pathological cerebral activities, based, also, on quantitative parameters.

This interesting feature of EEG has important applications for the clinical medicine and further data collection and analysis is in progress to investigate it.

Acknowledgements

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