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Long-range linear correlations and nonlinear chaos estimation differentially characterizes functional connectivity and organization of the Brain EEG

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Abstract

We obtained and compared linear and nonlinear estimation of synchronicity and internal organization of a set of electroencephalographic (EEG) time series recorded during the realization of cognitive tasks. Linear estimation consisted of the assessment of Spearman R correlations between pairs of EEG electrodes, andnonlinear estimation consisted in apply rescaled (R/S) analysis on the EEG signal to obtain the Hurst exponent which estimates the degree of predictability (order) of the signal in an unpredictable (chaotic) ongoing background activity. We found adifferential characterization of the coupled synchronicity between pairs of scalp electrodes and the estimation of chaos/no-chaos global balance of the signal. While H increases indicating a tendency towards persistent self-similarity (affinity) and self-organizing processes, the amount of pairs of electrodes highly correlated (R>0.85) diminish,suggesting a sort of counteracting dynamic of balancebetween spontaneously driven homogenizing long-range linear correlation tendency againstan inner brain mechanisms leading to persistent self-organization, information richness and heterogeneity.

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Keywords;Linear and nonlinear dynamics of EEG time series, Brain order and chaos, Spearman correlation, Hurst exponent.

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1. Introduction

In the traditional way to understand the brain functioning,it has been giving a special value to the synchronicity of the nervous cells' electric activity and the extension of the area involved in that synchronicity [1] [2] [3].

Different levels of synchronic clustering in the brain has served to define different scales of functional interconnectivity [4] [5].

In a fully interconnected brain [6] [7] one may expect a naturally-driven tendency to fall in full synchronicity, as Huygens (1629-1695) observed occurring spontaneously when a set of regular oscillators are in some way of contact or connection while they are left oscillating for a while [8].

Since those observations were made the subject of synchronization in biological coupled oscillators has been found ubiquitous in nature, appearing as one example for phenomena of non-equilibrium order-disorder transitions [9].

In the brain, extreme or long-term persistent synchronization at the level of neuronal ensembles is believed to be the cause for theemergence of pathological rhythms in the Parkinson disease and in the Epilepsy [10].

Predominant electroencephalogram (EEG) slow wave (0.1-4Hz) synchronization is characteristic of the deep sleep stage of the NREM sleep [11].

A spontaneous EEG alpha wave (8-12Hz) synchronization is observed in the occipital lobes while staying relaxed with eyes closed [12], which is rapidly disrupted when math mentation is imposed [13].

We are interested in contrast two different statistical indicators to evaluate:i) the degree of synchrony, and ii) the degree of internal organization of a set of EEG time series by mean of using Spearman R linear correlation andnonlinear Hurst exponent estimation of chaos and self-organization content of the signal.

The Hurst exponent (H) estimates the rate of the chaos in the time series analyzed. It renders information about the degree of self-organization and amount of information embedded in the signal through the search of persistent or anti-persistent tendencies in the way the signal oscillates in time [14].

Out of $H = 0.5$ (brown noise), fractal or pink noise range allows evaluating the order ↔ complexity ↔ chaos tendency and the local fractal characteristics of the process being studied. For self-affinity systems, Hurst exponent and fractal dimension (FD) are related by the formula $D = 2 – H$, so when $H = 0.5$ for brown noise, the fractal dimension $D = 1.5$, half away from 1 {the Euclidean dimension of a line) and 2 (the Euclidean dimension of a plane).

The bigger the fractal dimension the lower the Hurst exponent in their respective ranges ($1<FD<2$ and $0<H<1$). $H > 0.5$ reflects a persistent or long-memory underlying driving process concomitant with the manifested measured phenomena. For $H < 0.5$ values, short-memory processes or anti-persistent tendency actively minimize the emergence of recurrent local fractal self-affine patterns.

On previous works [15] [16] some of us suggested that H values for the EEG activity may reflect the chaos/no-chaos balance in the whole range of brain's frequencies oscillations. In awake basal conditions, we found that H values can be very high for delta band ($H = 0.75$ +/- 0.05), while low H values were found for theta and alpha bands. In resting conditions alpha waves had the lower H estimated values ($H = 0.2$ +/- 0.05), then increasing progressively from alpha to gamma oscillations [15] [16].

For any time series, it is expected that when $H > 0.5$ the more persistent and quasi-predictable self-organized patterns will be observed in the future. The estimation reflects that long-term memory process carries a higher degree of persistence with a tendency that moves the system out of random unpredictable oscillation towards more structured and repetitive patterns of persistent self-affine fluctuations.

When studying social economics human behavior using stock market indexes as indicators, it has been related the facts that when H increases, less estimated entropy (less information content) is empirically expected at the time that market efficiency increases [17].

In the transition between order and chaos, complexity allows the generation of non-equilibrium transient self-affine fractal patterns that, depending on its duration and regularity, will confer global organization and self-similarity ($\uparrow$H) to the system by minimizing local roughness ($\downarrow$FD).

When relating chaos, disorder, order, and entropy (a measure of disorder or unpredictability), it is necessary to make the distinction between information and thermodynamic entropy. When thermodynamic entropy is high, only disorder (featureless equilibrium) and chaos (incompressible uncertainty) are possible. Order and disorder have minimum information entropy, but chaos and complexity have high information entropy. Complexity emerges when low thermodynamic entropy and high information entropy conjugates,Fig. 1.

<table>
<tr><td rowspan="2">Thermodynamic Entropy</td><td>Low</td><td>Order</td><td>Complexity</td></tr>
<tr><td>Maximum</td><td>Disorder</td><td>Chaos</td></tr>
<tr><td rowspan="2" colspan="2">Entropy Dynamics</td><td>Minimum</td><td>High</td></tr>
<tr><td colspan="2">Information Entropy</td></tr>
</table>

Fig. 1. Entropy matrix showing the relationship between order, chaos, disorder, and complexity.

In the brain, it would be expected that when H increases ($H>0.5$), it may reflect minimization of thermodynamic entropy (maximizing the information (content) entropy), minimizing fractal dimension (FD) to allow the presence of less fractured, more organized, quasi-predictable transient states. Subsequently, this could lead to the triggering of counteracting strategies turning to decrease the information entropy of the system through the onset of anti-persistent mechanisms that antagonize against too much order into the chaos. Too much global synchronization and short-term transient predictable states may be physiologically closer to medical conditions or sometimes even specific pathologies [10][18]. When multiple oscillators are someway coupled there is a strong tendency to thespontaneousreaching ofgrowing synchronization with maximal short and long-term predictability. To avoid these extreme strictly rigid states, processes in the brain must oscillate between two extreme states of total persistency ↔ total anti-persistency; or, order (predictability) ↔ chaos (unpredictability). The system moves between the realms of constructive and destructive fractal oscillations orbiting around the field of non-information statistical random walk or neutral activity.

After all, it would be necessary to consider that nature always behaves in a non-linear manner and that physics and mathematics work mainly with idealized and over-simplified linear approaches to predict systems in short (temporal and spatial) terms.

A very common linear approach to investigate brain functionality has been to study the degree of correlation between local and distant areas of the brain cortex [19] [20]. Wave correlations and synchronization in the brain come along with the old history of electroencephalography when Hans Berger described the first (alpha) waves spontaneously appearing between 8-12 Hz frequency range, much better captured with high power at visuo-occipital regions of the brain when subjects close their eyes [1][21].

This high power synchronized oscillation disappears when the subject open the eyes or when imposing cognitive load implying mental math [13][22], so occipital alpha wave can be understood as a manifestation of global disengagement of visual perceptual and processing load when eyes are closed, condition that is abolished when perception and mental processing is put upon the brain. This alpha band synchronicity could be revealing a process of spontaneous synchronization driven by task load disengagement or the absence of task load. In a similar way, delta wave (0.5-4 Hz) in slow wave sleep state can represent the reach of an almost total brain synchronization driven by the progressive disengagement from conscious behavior. Our previous results also show that beta band desynchronizes when imposed a harder cognitive load on it [16]. It may be reflecting a sort of trade-off between global vs specific tasks challenges that could demand specific local or global desynchronization to privilege other even more specific networks synchronizing for processing and manage theperceptual and cognitive load.

2. Methods

Linear Spearman EEG inter-channel correlations and nonlinear chaos estimation were compared in two datasets of EEG recording for two groups of people. The first group consisted of 12 professionals pilots performing an abbreviated version of 15 questions of the Raven's Matrix test, and the second group consisted of 10 professional modern dancers during mental visuo-imagination of a future dance performance. We compared the number of pairs of electrodes correlated with very high (R>0.85) and very low (R<0.25) values of Spearman's R against the estimation of chaos content (Hurst exponent) of the EEG signal during two minutes of recording.

All subjects ranged from 25 to 35 years old, healthy and fit. The group of pilots was composed by 10 men and 2 women. The group of dancers was composed by 3 men and 7 women. Tasks performing were recorded during 2 minutes with Emotiv Research Edition EEG headset recorder [23] to obtain the signals of 14 channels from the scalp of the subjects according to the position of the standard 10/20 location system. Basal previous states were also recorded during opened and closed eyes in relaxed awake conditions. EEG signal was recorded at 128 Hz sampling rate and we choose beta (13-30 Hz) and gamma (30-64 Hz) ranges to investigate the relationship of the chaotic content of the signals and the degree of inter-channel correlations in the scalp. The EEG preprocessing, filtering and artifact cleaning was performed with EEGLAB and ADJUST toolboxes running in MATLAB 2008a.

3. Results

We explored the question about the relationship and the informative resolution of the correlation-synchronicity linear paradigm contrasted with anonlinearchaos estimator.

Figures 3 and 4 depict the brain maps of pairs of inter-channel correlations with Spearman's R>0.85 among the 14 EEG channels placed in the scalp of the subjects. Figure 4 shows beta and gamma higher positive correlation values (R>0.85) for dancers. Figure 5 represents the same information of figure 4 for pilots.

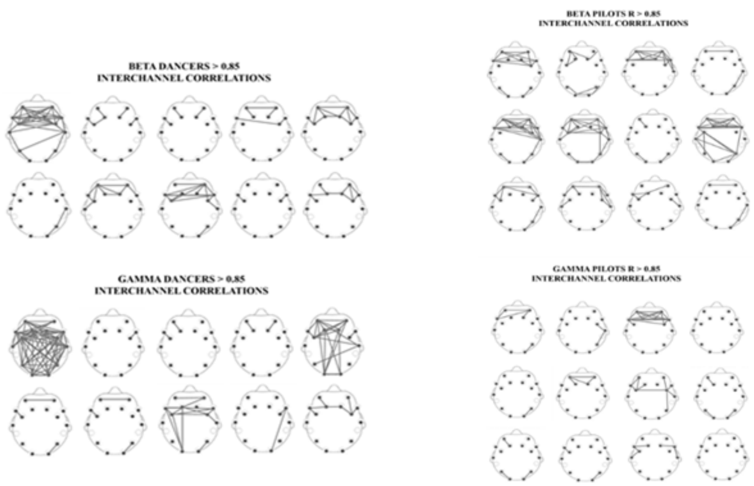

Fig. 2. Left: Dancers' inter-channel spearman R>0.85 correlations. Right: Pilots' inter-channel spearman R>0.85 correlations.

Besides the tendency to concentrate higher inter-channel correlations in frontal areas in almost the 60% of the subjects, individual differences, and different complexity of the inter-correlations patterns of connectivity makes difficult to extract more direct information. Not many differences comparing beta and gamma bands. Only in dancers, a slightly higher synchronized activity was found for gamma oscillation.

To go further in the comparison between linear and nonlinear procedures in a way to understand the EEG brain phenomenology we summed up the number of higher (R>0.85) and lower (R<0.25) inter-channel correlations and plotted against the H values associated with the subjects in the specific conditions. Figures 6 and 7 shows the negative correlations that we found when relating the number of pairs of EEG channels highly synchronized, against the value of H estimation for beta oscillations.Figure 8 and 9show the same negative correlated tendency when comparing H estimations for dancers and pilots in gamma band.When contrasting dancers and pilots according to the number of those pairs of inter-channels correlations with low Spearman's R values (R<0.25) for the beta band, we found a positively correlated tendency. While the number of lower Spearman's inter-channel (R<0.25) correlations increases, the value of estimated H increases as well. When comparing dancers and pilots according to the number of pairs of inter-channels correlations with low Spearman's R values (R<0.25) for the gamma band (Figure 12 and 13), we found no clear tendency further than a slightly negative correlation between the number of low Spearman's R values inter-channel correlations and the increase of H values more evident in gamma oscillation.

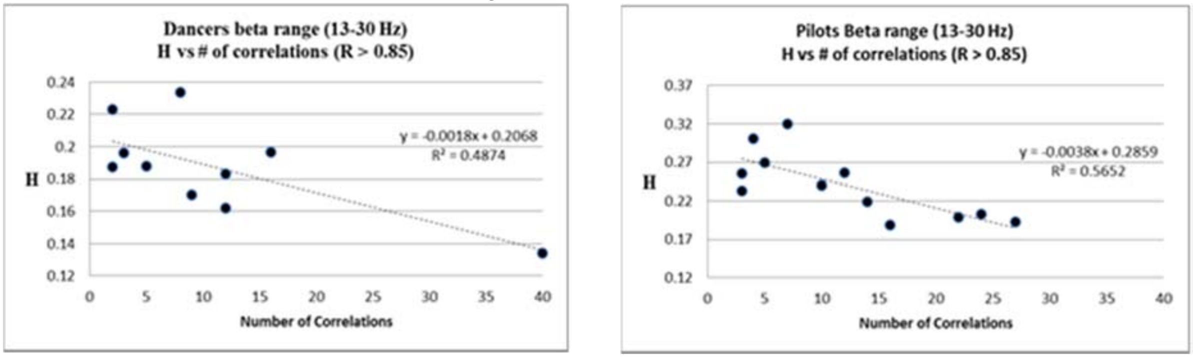

Fig. 3. Left: Dancers' H against the number of Spearman's R>0.85 inter-channel correlations in the beta band.Right: Pilots' H against the number of Spearman's R > 0.85 inter-channel correlations in the beta band.

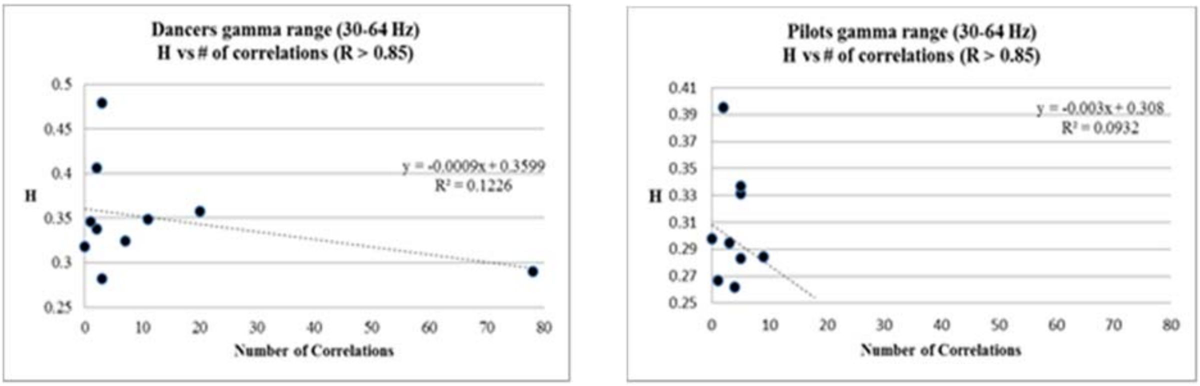

Fig. 4. Left: Dancers H against the number of Spearman's R>0.85 inter-channel correlations in gamma band.Right: Pilots' H against the number of Spearman's R>0.85 inter-channel correlations in gamma band.

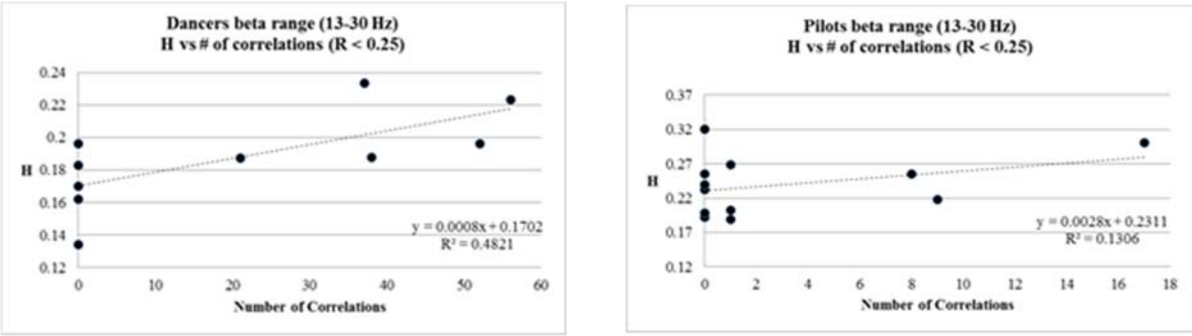

Fig. 5. Left: Dancers’ H against the number of Spearman’s R<0.25 inter-channel correlations in the beta band.Right: Pilots’ H against the number of Spearman’s R<0.25 inter-channel correlations in the beta band.

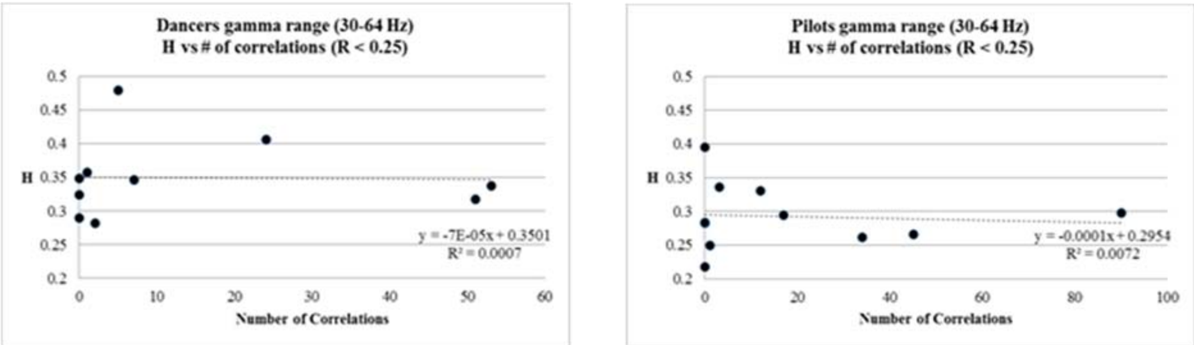

Fig. 6. Left: Dancers and Pilots’ long-term H against the number of Spearman’s R<0.25 inter-channel correlations in gamma band.Right: Pilots’ H against the number of Spearman’s R<0.25 inter-channel correlations in gamma band.

4. Discussion

We found interesting results when comparing linear and nonlinear estimators of the functional interconnectivity and organization of the brain for time series obtained from EEG beta and gamma bands.Consistently we found that when whole brain beta and gamma bands H values estimation increase this is associated with the decrease of the number of pairs of electrodes highly correlated (R>0.85).Congruently and especially for thebeta band, we found that the values of H increase with a number of pairs of electrodes weakly correlated (R<0.25). These last results are not so evident when observing gamma band where seems to be no such relationship. These results coincide with the idea that during a mental task global brain desynchronization occurs to allocate more specific (local) processing resources to solve the imposed cognitive task.

At a subsurface level of the system, H increase indicating that the brain performs more self-similar (self-affine) dynamics leading to long-term memory and more persistent processes.Results are strongly consistent with the function of thebeta band which is assumed to be related to awake and conscious conditions while facing relatively complex concrete real-time cognitive tasks.

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5. Conclusions

In considering the intrinsic nonlinear nature of all natural phenomena we contrasted the relationship between applying a linear estimator of EEG inter-channel correlation and a nonlinear estimator of the degree of organization of the brain, based on self-similar and persistent characteristics of the time series generated by the electrical activity of the brain surface (EEG).

Moving from linear to nonlinear perspective allows integrating the comprehension of complex systems under the laws that govern the actual behavior of self-organized systems like the brain.

The relationship between H and other nonlinear parameters estimators allow to differentially relatethe nature of the brain processing at different temporal and spatial scales in relation to the degree of mutual synchronic interaction; order or disorder; chaos or predictability; and self-organization in acomplex system with an active counterbalance between thermodynamic and information entropy levels.

The use of complementary linear and nonlinear tools to detect tendencies toward order and chaos in the brain functioning, or specific characteristics of this dynamic balance in individuals under specific treatment conditions, during allopathic or naturopathic medical scrutiny, can be useful to explore in more detail integrated multi-level diagnostic systems,shading some light on the not so apparent, hidden underlying processes that may be involved in the symptomatology observed.

An initial linear and nonlinear parameters diagnosis and the monitoring of the time course of the changes of these variables associated with a particular treatment can allow the quantitative evaluation of the healing process.

Further research is also needed to build an extended database of normal variability vs pathological parameters valued under the light of complex systems perspective and chaos theory applied to human health and disease conditions.

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