Wavelet Entropy Differentiations of Event Related Potentials in Dyslexia

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Abstract—**The wavelet entropy (WE) of rest electro-encephalogram (EEG) and of event-related potentials (ERP) carries information about the degree of order or disorder associated with a multi-frequency brain electrophysiological activity. In the present study, WE, relative WE and WE change were estimated for the EEG and ERP signals recorded during a working memory task, from dyslectic children and healthy subjects. The analysis of the two groups (controls vs dyslectics) revealed differentiations mainly in relative WE and WE change that takes into account the variability of rest EEG. These findings indicate that the WE can be employed as a quantitative measure for monitoring EEG and ERP activities and may provide a useful tool in analyzing electrophysiological signals associated with dyslexia.**

I. Introduction

THE human brain function is determined by activation and interaction mechanisms of the millions of neurons from which it is constituted. Their oscillatory activity is increasingly thought to get synchronized during physiological or pathological brain states, at stimulation or during the performance of certain tasks (e.g. sleep-wake states, increased attention tasks, optical stimulation, epileptic seizures, etc.) [1]. Dyslexia constitutes a specific reading disability, a condition characterized by severe difficulty in the mastery of reading despite normal intelligence or adequate education [2]. Electrophysiological studies have shown that there are physiological deficits in dyslectic subjects [3][4], which may affect cognitive functions of the brain such as selective attention, working memory, audio or language process. Deficits can be estimated by various time and frequency domain measures or their projection in time-frequency plane. The main advantage of the latter approach is that specific events and components can be localized simultaneously in time and frequency.

The electroencephalogram (EEG) reflects activity of ensembles of intracranial generators producing oscillations tuned in specific frequencies. If a stimulus takes place, brain's response activates generators which begin to act together in a coherent way producing the event-related potentials (ERP). This can be thought as the transition of a system from a general disorder to a state of increased order.

One way to investigate this hypothesis is to evaluate the entropy of EEG/ERP recordings. Entropy is a physical measure derived from thermodynamics to describe the order/disorder of a physical system. High entropy values equal to high level of disorder of a system, whereas low values describe a more ordered system capable to produce some work. Furthermore, entropy was adapted for information theory by Shannon as a measure of information comprised in a given amount of signals. It addresses and describes the irregularity, complexity, or unpredictability characteristics of a signal.

Spectral entropy is based on the Fourier power spectrum and measures how widespread or concentrated the spectrum is. A sinusoidal signal, for example, is depicted in the frequency domain by a single, narrow peak at the frequency of the signal and therefore its entropy has a low value. On the contrary, the representation of random activity (e.g. white noise) in the frequency domain is spread in a wide band area, yielding a high entropy value. Similarly, since ERP signals are defined as the changes the EEG undergoes in temporal relation to a defined event, one might consider that they correspond to the transition of a system from a disordered to an ordered state and reversely [5].

However, the use of Fourier transform for spectral estimation has two main disadvantages. Firstly, it does not take into account the time evolution of frequency patterns and, thus, no time information regarding entropy values can be obtained. Secondly, it requires the stationarity of the signal analyzed, which is also not the case for ERP signals.

In order to overcome these limitations, the estimation of entropy can be obtained by the use of wavelets. The wavelet transform, provides a time-frequency representation of the signal with optimal time-frequency resolution. This method requires no stationarity of the signal analyzed and hence, is suitable for the analysis of ERP. Similar to Fourier entropy,

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wavelet entropy reflects the degree of order/disorder of a system, but also provides additional information about the underlying dynamic processes associated with the signal [6]. In the present work, wavelet-based entropy and other related quantifiers [7] that have been used in other studies [8][9][10][11][12][13], were used to evaluate ERP recordings derived from both dyslectic and control individuals during a memory performance test.

II. Methods

A. Wavelet transform

Wavelet transform was firstly introduced in 1984 by Grossmann and Morlet, as an extension of the Fourier and Gabor transform. Similar to Gabor transform, the wavelet transform uses a time window of varying width, wide for low frequencies and narrow for high frequencies. As a result, the time-frequency resolution is high and accurate for all frequencies revealing the time evolution of frequencies in the analyzed signal [14].

Several reports have been published in order to accent the adequacy of wavelets on ERP processing and explication, however, its successful application depends on few considerations: the selection of the proper algorithm, the mother wavelet used and data preprocessing. In this study, the discrete wavelet transform was used since it provides a non redundant representation of the signal and offers the advantage of the multiresolution decomposition [15]. According to the multiresolution scheme, a waveform *x(t)* is decomposed into approximation A_j (low frequency) and detail C_j (high frequency) components by its convolution with scaling $\phi_{j,k}(t) = 2^{-j/2}\phi(2^{-j}t - k)$ and wavelet $\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k)$ family functions at time *k=1,2,…,N* and level of analysis *j=1,2,…J*. The family functions are generated by dilation and translation of unique admissible scaling *φ(t)* and mother wavelet *ψ(t)* functions and constitute an orthonormal basis [16]. In signal analysis, scaling functions are considered as low pass filters, whereas mother functions as high pass filters. The wavelet expansion of the signal can be defined as

$$x(t) = \sum_{k=1}^{N} A_j(k)\phi_{j,k}(t) + \sum_{j=1}^{J}\sum_{k=1}^{N} C_j(k)\psi_{j,k}(t) \qquad (3)$$

Therefore, ERP can be decomposed by levels which correspond to the traditional bands of physiological EEG.

Furthermore, a compactly support biorthogonal wavelet of order 3, often referred as the most suitable for ERP wavelet analysis was used. Biorthogonal wavelets resemble the patterns of variation in the original ERP signal and provide the maximum allowed by the uncertainty principle time-frequency resolution [17]. They are symmetrical and smooth and hence they do not produce phase distortion and discontinuities in the reconstructed waveforms. Finally, since they are semiorthogonal the issue of the orthogonality between the levels of decomposition still holds [18].

Each ERP signal was decomposed in 7 levels and since the sampling frequency was 1000Hz the desirable bands were obtained: 16-32Hz (beta), 8-16Hz (alpha), 4-8Hz (theta) and 0-4Hz (delta). The data padding was set to periodic to cope with the boundary effects.

B. Wavelet entropy

A measure estimated by the wavelet coefficients to provide quantitative information about the order/complexity of signals is the wavelet entropy. It has also been used in several works concerning several issues such as the neurological status of the brain following global cerebral ischemia by hypoxic-ischemic cardiac arrest [19], EEGs ordering/disordering during sleep [20][21] and seizures [8][21].

In order to calculate the wavelet entropy of the signal, the wavelet coefficients $C_j(k)$ were obtained at each resolution level *j*. The energy at each time sample *k* can be calculated by equation (4)

$$E(k) = \sum_{j=1}^{J} |C_j(k)|^2 \qquad (4)$$

and the total energy by

$$E_{tot} = \sum_{j=1}^{J}\sum_{k=1}^{N} |C_j(k)|^2 = \sum_j E_j \qquad (5)$$

The *relative wavelet energy*, which defines energy's probability distribution in scales is given by

$$p_j = \frac{E_j}{E_{tot}} \qquad (6)$$

Obviously, $\sum_j p_j = 1$ and the distribution p_j is considered as a time-scale density. The *wavelet entropy* is, in turn, defined as

$$H_{WT}(p) = -\sum_{j=1}^{J} p_j . \log_2[p_j] \qquad (7)$$

As it has already been mentioned, the value of wavelet entropy can provide estimation of the order of the decomposed signal and subsequently of the order of the system it represents. The same differences in wavelet entropy value of a sinusoidal and a multi frequency signal, described above, are expected in a disordered EEG and a more ordered ERP signal (lower entropy value).

C. Relative wavelet entropy and wavelet entropy change

Relative wavelet entropy is another useful measure of order/disorder comparing a waveform with another. It depicts how similar a probability distribution p_j is with respect to another probability distribution q_j taken as a reference. The probability distributions p_j , q_j could represent two different signals or two different parts of the same signal [1]. In order to study temporal evolution, the analyzed signal is divided into temporal windows of length L and for each interval *i*, *i=1,…,N*$_T$. If $E_j^{(i)}$ is the wavelet energy at resolution level *j* included in the time interval *I*, then the mean wavelet energy is given by

$$\overline{E_j} = \frac{1}{N_T}\sum_{i=1}^{N_T} E_j^{(i)} \tag{8}$$

and the mean probability distribution q_j is given by

$$\tilde{q}_j = \frac{\overline{E_j}}{\sum_{j=1}^{J}\overline{E_j}} \tag{9}$$

The mean wavelet entropy representative for the whole time interval can be defined as

$$\overline{H_{WT}}(q) = -\sum_{j=1}^{J}\tilde{q}_j.\log_2\tilde{q}_j \tag{10}$$

Relative wavelet entropy is calculated from the following equation

$$H_{WT}(p\,|\,q) = -\sum_{j=1}^{J} p_j.\log_2[\frac{p_j}{\tilde{q}_j}] \tag{11}$$

An aspect of interest is the change of entropy in relation to a specific mark considered to be as reference. In EEG/ERP analysis the relative change of the ERP against the background EEG activity before stimulus can give informative results. This change (WE change) can be quantified by the metric

$$\Gamma(i) = \frac{H_{WT}^{(i)} - \overline{H}_{WT}^{(EEG)}}{\overline{H}_{WT}^{(EEG)}}\cdot 100\% \tag{12}$$

for each time interval *i* in which $\Gamma<0$ denotes that post-stimulus signal shows a higher degree of order than the reference EEG signal, and its value presents the difference between the two signal segments in percents.

III. Application

A. Subjects

The study involved 57 children from which 38 (26 boys and 12 girls) were outpatient cases who had been diagnosed as having dyslexia according to the 10th edition of the International Classification of Diseases (ICD-10) and the rest 19 children (7 boys and 12 girls) were control sibling of the dyslectic group. The mean ages and the standard deviations for the dyslectic children and for the controls were 11.47±2.12 and 12.21±2.25 years, respectively. Their mean ages did not differ significantly (non-significant t-test). In each case, the following assessments were performed: child psychiatric examination, psychological examination and educational evaluation. The Wechsler Intelligence Scale for Children – Third Edition (WISC-III) [22] was used to obtain the IQ of each child. The assessment of educational attainment included reading, comprehension, spelling and arithmetic ability. Participants did not enter the study if they had (a) clinically notable neurological disease (including seizure disorder), (b) a history of head injury, (c) hearing difficulties and (d) attention deficit disorder and hyperkinetic syndrome.

B. Experimental setup

The subjects were evaluated with the digit span Wechsler Auditory test [23], [24]. For each trial of the experiment, rest EEG signal was recorded for 500msec. A single sound tone of either high (3000 Hz) or low frequency (500 Hz) was presented to the subjects through earphones, followed by the numbers which had to be memorized.

Table 1: Outline of the experimental procedure

Time period	Action
AB (500ms)	Recording of EEGs.
BC (100ms)	Warning stimulus (500 or 3000Hz, 65dB)
BD (1000ms)	Recording of ERP signal.
DE (varies) (Not in scale)	Computerized administration of the sequence of numbers
EF (100ms)	Repetition of warning stimulus (500 or 3000Hz, 65dB)

If the frequency of the signal tone was low, the subjects had to recall the numbers in the same order with that presented, else (high frequency tone) the subjects had to recall the numbers in the reverse order. The total task consisted of 52 repetitions for a period of about 45 min. An outline of the procedure is provided in Table 1.

C. Data Recording and Acquisition

The children's EEG/ERP signals were recorded at 15 electrodes (Fp1, F3, C5, C3, Fp2, F4, C6, C4, O1, O2, P4, P3, Pz, Cz, Fz) according to the 10–20 international system, referred to both earlobes. The Ag/AgCl electrodes were attached to the scalp with adhesive cream in order to keep the electrode resistance below 5 kΩ. An electrode placed on the subject's forehead served as ground. The passband of the amplifiers was set from 0.05 Hz to 35 Hz. During the recordings, the subjects had their eyes closed in order to minimize eye movements and blinks. Eye movements were recorded through electro-oculogram (EOG) and recordings with EOG higher than 75 μV were rejected. All signals were sampled at frequency of 1 kHz so that for signals in the frequency range 0–35 Hz the Shannon theorem is over satisfied. Since noise (signals that are not EEG/ERP) is considered to be a random process with zero mean value, the EEG/ERP signal's SNR was improved by averaging across the 52 trials of the experiment.

IV. RESULTS

A. Time-dependent entropy

The wavelet entropy was applied to EEG/ERP signals in order to evaluate differences in complexity between controls and subjects with dyslexia. The analyzed signals were divided into overlapping time windows with a step of 20 samples. This enables the study of temporal evolution of entropy dynamics over time. The window length plays a significant role for the analysis and the accuracy of the results. In this study, we used a time window length of 128 samples (corresponding to 128 ms) in order to contain at least one spectral coefficient from each frequency band. It was shown that such window size is appropriate for the analysis of EEG signals, as the entropy does not increase dramatically by increasing the window size [25]. A typical behavior of entropy over time can be seen in Fig.1.

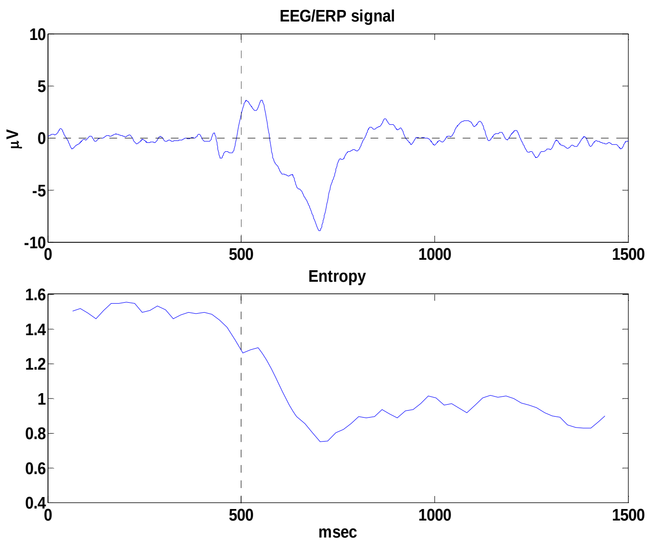

Fig. 1. EEG/ERP signal (upper chart) and its corresponding wavelet entropy (lower chart) for a typical electrode. Vertical dashed line denotes the stimulus onset and the beginning of ERP signal.

It can be observed that the entropy has relatively high values for rest EEG signal. At the stimulus onset and the beginning of ERP signal, there is a decrease that is ought to the synchronization and the dominance of a specific band of frequencies [26]. After the presence of ERP components, entropy increases again to reach values of rest EEG.

Data were divided into the factors group (controls, dyslectics) and auditory stimulus frequency (high, low, all frequencies). The analysis was performed for each type of stimulus frequency separately, because stimulus affects electrical events in terms of EEG frequency synchronization or tuning [1].

Both high and low frequency stimuli were investigated but differences in low frequency stimulus type were not that pronounced. Below, the results obtained for high frequency stimulus type are presented. The mean wavelet entropies, relative wavelet entropies and wavelet entropy changes of controls and dyslectics for each time window were calculated. The time evolution of mean entropies for both groups, all electrodes and high frequency induced stimulus are shown in Fig.2.

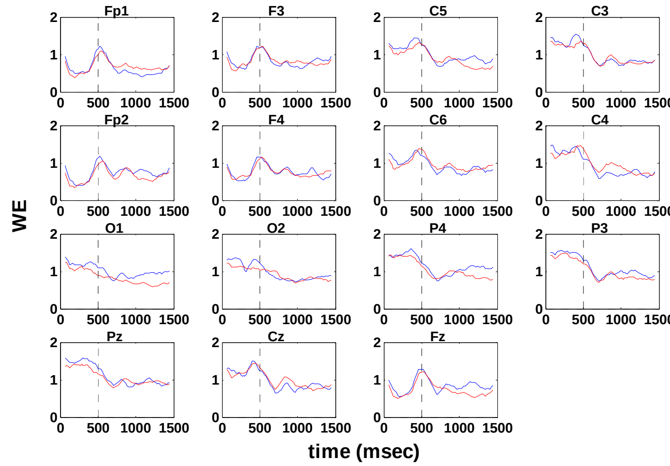

Fig. 2. Mean entropy of 15 electrodes for controls (blue line) and dyslectics (red line) for high frequency stimulus.

Then, relative wavelet entropy (RWE) was calculated in order to quantify change of entropy in relation to rest EEG (before stimulus onset). This is of great importance mainly in children because it takes into account the great variability of EEG signals in childhood. Its mean waveforms in controls and dyslectics for all electrodes and for high stimulus frequency are shown in Fig.3.

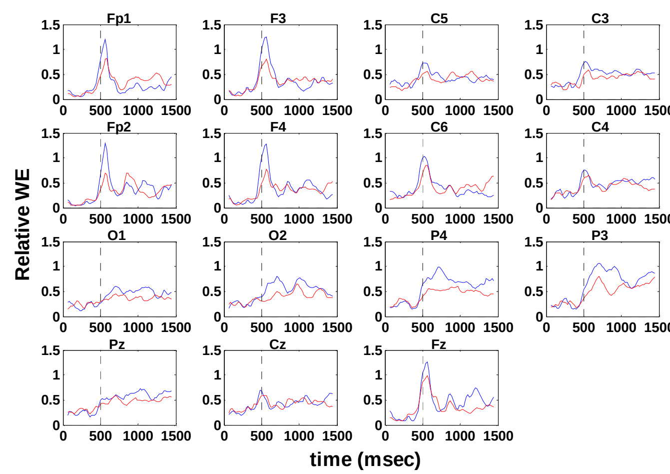

Fig. 3. Mean relative wavelet entropy of 15 electrodes for controls (blue line) and dyslectics (red line) for high frequency stimulus.

As it can be observed, controls appear to have higher relative wavelet entropy values than dyslectics for a short time interval after the onset of stimulus (around ERP component N100). This phenomenon is apparent mainly in frontal electrodes (Fp1, F3, Fp2, F4, Fz). In parietal electrodes (P4, P3) the difference between high values for controls and low values for dyslectics is maintained for a long period after the stimulus.

Finally, the WE change Γ was calculated to quantify the changes in entropy in relation to mean entropy of rest EEG. Statistical analysis was performed in order to evaluate mean values of WE change that achieve statistical difference between groups.

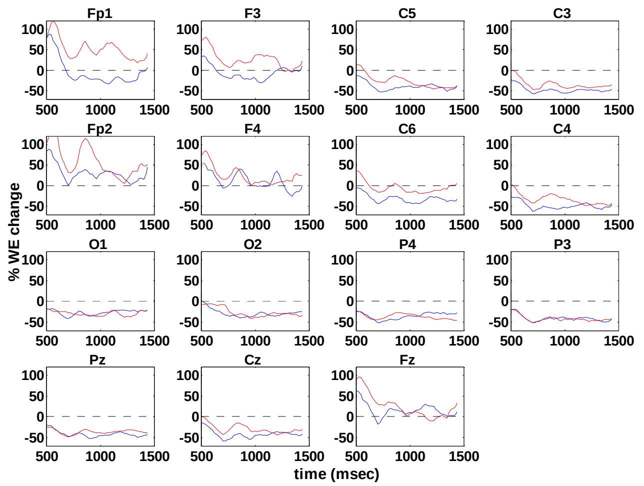

Fig. 4. Mean wavelet entropy changes of 15 electrodes for controls (blue line) and dyslectics (red line) for high frequency stimulus.

The null hypothesis is that there is no difference of the mean values of WE change between two groups (controls, dyslectics) in a given time-location element. In order to use robust parametric statistical tests, possibly non-normal distributions of the energy values must be taken into account. So, when the normality of data was not satisfied, the logarithmic transformation, a common and effective normalization transformation [27], was applied.

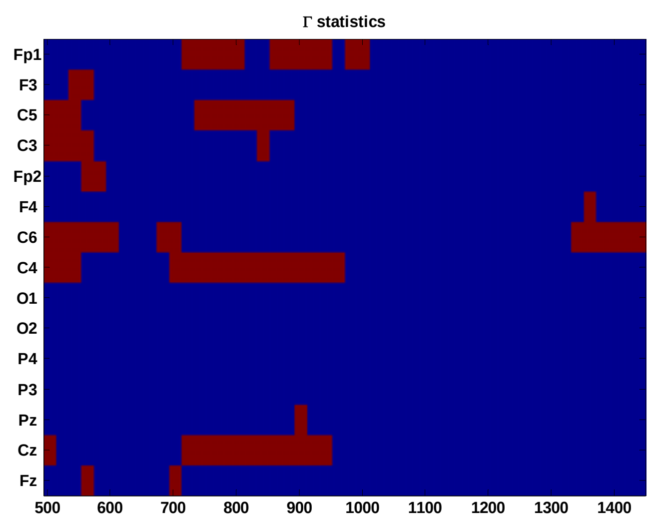

Fig. 5. WE change (Γ) time-location statistics of 15 electrodes between controls and dyslectics for high frequency stimulus. Red color denotes rejection of null hypothesis ($p<0.05$).

The mean wavelet changes of controls and dyslectics and their time-location statistics are shown in Fig. 4 and Fig. 5, respectively. Significant differences appeared mainly in Fp2, F3, C3, C5, C6, C4 in the first 100 msec after the stimulus and in Fp1, C5, C4, Cz electrodes around the P300 peak. However, there were no clear trends in time-location statistics.

As a general conclusion, differences appeared mainly in frontal and central electrodes (Fp1, F3, C5, C3, C6, C4, Cz) within 500 msec after the stimulus onset.

V. Discussion

In this study, quantifiers based on wavelet entropy were used to reveal differentiations in EEG/ERP signals between dyslectics and controls. WE, relative WE and WE change were estimated for the EEG and ERP signals recorded from dyslectic children and control siblings elicited during a working memory task.

Analysis showed that there is stimulus type effect as regards their entropy quantifiers so the analysis was performed for each stimulus type separately and focused on high frequency stimulus type where more pronounced differentiations appeared. In this kind of stimulus type, differences appeared mainly in relative WE and WE change. These measures are considered to be more objective because they calculate entropy in relation to its background EEG before stimulus, so it has additional meaning taking into account the great variability of EEG signals in childhood.

Compared with dyslectics, controls showed higher relative entropy near stimulus and in the time window corresponding to the N100 ERP component, in the majority of electrodes and in frontal-central regions. In some cases (P4, P3, C3, O2 electrodes), this phenomenon appeared also for a prolonged time interval. According to this, the reaction of controls to the stimulus is more intense as reflected in relative entropy. On the other hand, signals of dyslectics don't appear to change significantly their entropies' characterististics in the transition from rest EEG to ERP.

The evaluation of these changes was depicted in WE change. Controls demonstrated increased amendment (rapid alteration) as compared to dyslectics with localization on frontal-central leads and in the time windows corresponding to the N100 and P300 ERP components, achieving statistical significance in many leads.

Measures of the entropic patterns of response sequences lead to a different level of information with regard to the information processing in dyslexia. In particular, two classes of questions arise; firstly, how the dyslectics organize the sequence of responses and secondly, how they process information as a function of naturally occurring neural oscillations that link distinct brain regions e.g. as they are presented by the obtained abductions (electrode leads) which correspond to significant differences between controls and dyslectics.

Considering the above stated results, it is reasonable to hypothesize that the dyslexia-associated differences observed here may be related to different strategies activated due to dyslexia-related functional brain organization as indicated from psychophysiological and neurobiological studies [28][29]. In corroboration to this notion, there appears to be consistent evidence that EEG and ERP patterns vary systematically with dyslexia [30]. Given that the N100, and P300 components are conceptualized as the physiological correlates of the attentional and working memory operation [31][32][33], the present findings indicate that dyslectic children exhibit an altered and difficult organization process concerning the attentional working memory operation as they are reflected by the WE variations resultant in the time windows of the N100 and P300 components of ERP. Results point also to a dyslexia-related deficit in recruitment of prefrontal-, frontal-, as well as central structures for integrating the electrophysiological activities associated with the N100 and P300 components of ERP.

Finally, these findings indicate that the WE can be employed as a quantitative measure for monitoring the EEG and ERP activities and may provide a useful tool in analyzing electrophysiological signals associated with dyslexia.

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