Wavelet entropy: a measure of order in evoked potentials

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Wavelet entropy in event-related potentials: a new method shows ordering of EEG oscillations

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Abstract. In this work we show the application of a measure of entropy defined from the wavelet transform, namely the wavelet entropy (WS), to the study of event-related potentials (ERPs). WS was computed for ERPs recorded from nine healthy subjects with three different types of stimuli, among them target stimuli in a cognitive task. A significant decrease of entropy was correlated with the responses to target stimuli (P300), thus showing that these responses correspond to a more "ordered" state than the spontaneous EEG. Furthermore, we propose the WS as a quantitative measure for such transitions between EEG ("disordered state") and ERP ("ordered state").

1 Introduction

Although it is unclear how the immense number of neurons of the human brain interact to produce different functions, oscillatory activity is increasingly discussed as one of the possible mechanisms. Regarding the functional significance of this activity, it is of major interest to investigate how such "brain oscillations" – as far as they are visible in the EEG – get synchronized by stimulation or during the performance of certain tasks. Issues such as these can be addressed by applying methods of systems analysis (e.g. Fourier transformation) to event-related potentials (ERPs, i.e. the changes the EEG undergoes in temporal relation to a defined event). In this framework (Başar 1980, 1983, 1998, 1999), the transition between the EEG and the ERP has been suggested to correspond to a transition from a disordered to an ordered state.

Different approaches have been suggested to *quantify how brain oscillations get ordered* (i.e. tuned in frequency) by different processes. Among these possibilities, an estimation of *spectral entropy*, that is, a measure of the distribution of the power in the frequency domain, seems very suitable. In this work we present the application of wavelet entropy (WS; Blanco et al. 1998), an entropy defined from the wavelet transform, to the analysis of ERPs. WS gives a quantification of the frequency content of the EEG signals and, moreover, is an ideal candidate for measuring how spontaneous oscillations of the ongoing EEG get ordered upon stimulation. While previous entropy measurements required long periods of observation, the new method is suitable for short EEG segments such as ERP recordings, thus exploiting their precise temporal relation to certain tasks. This method was recently successfully applied for studying the ordering of the EEG during grand mal epileptic seizures (Blanco et al. 1998; Rosso et al. 1998).

1.1 The relationship between EEG and ERP: the "resonance hypothesis" of ERP generation

Offering an alternative to the conventional view of ERPs as signals being added to the background EEG, Başar (1980) pointed out that ERPs might arise from the ongoing EEG by means of a resonance phenomenon. According to this "resonance hypothesis" of ERP generation, the EEG consists of the activity of an ensemble of generators producing oscillations in several frequency ranges, which are active in a very complex manner. Upon stimulation they begin to act together in a coherent way. This transition from a disordered to an ordered state, a resonance phenomenon resulting in synchronization and enhancement of EEG activity, gives rise to "event-related oscillations" in several frequency ranges (e.g. "alpha response": a damped 10-Hz oscillation of approx. 200–300 ms duration, "gamma response" (40 Hz), etc.). The superimposition of event-related oscillations in various frequency channels (4 Hz, 10 Hz, 20 Hz, 40 Hz, etc.) gives rise to the compound ERP. In this respect, Sayers et al. (1974) stated that effective stimuli act by synchronizing the phases of spectral components of the spontaneous EEG activity already present.

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Experimental investigations of the relationship between prestimulus EEG and the configuration, latency, and amplitude of ERPs have attracted increasing attention in recent years (Arieli et al. 1996). With respect to human EEG, several studies have focused on either (1) the influence of prestimulus spectral EEG patterns on the ERP (Romani et al. 1988; Brandt et al. 1991; Başar et al. 1998) or (2) ontogenetic differences in EEG resulting in ERP differences (Yordanova and Kolev 1996). Resonance phenomena in sleep EEG have been studied by Röschke et al. (1995).

1.2 Wavelet entropy gives a time-varying measure of order of the EEGs

According to the resonance hypothesis outlined above, stimulation leads to an "ordering" of the spontaneous EEG (i.e. a transition to a more synchronized, less complex system). A natural approach for quantitatively measuring the degree of order of EEG signals is to consider their spectral entropy, as defined from the Fourier power spectrum by Powell and Percival (1979). Spectral entropy is a measure of how concentrated or widespread the Fourier power spectrum of a signal is. An ordered activity, like a sinusoidal signal, is manifested as a narrow peak in the frequency domain. This concentration of the frequency spectrum in one single peak then corresponds to a low entropy value. On the other extreme, a disordered activity (e.g. the one generated by white noise or by a deterministic chaotic system) will have a wide-band response in the frequency domain, thus being reflected in higher entropies.

Inouye et al. (1991, 1993) were the first to apply the spectral entropy to the study of brain signals. Furthermore, they defined an "irregularity index" as a measure of regularity or synchronization, thus characterizing different EEG states. Similarly, Stam et al. (1993) defined an "acceleration spectrum entropy" from the second derivative of the signal and reported differences in several pathological conditions (Jelles et al. 1995) and during mental activation (Thomeer et al. 1994). However, in the search for a method for entropy measurements in short non-stationary data segments, such as ERPs, methods based on the Fourier transform (such as the spectral entropy) have distinct disadvantages. The Fourier transform requires stationarity of the signal, the EEG being highly non-stationary (Lopes da Silva 1993; Blanco et al. 1995). Furthermore, the Fourier transform does not give the time evolution of the frequency patterns, and in consequence the spectral entropy is not defined in time.

These limitations can be overcome by defining a time-evolving entropy from a time-frequency representation (a representation of the frequencies evolving in time) rather than from the Fourier transform. In the case of ERPs, such improvement would exploit the precise temporal relation of changes in the ongoing EEG to certain tasks. In this respect, Blanco et al. (1998) defined an entropy measure, namely the wavelet entropy, from the wavelet transform. The wavelet transform is a relatively new method of time-frequency analysis that proved to have several advantages over previous methods (Mallat 1989; Chui 1992; Strang and Nguyen 1996). Firstly, the wavelet transform does not require stationarity. Secondly, with the wavelet transform, the time evolution of the frequency patterns can be followed with an excellent time-frequency resolution. The advantages of the WS are particularly important when analyzing ERPs for the following reasons:

1. Since the definition of spectral entropies is based on the distribution of the activity in the frequency domain, a high frequency resolution allows an accurate measure of the entropy.
2. A high time resolution is crucial in ERPs because the relevant responses are usually limited to a fraction of a second.

2 Methods

2.1 Subjects and paradigms

Experiments were carried out with nine voluntary healthy subjects (21–29 years old, 4 females) without any neurological deficit or medication known to affect the EEG. In an acoustically isolated and dimly illuminated room two types of experiments were performed (for more details see Schürmann et al. 1995):

1. Visual evoked potential (VEP; $n = 100$ trials): subjects were watching a checkerboard pattern (side length of the checks: 50′) displayed on a computer monitor (viewed from a distance of 140 cm). The stimulus was a checker reversal (the reversed pattern was shown for one second, then the original pattern was displayed again). The intensity of the checkerboard patterns was approximately 40 lx (background illumination approximately 5 lx).
2. Non-target/target stimuli ($n = 200$ trials): subjects were watching the same pattern as above. Two different stimuli were presented in a pseudorandom order. Non-target stimuli (75%) were pattern reversal, and target stimuli (25%) consisted of a pattern reversal with horizontal and vertical displacement of one-half of the square side length. Stimulus intensity and duration were as above.

After seeing a demonstration of both types of stimuli, subjects were instructed to attend to target stimuli and to mark them mentally (Polich 1991; Polich and McIsaac 1994). To avoid even minor motor artifacts possibly caused by behavioural responses, no further instructions were given. The inter-stimulus interval varied pseudorandomly between 2.5 and 3.5 s.

2.2 Data recording and processing

Recordings were made following the international 10/20 system from seven different electrodes (F3, F4, Cz, P3, P4, O1, O2) referenced to linked earlobes. A bipolar electro-oculogram (EOG, vertical and horizontal) was recorded for off-line artifact rejection. Data were amplified with a high-pass filter of 0.1 Hz and a low-pass filter of 70 Hz. For each single trial, 1024-ms (256 data) pre- and post-stimulus EEGs were digitized with a sampling rate of 250 Hz (12-bit A/D converter) and stored on a hard disk (note that the length of the post-stimulus EEG corresponds to the length of time the reversed pattern was visible). After visual inspection of the data, 30 trials free of artifacts, taking into account all EEG channels, were selected for each type of stimulus (VEP, non-target, and target) for future analysis.

2.3 Wavelet decomposition

The wavelet multiresolution decomposition method (Mallat 1989) was used for separating the signal by scales, defined in agreement with the traditional frequency bands used in physiological EEG analysis. This method arranges successive wavelet transforms in a hierarchical scheme that allows decomposition of the signal (see Fig. 1). It was applied to each single sweep using a quadratic B-spline function as mother wavelet. Quadratic B-splines are semiorthogonal functions with compact support (i.e. they do not extend to ± infinity) and nearly optimal time-frequency resolution (Chui 1992; Strang and Nguyen 1996). Details of the multiresolution scheme and its implementation are given in previous works (Blanco et al. 1998; Demiralp et al. 1999; Quian Quiroga and Schürmann 1999).

After a five-octave wavelet decomposition ($j = 1,\ldots,5$), the components of the following bands were obtained: 63–125 Hz, 31–62 Hz (gamma), 16–30 Hz (beta), 8–15 Hz (alpha), 4–7 Hz (theta). The residue, 0.1–4 Hz, corresponds to the delta band. For simpler notation, it will be referred to as $j = 6$.

For each subject the results of the wavelet decomposition of the 30 single sweeps were averaged, obtaining the mean wavelet coefficients $\tilde{C}_{i,j}$, where the index i denotes time and the index j denotes the different resolution levels.

2.4 Wavelet-entropy

Once the mean coefficients $\tilde{C}_{i,j}$ are known, the energy for each time i and level j can be calculated as

$$E_{i,j} = \tilde{C}^2_{i,j}$$

Since the number of coefficients for each resolution level is different, we redefine the energy by calculating, for each level, its mean value in successive time windows ($\Delta t = 128$ ms, this window being the minimum one including at least one coefficient in every level) denoted by the index k, which will now give the time evolution. Then, the mean energy will be

$$E_j^{(k)} = \frac{1}{N} \sum_{i=k_0}^{k_0+\Delta t} E_{i,j}$$

where k_0 is the starting value of the time window ($k_0 = 1,\ 1 + \Delta t,\ 1 + 2\ \Delta t, \ldots$) and N is the number of wavelet coefficients in the time window for each resolution level. For every time window k, the total mean energy can be evaluated as

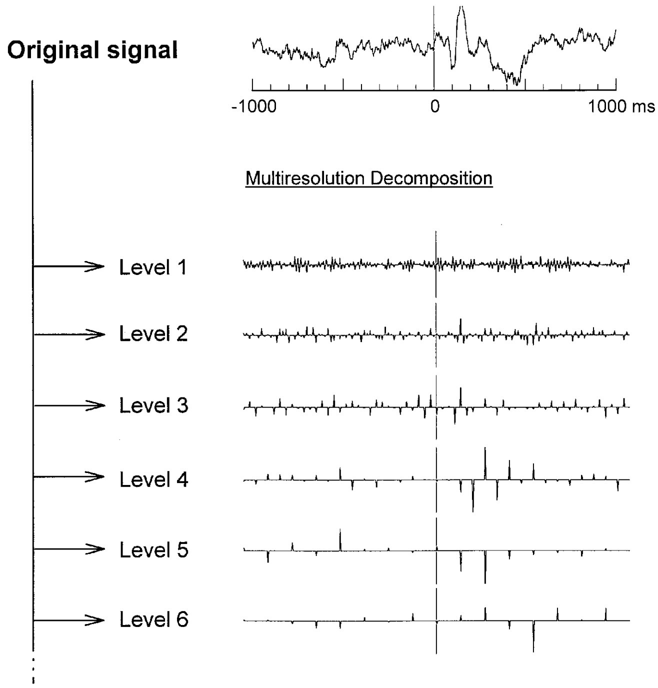

Fig. 1. Decomposition of an event-related potential in different scale levels by using the multiresolution decomposition method. Low levels correspond to high frequency coefficients and high levels to the low frequency ones

$$E_{\mathrm{tot}}^{(k)} = \sum_j E_j^{(k)}$$

and the probability distribution for each level can be defined as

$$p_j^{(k)} = \frac{E_j^{(k)}}{E_{\mathrm{tot}}^{(k)}}$$

Clearly, for each time window k, $\sum_j p_j^{(k)} = 1$ and then, following the definition of entropy given by Shannon (1948), we define the time-varying wavelet entropy (for further details see Blanco et al. 1998) as

$$WS^{(k)} = -\sum_j p_j^{(k)} \cdot \log_2 p_j^{(k)}$$

2.5 Statistical analysis

Mean WS values in an interval of 1 s pre- and post-stimulation were subjected to a repeated measures analysis of variance (ANOVA) with three factors: time (pre-stimulus vs. post-stimulus), condition (VEP, non-target, target) and electrode (F3, F4, Cz, P3, P4, O1, O2). A Greenhouse–Geisser correction was applied to the analysis of factors with more than two levels.

After ANOVA, mean WS values in an interval of 1 s pre-stimulation were also compared to those in the corresponding 1-s interval post-stimulation by means of t-test comparisons. This was done for each condition and electrode, resulting in a total of 21 pairwise comparisons.

3 Results

The wavelet entropy was tested with three different computer-generated time series: (1) a pure sinusoidal signal with a frequency of 12 Hz (signal 1); (2) a white noise signal (signal 2); and (3) a signal composed of the average of the two previous ones (signal 3). The random signal was obtained from the white noise function generator. The generated time series were sampled at a frequency of 250 Hz and the number of data for each time series was 512, in correspondence with the measurement characteristic of experimental time series (EEG-ERP time series) to be analyzed in this work. The wavelet entropy was evaluated in sliding non-overlapping time windows of length $\Delta t = 128$ ms.

The mean value of the WS over the considered total time interval of 2048 ms (512 data) was 0.15 for the first signal, 0.53 for the second, and 0.36 for the third. The standard deviation was almost zero for signal 1 (pure sinusoidal) and 0.035 for the other two signals. As expected (see Sect. 1.2), the WS is higher for the noisy signal 2 (which has a broad-band spectrum) and minimum for the sinusoidal one (which has a narrow-band spectrum). Note that for the case of signal 3, which is a linear combination of the two previous signals, the WS mean value is in between the extreme cases previously discussed.

The event-related responses of one typical subject are shown in Fig. 2 (the results of the grand average being qualitatively similar; see Fig. 5). In both cases, two major positive deflections are observed after stimulation, with different topographic maxima:

1. For all conditions, a positive deflection around 100 ms is visible. As expected, this P100 response has an occipital maximum. In this location, it clearly exceeds 10 μV. It is followed by a negative deflection of smaller amplitude.

2. In the target condition, a marked slow positive wave with a peak between 400 and 500 ms is observed. This expected P300 response is visible in all electrode locations. An amplitude maximum (of approximately 25 μV) is observed in the parietal recording. For all locations, this P300 response is of distinctly larger amplitude than the positive waves observed at this latency for VEP and non-target.

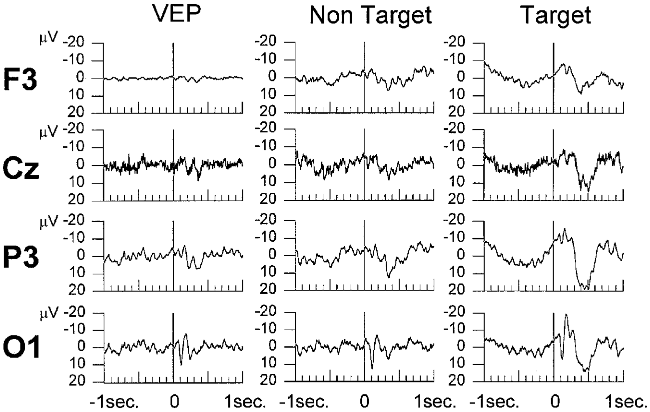

Fig. 2. Evoked responses of typical subject C.G. (only left electrodes shown; in the corresponding positions of the right hemisphere, roughly similar data were observed). The *left column* corresponds to VEP, the *middle column* to responses following Non-target stimuli, and the *right column* to responses to target stimuli

Figure 3 shows the results of time evolution for total energy (continuous line) and the energy frequency bands

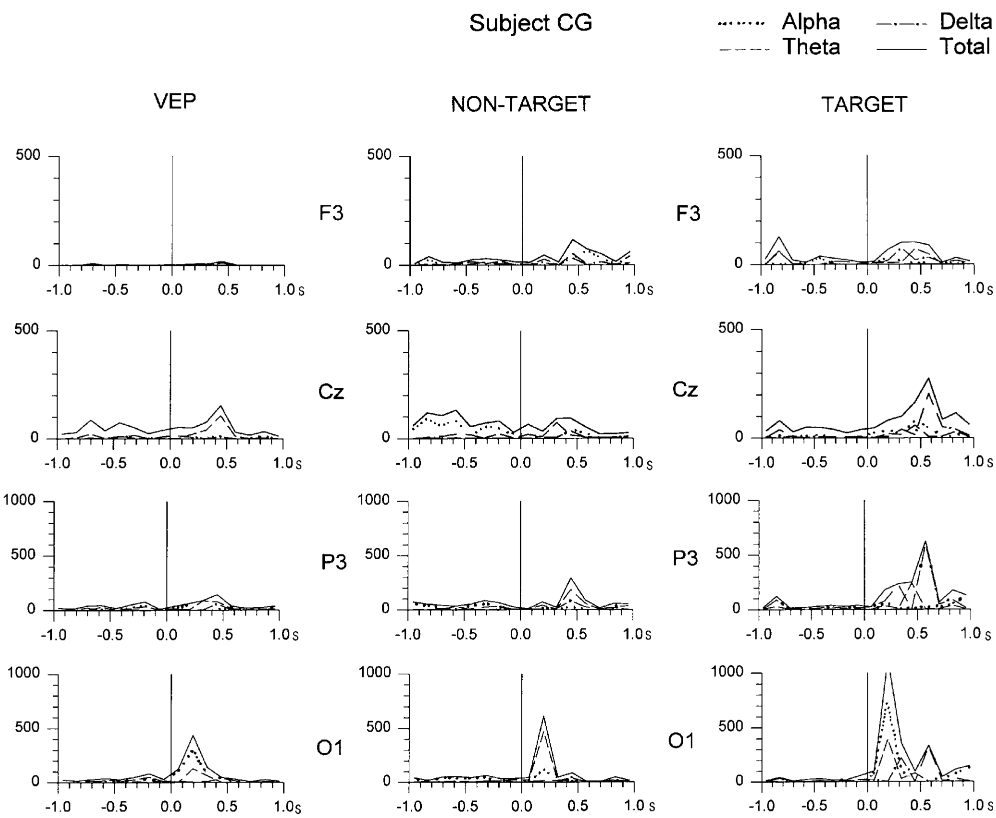

Fig. 3. Total and mean energy per band corresponding to the evoked responses of the same subject (C.G.) as in Fig. 2 (only left electrodes shown). The x-axis shows time in seconds, the y-axis, energy in arbitrary units

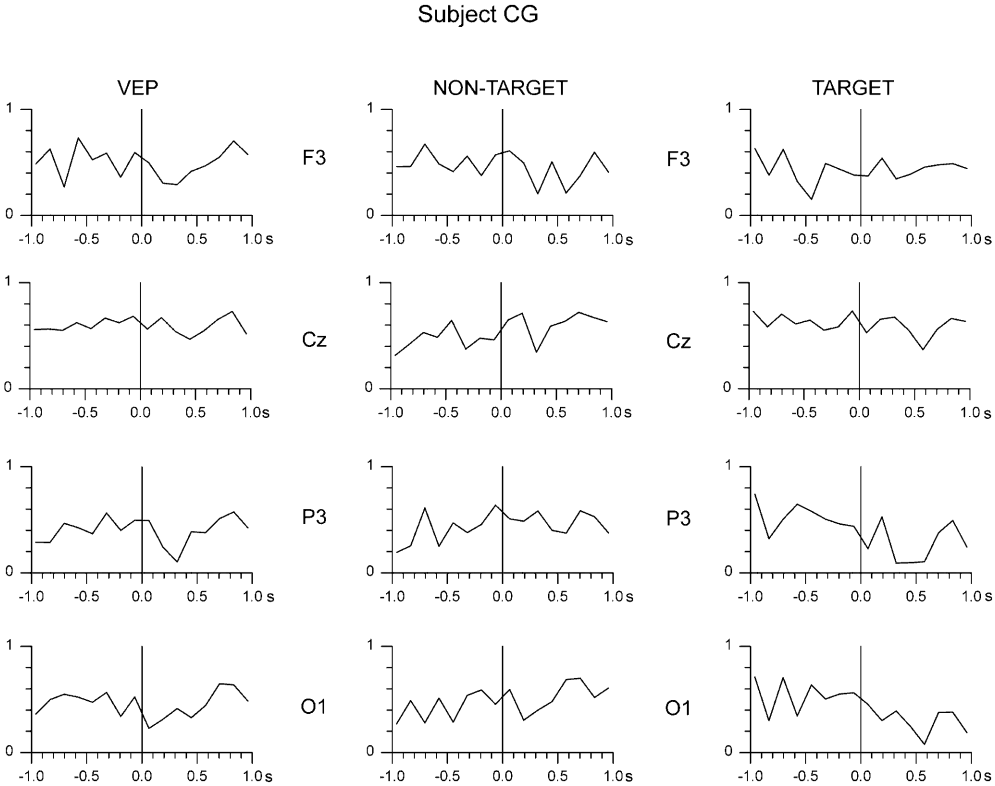

Fig. 4. Entropy corresponding to the evoked responses of the same subject (C.G.) as in Fig. 2 (only left electrodes shown). The x-axis shows time in seconds, the y-axis, entropy in arbitrary units

(wavelet resolution levels $j = 4$, 5 and the residue $j = 6$), evaluated in sliding non-overlapping time windows of length $\Delta t = 128$ ms, for the ERP of the same subject as in Fig. 2. Only the time evolution of the lower frequency bands (alpha, theta, and delta) are plotted since the higher ones ($j = 1$, 2, and 3) showed no relevant contribution to the total energy. All stimulus types show alpha and theta band power increases in occipital locations at 100–200 ms, correlated with the P100-N200 complex. Only upon target stimulation is an increase in the posterior locations (P3, O1) visible in the delta band at 500–600 ms, this increase being related to the cognitive response (P300).

Results of the time evolution of the WS for successively non-overlapping time intervals ($\Delta t = 128$ ms) for the same subject are shown in Fig. 4. Decreases in the entropy are more pronounced in the posterior sites upon target stimulation, strongly correlated with the topography of the P300 response. There are no decreases of entropy in the P100-N200 time window. This is in agreement with the distribution of energy described in Fig. 3, since the P100-N200 peaks have a wide-band frequency composition owing to the fact that they correspond to event-related alpha and theta oscillations (Başar 1980, 1998, 1999). On the other hand, the P300 response corresponded to a wave of an event-related delta oscillation ("pure delta response"), thus having a lower entropy. It is very important to note that the wavelet entropy results are not directly related to those regarding energy. This can be seen clearly, for example, when analyzing the target response of electrode O1, where there is a high energy increase (order of two times), compared with the corresponding energies associated with visual and non-target modalities, at about 200 ms without significant changes in the wavelet entropy for this time (see Fig. 4).

Considering the whole group of subjects, the grand average of the event-related responses and the corresponding WS are shown in Figs. 5 and 6, respectively. As pointed out with the typical subject, posterior decreases of the WS are observable upon target stimulation at about 600 ms. These decreases are clearly correlated with the definition of the P300 response (as to latency and topography). On the contrary, P100-N200 peaks

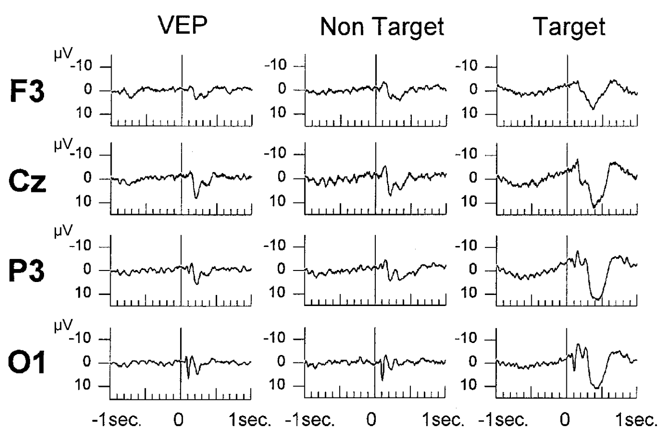

Fig. 5. Grand average of the event-related responses for the nine subjects (only left electrodes shown)

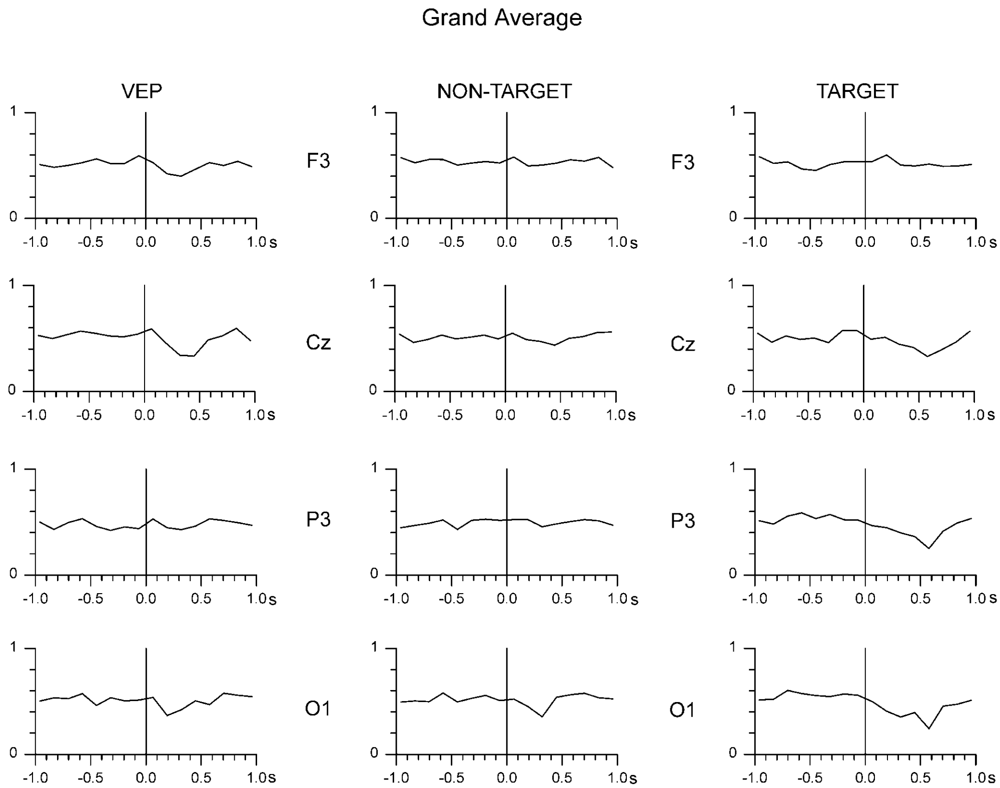

Fig. 6. Grand average of the entropy for the nine subjects (only left electrodes shown). The *x*-axis shows time in seconds, the *y*-axis, entropy in arbitrary units

produced no relevant decreases in the entropy (consistent with generation of these peaks by a wider range of frequencies, in particular theta and alpha). These results were statistically verified by means of a repeated measures three-way ANOVA analysis. In agreement with the observations reported above (i.e. post-stimulus decreases in the non-target condition, more pronounced in the posterior electrodes), significant changes were only related to the factor time ($P < 0.005$) and to the interactions time × condition ($P < 0.001$) and time × condition × electrode ($P < 0.01$).

The correlation of the WS decreases with the P300 responses was further verified by means of pre- and post-stimulus *t*-test pairwise comparisons. In Fig. 7, we present the results of the statistical analysis for all the electrodes considered in this work (F3, F4, Cz, P3, P4, O1, O2) and for the three conditions analyzed (VEP, non-target, and target). As shown in Fig. 6, wavelet entropies are lowest in posterior electrodes (parietal and occipital) upon target stimulation. For this condition, significant pre-stimulus versus post-stimulus differences were observed ($P < 0.05$ for electrode P4; $P < 0.01$ for electrodes P3, O1, and O2).

4 Discussion

In this work, we applied the wavelet entropy (Blanco et al. 1998) to the study of ERPs for the first time. The information obtained with the wavelet entropy proved to be not trivially related to the energy and consequently to the amplitude of the signal. This means that with this method, new information can be accessed with an approach different from the traditional analysis of amplitude and delays of evoked responses. In particular, WS gives a quantitative characterization of EEGs, its physiological interpretation being very rich due to its relation to order, frequency synchronization, and tuning.

The relationship between EEG and ERP as a resonance phenomenon or transition from a disordered to an ordered state (Başar 1980) is one of the questions to which WS can be usefully applied, yielding a temporal description and resolution not reachable with earlier methods. In this framework, WS is a natural measure of the frequency stabilization of different EEG oscillations upon stimulation. Resonance is related to a decrease of entropy, since only some of the spontaneous oscillations of the ongoing EEG will be enhanced or synchronized after stimulation, thus giving a more ordered frequency distribution than the broad-band spectrum of the EEG. This relation was shown with computer simulations, in which disordered (broad-band) signals had higher entropy than those corresponding to ordered (narrow-band) behaviors. We should remark, however, that it is not possible with WS to distinguish between disordered signals of stochastic nature and those generated by a deterministic non-linear chaotic system, both having a broad-band spectrum.

In agreement with previous findings (overview in Regan 1989), the P100 peak was best defined in occipital locations. Furthermore, its independence from task points towards a relation between this response and primary sensory processing. With respect to the reso-

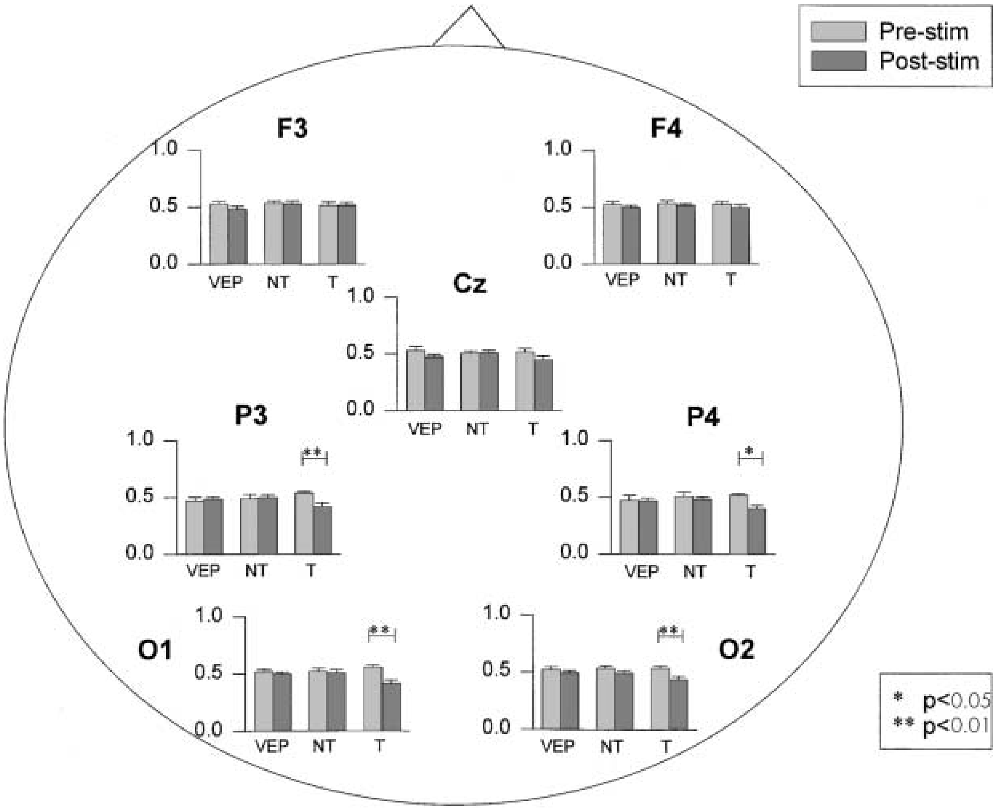

Fig. 7. A t-test comparison between pre- and post-stimulus entropy mean values. The y-axis shows entropy in arbitrary unit. NT, non-target; T, target

nance hypothesis (see introduction), it is interesting to analyze the frequency characteristics of different ERP peaks to understand the response mechanisms involved in their generation. The distribution of energy in the frequency domain shows that P100-N200 responses correspond to a wide range of frequencies (mostly theta and alpha bands). In the framework of the resonance hypothesis, these responses did not produce any significant decreases of entropy compared with the normal ongoing EEG, due to the wide-band frequency distribution of the involved generators. Data supporting the involvement of event-related alpha and theta oscillations in the generation of these peaks was already reported by Stampfer and Başar (1985), who obtained a similar result by digitally filtering auditory-evoked potentials in humans.

In accordance with previous evidence (Regan 1989; Başar-Eroglu et al. 1992; Polich and Kok 1995), the P300 positive deflection was observed upon target stimuli, best defined in parietal and occipital electrodes at about 500–600 ms. These P300 responses, typically related to a cognitive process, showed a significant decrease in the WS since they involved only event-related delta oscillations. Although the correlation between the P300 and the entropy decreases is clear due to their common appearance only upon target stimuli and their posterior localization, a difference of about 100–200 ms was observed between them. This is because after the P300 there is a positive slow rebound in the delta range (see Fig. 3). Consequently, although the amplitude maximum of the P300 is at about 400–500 ms, the P300 complex can be viewed as a delta wave extending up to larger latencies. A similar observation was made by Stampfer and Başar (1985): after filtering in the delta band the responses to target stimuli of an auditory oddball paradigm, they described the presence of a negative deflection at about 600 ms as a continuation of the positive P300 deflection.

Due to the relation between the P300 and the entropy decreases, it can be tentatively assumed that the cognitive (P300) response involves a higher degree of order than that of the ongoing EEG. This is due to the localized frequency activity in the delta band of these components. It is interesting to remark that Molnar et al. (1995), by using the "point correlation dimension", that is, a measure of complexity derived from the theory of non-linear dynamical systems adapted for non-stationary data, found a decrease in the complexity of the EEG correlated with the P300. Remarkably, even though this result was obtained by using a completely different approach, it is in full agreement with the frequency ordering we observe correlated with the P300.

Data supporting the importance of event-related delta oscillations in the generation of the P300 has been reported in several previous works. Başar-Eroglu et al. (1992), by using an auditory oddball paradigm in 10 subjects, pointed out the contribution of event-related delta oscillations to the P300 wave, suggesting that they are related mainly to decision making and matching. Schürmann et al. (1995) also investigated event-related delta oscillations and their relationship to the P300 wave, finding delta enhancement upon target responses even in single-trial ERPs. In particular, their results suggested that the P300 response is an event-related "pure delta" oscillation, a finding consistent with our results in terms of wavelet entropy (transition from disordered state to ordered state of "pure delta"). Furthermore, they obtained better averaged responses by selectively averaging single trials with an enhanced delta response. A similar result was recently reported by Demiralp et al. (1999), who applied a wavelet multiresolution decomposition to event-related potentials and used the delta coefficients as discriminators on a single-trial basis.

Finally, we should remark that the wavelet entropy was defined from the mean wavelet coefficients $\tilde{C}_{i,j}$, thus canceling the contribution of event-related oscillations not time locked to the stimulus (induced oscillations) in the calculus of the entropy. In other words, WS as implemented in this work is suitable for studying only the contribution of time-locked (evoked) oscillations in the ordering of the EEG signal after stimulation.

As to the WS method in general, further implementations are in progress to optimize the results by having more frequency bands. This would allow a more accurate definition of the entropy and moreover will allow the definition of the entropy for different frequency bands. In the case of ERPs, however, this is difficult, since a high time resolution is needed, thus limiting the frequency resolution due to the uncertainty principle.

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References

Arieli A, Sterkin A, Grinvald A, Aertsen A (1996) Dynamics of ongoing activity: explanation of the large variability in evoked cortical responses. Science 273: 1868–1871

Başar E (1980) EEG-brain dynamics. Relation between EEG and brain evoked potentials. Elsevier, Amsterdam

Başar E (1983) Toward a physical approach to integrative physiology. I. Brain dynamics and physical causality. Am J Physiol 245: R510–R533

Başar E (1998) Brain function and oscillations. I. Brain oscillations. Principles and approaches. Springer, Berlin Heidelberg New York

Başar E (1999) Brain function and oscillations. II. Integrative brain function. Neurophysiology and cognitive processes. Springer, Berlin Heidelberg New York

Başar E, Rahn E, Demiralp T, Schürmann M (1998) Spontaneous EEG theta activity controls frontal visual evoked potential amplitudes. Electroencephalogr Clin Neurophysiol 108: 101–109

Başar-Eroglu C, Başar E, Demiralp T, Schürmann M (1992) P300-response: possible psychophysiological correlates in delta and theta frequency channels: a review. Int J Psychophysiol 13: 161–179

Blanco S, García H, Quian Quiroga R, Romanelli L, Rosso OA (1995) Stationarity of the EEG series. IEEE Eng Med Biol 14: 395–399

Blanco S, Figliola A, Quian Quiroga R, Rosso OA, Serrano E (1998) Time-frequency analysis of electroencephalogram series (III): information transfer function and wavelets packets. Phys Rev E 57: 932–940

Brandt ME, Jansen BH, Carbonari JP (1991) Prestimulus spectral EEG patterns and the visual evoked response. Electroencephalogr Clin Neurophysiol 80: 16–20

Chui C (1992) An introduction to wavelets. Academic Press, San Diego, Calif

Demiralp T, Ademoglu A, Schürmann M, Başar-Eroglu C, Başar E (1999) Detection of P300 waves in single trials by the wavelet transform. Brain Lang 66: 108–128

Inouye T, Shinosaki K, Sakamoto H, Toi S, Ukai S, Iyama A, Katzuda Y, Hirano M (1991) Quantification of EEG irregularity by use of the entropy of the power spectrum. Electroencephalogr Clin Neurophysiol 79: 204–210

Inouye T, Shinosaki K, Iyama A, Matsumoto Y (1993) Localization of activated areas and directional EEG patterns during mental arithmetic. Electroencephalogr Clin Neurophysiol 86: 224–230

Jelles B, Achtereekte HAM, Slaets JPJ, Stam CJ (1995) Specific patterns of cortical dysfunction in dementia and Parkinson's disease demonstrated by the acceleration spectrum entropy of the EEG. Clin Electroencephalogr 26: 188–192

Lopes da Silva FH (1993) EEG analysis: theory and practice. In: Niedermeyer E, Lopes da Silva FH (eds) Electroencephalography: basic principles, clinical applications and related fields, 3rd edn. Williams and Wilkins, Baltimore, Md., pp 1097–1123

Mallat S (1989) A theory for multiresolution signal decomposition: the wavelet representation. IEEE Trans Patt Anal Mach Intell 2: 674–693

Molnar M, Skinner JE, Csepe V, Winkler I, Karmos G (1995) Correlation dimension changes accompanying the occurrence of the mismatch negativity and the P3 event-related potential component. Electroencephalogr Clin Neurophysiol 95: 118–126

Polich J (1991) P300 in clinical applications: meaning, method and measurement. Am J EEG Technol 31: 201–231

Polich J, Kok A (1995) Cognitive and biological determinants of P300: an integrative review. Biol Psychol 41: 103–146

Polich J, McIsaac HK (1994) Comparison of auditory P300 habituation from active and passive conditions. Int J Psychophysiol 17: 25–34

Powell GE, Percival IC (1979) A spectral entropy method for distinguishing regular and irregular motion of Hamiltonian systems. J Phys A: Math Gen 12: 2053–2071

Quian Quiroga R, Schürmann M (1999) Functions and sources of event-related EEG alpha oscillations studied with the wavelet transform. Clin Neurophysiol 110: 643–655

Regan D (1989) Human brain electrophysiology. Evoked potentials and evoked magnetic fields in science and medicine. Elsevier, Amsterdam

Romani A, Callieco R, Cosi V (1988) Prestimulus spectral patterns and the evoked auditory vertex response. Electroencephalogr Clin Neurophysiol 70: 270–272

Röschke J, Mann K, Riemann D, Frank C, Fell J (1995) Sequential analysis of the brain's transfer properties during consecutive REM episodes. Electroencephalogr Clin Neurophysiol 96: 390–397

Rosso OA, Quian Quiroga R, Blanco S, Figliola A, Başar E (1998) Wavelet-entropy applied to brain signal analysis. In: Theodoridis S, Pitas I, Stouratis N, Kalouptsidis N. Signal Processing IX, Theories and Applications. Typorama, Patras, pp 2445–2448

Sayers BM, Beagley HA, Riha J (1974) The mechanism of auditory evoked EEG responses. Nature 247: 481–483

Schürmann M, Başar-Eroglu C, Kolev V, Başar E (1995) A new metric for analyzing single-trial event-related potentials (ERPs): application to human visual P300 delta response. Neurosci Lett 197: 167–170

Shannon CE (1948) A mathematical theory of communication. Bell Syst Technol J 27: 379–423; 623–656

Stam CJ, Tavy DLJ, Keunen RWM (1993) Quantification of alpha rhythm desynchronization using the acceleration spectrum entropy of the EEG. Clin Electroencephalogr 24: 104–109

Stampfer HG, Başar E (1985) Does frequency analysis lead to better understanding of human event related potentials. Int J Neurosci 26: 181–196

Strang G, Nguyen T (1996) Wavelets and filter banks. Wellesley-Cambridge Press, Wellesley, Mass

Thomeer EC, Stam CJ, van Woerkom TCAM (1994) EEG changes during mental activation. Clin Electroencephalogr 25: 94–98

Yordanova J, Kolev V (1996) Developmental changes in the alpha response system. Electroencephalogr Clin Neurophysiol 99: 527–538