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Individual Differences in the Order/Chaos Balance of the Brain Self-Organization

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Abstract We used fractal geometry and fractal dimension introductory argumentation as a framework to start understanding dynamical and complex biological systems to then introduce Hurst exponent estimation of chaos/no-chaos balance trend to explore the phenomenology and the information content of EEG data through time. We searched for measure *proxy* dynamical variables as potential biomarkers and/or endophenotypes that help us to figure out the multidimensionality and different time-scale of simultaneous and crossed functional phenomena that manifests in the brain during executing any challenging task. We found consistencies in the way intra- and inter-individual differences express themselves through the EEG time series data analysis, and some degree of specificity and specialization in the frontal, temporal and occipital locations as well as brain interhemispheric cross-talk interaction modulating the chaos/no-chaos balance in the brain, during a projective process of imaging a dancing choreography. We recorded the brain activity of $N = 9$ professional dancers while executing the instruction of to imagine (by mean of a typical projective visualization) a future dancing performance as part of the requirement for to approve a specialization modern dance course and workshop (*Kosmos In Movement*, 2015).

Keywords Fractal geometry · Chaos · Dynamical systems · Brain · EEG · Time series

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1 Introduction

Try to answer the question of how the brain processes data and concurrently performs executive functions has been approached from many points of view. Most of them mainly concern to functional relationships and dependence between multiple and variable areas or locations in the brain [1–3]. In general, it is well understood a hierarchical topology with more or less specific areas dedicated to sensorial, processing and executive functions [4–6]. In the cortex, this differentiation is carried out by the cortical columns, which are the structural and functional units which are processing and rendering information along the cortex. The cortex areas locally differentiate by the relative proportion of the nervous cell types that compose the six layers that every cortical column has (Fig. 1).

Since 1924, when Hans Berger recorded the first wave of electrical activity coming from a human brain [7], this organ has been extensively explored across the study of the EEG. The bio-electrical signal generated by the brain can be recorded from the scalp by means of placing electrodes sensible enough to detect the tiny differences of voltage that comes from the activity of the brain surface. All this happening below a layer of skin, a plate of bone, and three layers of laminar tissue filled with liquid. Once the electrical signal is amplified, it is seen as a continuous trace that moves up and down in time around a central (0 μvolts) stationary tendency (Fig. 2).

Quantitative analysis of the EEG data has been done mainly on spectral analysis by means of Fourier or wavelets decomposition [8–11]; auto-correlation, cross-correlation [12,13]; and coherence analysis [14,15]. Much of the research has been

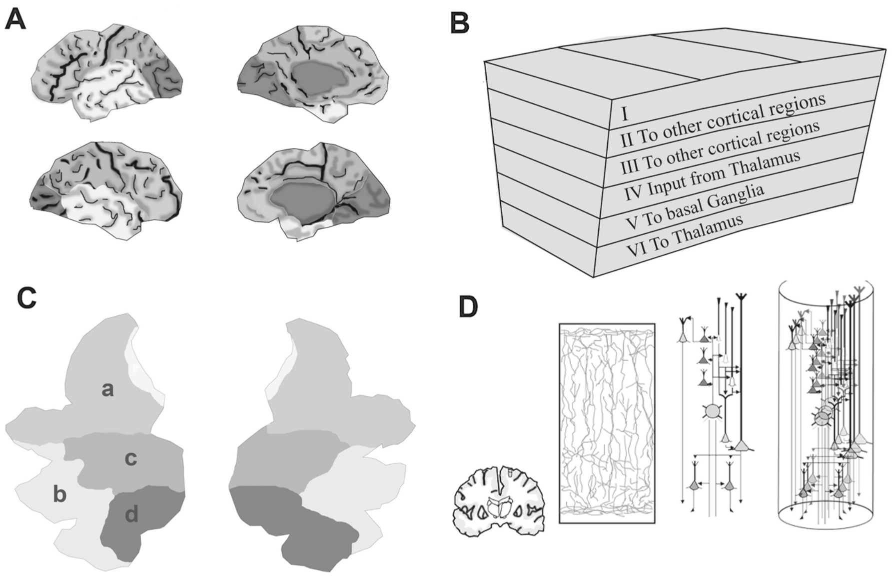

Fig. 1 Brain cortical structure. **A** Brain areas in the whole brain; **B** Functional structure of cortical layers I–VI; **C** Brain main areas in the plane. *a* Frontal; *b* Temporal; *c* Parietal; and *d* Occipital. **D** Neurons depicted in a cortical column

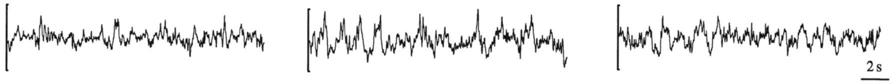

Fig. 2 Typical EEG traces from three different electrode locations

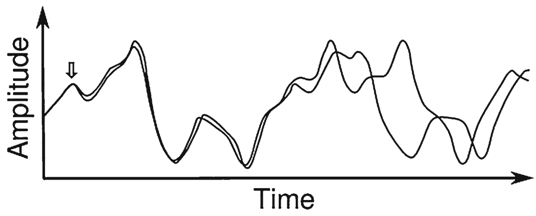

Fig. 3 Sensitivity to initial conditions. The *arrow* indicates tiny different initial conditions for both phenomena

also dedicated to the study of evoked response potentials, which search in the spontaneous reaction of neurons in response to specific stimulus [16,17].

All of these approaches have thoroughly explored the linear aspects of the EEG phenomenology, expressed in terms of average differences between variables submitted to a scientific question, through the artifact of an experiment. Much of these explanations are constructed in terms of a set of variables that, in one way or another, in conjunction involves energy intensity differences and a set of temporal (synchrony, phase) and frequency (tuning) correlations between brain (electrode) locations and electrical activity.

Just recently, complementary to this classic approach, a non-linear scope has emerged with the aim to re-understand old and new phenomena by looking at them with new eyes, with the eyes and language of dynamic, complex and unpredictable systems [18–20]. The language of this approach is written in fractal algorithms which can be as simple as a one variable equation, but with the property of amplify its rendering through iterate a recursive function that applies the original and rather simple instruction over the result just obtained after apply the same operation. In this way, we get a dynamic system, a system that cannot be easily characterized by linear math, because in this non-linear realm, chaos and uncertainty governs and where we can assert that not always *bigger is better*. Here all depends on everything, and on just one thing: initial conditions [21–23].

The fact that dynamical systems are very sensitive to initial conditions is understood in terms of that any difference that we may consider tiny or negligible in the elements that drive the course of a phenomenon now, after some iteration of the process will unavoidable conduce to very different trajectories (and consequences) in the future of the systems (Fig. 3).

The only light that can slightly narrow and delimitate the otherwise totally unpredictable possible future trajectories of a dynamical system is the detailed knowledge that we can have of the conditions that put the system in motion at the beginning. It sounds more or less reasonable when we think about isolated systems, with very clear and defined boundaries and known initial conditions. And in restricted conditions like such it does works, but when we are talking about living systems what happen here is that any moment in the life of a living being sets a new set of initial conditions for quasi-predictable futures.

In this scenario, it looks like the only we can expect to find when studying living organisms, is variability. In fact, it has been shown that even in the most carefully designed experimental protocols made to ensure experimental replicability, there are unexpected differences in the individuals, even out of the range of the reasonable expected along normal differences, and even in largely selected genetic mouse strains [24].

In understanding human diseases and their recovery, rather little attention has been posed on to know more about the people in the mid-range of the normally distributed statistically average people. Those who live the everyday life in standard conditions and that never would go to a hospital to take an electroencephalogram of him or herself, without, or unless, having received precise indication from a clinician.

In studying the brain, a lot of knowledge has been accumulated investigating the plethora of neurological conditions that populate the DSMs, but rather little is known about how the brain works in normal or standard conditions, when people face daily challenges *on-the-go*, and/or have to solve different problems *on-demand*. In this last kind of investigation we expect to be faced to the crude human variability and unpredictability. And it will be much more expected now under the light, scope and language of dynamical systems.

2 Fractal Dimension (D)

Fractal dimension is central in fractal geometry because it breaks the classical integer Euclidean spatial dimensions in which we are comfortable to think (dimension '0' for a point; '1' for a line; '2' for a plane; and '3' for a volume), by intercalating fractional values of dimensions, for natural and mathematical objects, *in-between* the Euclidean dimensions. Classical geometry deals with ideal lines, figures, forms and objects, those we never find in nature, unless made by human beings. Fractal dimension qualify the degree of *roughness* built up over an ideal *smooth* Euclidean dimension, in such a way that while D increases from dimension 1 to 2, for example, what it is saying is that a line (of dimension 1) can gradually reach a plane (dimension 2). How can it be possible? Figure 4 depicts the random walk trajectory of a single photon, released at the center of an area, and that have to move across an optically dense region until reach the limit and escape off the encircled area. We can see that the cumulated trajectory of the photon between starting and escape point can, progressively, fill the plane area. Depending on the circumstances, sometimes the photon finds a fast way to scape while, in others, it take substantially longer. But in both cases the way the photon moves across the dense area is the same and depends on the angles of interaction between the photon and the particles that made the medium. The trajectory traced by photons in these circumstances can be described by a fractal trajectory called random walk (Brown noise or Brownian motion) that eventually can overlay all the necessary points to cover a 2D plane. So, fractal dimension for this mathematical object known as random walk has a D value of 1.5.

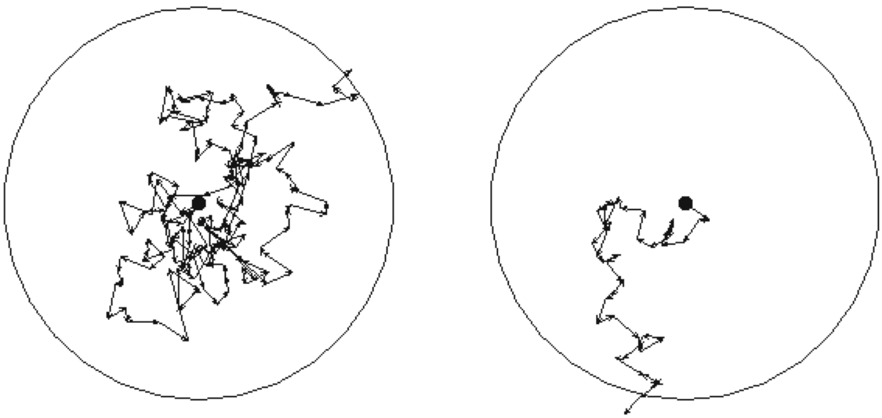

Fig. 4 Example of Compton scattering Brownian motion (Random walk) of a photon

3 Chaos, Non-chaos and Hurst Exponent

Another way to study the meaning of the trajectory of a 1-D system in the range of the fractal dimension is to look at into temporal aspects of the time series like auto-correlation; self-similarity; and short- and long-memory underlying processes. For example, Brownian motion describes a trajectory that is totally uncorrelated with respect to previous behavior, so it is impossible to predict future positions or trajectories. It can be said that random walk has no preferred locations or that the "preferred" locations are equally distributed in time and space. Something similar occurs with *white noise*, which is the kind of sound that contains equal representation of all the audible range of frequencies. There is no information in white noise, not in brown as well. There are not underlying processes driving the behavior of these trajectories because they are statistically driven, no tendency and no long-memory processes.

Total unpredictability renders for chaos but complex systems, as living organisms, are characterized by oscillate between order and chaos (and between cooperation and competition) [25–27], so we need to look for other range of noise (out of white and brown) to search for more interesting dynamics, those who may involve quasi-predictable trajectories, self-similar information-driven procedures with short or long-memory underlying processes involved. We can find this kind of phenomena in the realm of pink (fractal) noise, which moves between white and brown (Fig. 5) and have the property to transiently manifests self-organized behavior which can vary in the degree of self-similarity, autocorrelation, short/long memory and fractal content, in a way that it is possible to deduce an information driven processing modulating the overall behavior of the trajectory. These fractal objects are understood as dynamic attractors, which are a kind of biased tendencies for statistical distribution in time and space where the trajectory of the system is intermittently attracted to so they appear characterized as very organized short-life items emerging stochastically from a chaotic uncorrelated background.

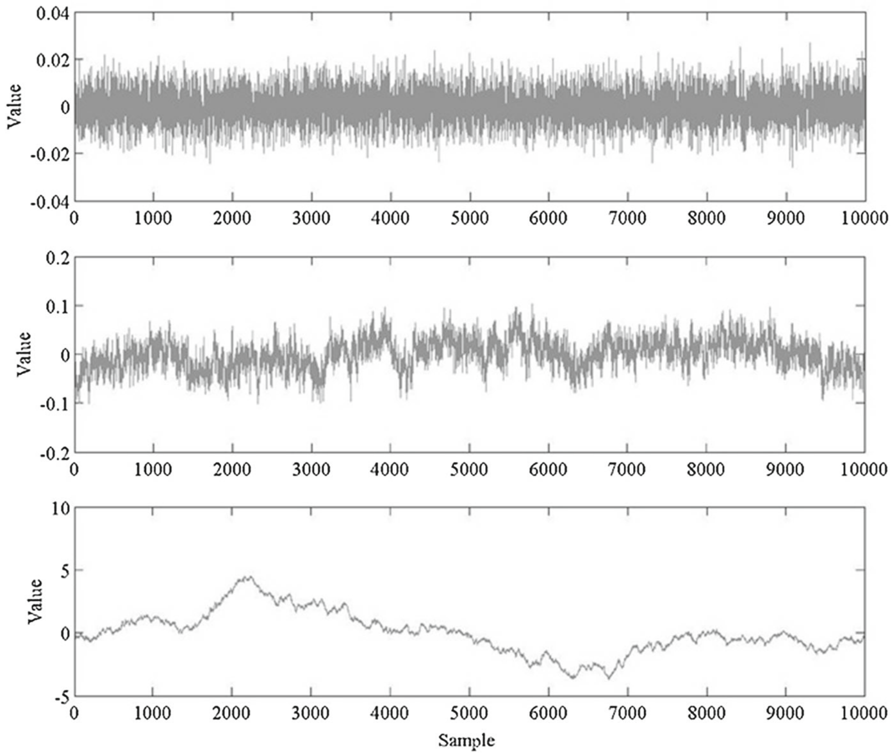

Fig. 5 Examples of white, pink and brown noise time series

Interestingly, in nature many time-dependent processes falls into the category of fractal noise [28–30] and the EEG brain signal is one of them [35,36].

The formula $D = 2 - H$, relates Fractal Dimension (D) with H (Hurst exponent). While the former measure the degree of roughness of the trajectory in a 1-D $\rightarrow$ 2-D fractional dimensional range, the latter estimate the rate of chaos in the signal with values that range from 0 (total unpredictability or chaos), to 1 (total predictability), a *proxi* way to evaluate the self-organized (order) content in a chaotic medium [31].

4 Chaos and Self-Organized Content in the Brain

Transient fractal self-organized elements has been described emerging from the chaotic background of the EEG brain activity [32] to count for the ordered counterbalance that the brain must do against total unpredictability, to render time-space organized patterns of activity that must be reasonable related with information processing.

Many recent approaches to non-linear dynamics and predictability in chaotic physiological environments suggest that the more ordered is the process, the more pathological it is, so we have to be cautious in interpret results under our own view of what is good or bad for the organism. It may seem counterintuitively to think that keeping chaos as a rule for functioning is healthier than maintain strict order and regularity. It has been shown that physiological parameters like heart beat rate are healthy when the time series of the beat rate have a rather unpredictable trajectory in between physiological ranges than a predictable one. When we find predictability and extreme regularity of the physiological function it is a sign of illness [33–35]. Along we get older in life our brain activity loses complexity and the functional trajectories of brain processing turn to be less chaotic or more predictable [36].

Looking at the chaos/order balance in the EEG brain activity, it has been shown a relationship between Hurst Exponent (H) and the EEG brain frequency bands that characterize diverse modes of the functional brain. High values of H arise in delta band (0–4 Hz), while lowest values of H has been detected for alpha band (8–13 Hz). Going up from alpha to beta (13–30 Hz) and gamma band (30–64 Hz), it is observed a gradual increase of H values which can be interpreted in terms of the functional constraints toward order that demand brain data processing while working with more complicated information [31]. While delta wave can be considered as a very structured self-dedicated *house-keeping* process it is not strange that high H values reflects high organization and not-chaotic processes happening in the brain. Delta waves characterize the kind of brain activity that predominates during deep highly synchronized slow-wave sleep, so it is reasonable to think in this activity as a very organized self-dedicated process that the brain performs while we rest our consciousness.

When the brain is submitted to a cognitive challenge (like an intelligence test), H values rises with the transition that separate the solving of the easy and difficult questions. In the same transition, the average inter-channels beta correlations (R) fall from 0.4 to 0.15 when the brain is faced to the difficult part of the test indicating a separation of functioning (electrodes desynchronization) to solve the more difficult part of the test [37]. This reflects the same decay in synchrony and amplitude tendency that is observed in the whole brain frequency range when we travel from low frequencies (delta) band, to high frequency (gamma) band in the sleep-awake-cognitive axis of brain attention and cognitive processing.

All these consistencies of the phenomena and the non-linear tools that can be used to characterize them allow the use of these *proxi* indicators of the functional substructure underlying the phenomena that we are seeing, an EEG trace. At this point, we reach a point in which never mind about the reductionist's conflict about if what we are seeing is the cause of the brain phenomena or just a kind of resonant effect of the hidden and still not fully understood machinery that allow the brain to work. Strong dependence (or sensitivity) to initial conditions annihilates the problem because complex systems doesn't conciliate with the idea of cause and effect. In this new mathematical realm of non-linearity and fractal geometry, the only thing we know is that an EEG trace occurs in the brain concurrently with the behavior that we are observing or testing. We also know that this electrical oscillatory signal contains the whole range of detectable frequencies that we are able to capture with our apparatuses, and that in this whole range of frequencies there will be all the trajectories involved in all the brain processes that are occurring at the moment. Contrary of what we can think, all this apparent cacophony of noise superficially seen in an EEG trace is plenty of information and his behavior (pattern of oscillation) reflects the functional underlying mechanisms that render the processes that must be implemented for the brain to deal with the on-going present.

5 Individual Differences for Data Processing

It can be reasonable expected that every person on the planet have a different neural architecture, resembling the general pattern depicted in Fig. 1, but differing in a multiplicity of free scale dimensions (structural, functional, behavioral, psychological, experiential, etc.). Besides, it is evident that each person on earth has more than tiny differences in initial conditions so we expect trajectories that exponentially separate from each other while minimizing similitudes in the future.

For complex adaptive systems like all the living organisms, and like us, humans beings, living in a descriptive-explanatory domain with respect to what we refer as *reality*, it is easy to see that every single moment of our own life sets for a new set of initial conditions which are the only things that worth wide to know in a dynamical system, as early as possible, to have a minimal foresight confidence about possible future trajectories. When we study human beings, unless we are studying them because they are part of a specific medical condition category, we start to find individual differences as the norm. We can measure them in terms of how close or far can be located different trajectories of functional processing, in comparing them as *proxy* non-linear variables that measure the tendency to chaos against self-organization in the data variability (trajectory).

These individual differences that we start to detect can be very informative about the chaos/order balance in the brain processes. If we think about a developing brain as a system that learns successful correlations, between order/chaos; competition/cooperation brain functioning; and a set of external conditions, it is expected that the brain will operates progressively learning until to get the lowest energy expenditure and the highly efficiency that can be reached in the given conditions. Depending on the infinite particular different routes (trajectories) that could been followed by this learning brain during the past, we will expect finding infinite different strategies learned to face problems in life, but all of them had to deal with the same energy and information processing resources optimization, the chaos/order and competition/cooperation balance.

6 Experiment

With the aim to test these non-linear methods for understanding and estimating valuable variables of dynamical systems, we recorded the brain activity of 9 (N = 9) professional dancers while executing the instruction of to imagine (through a typical projective visualization) a future dancing performance that will be one of the evaluations required for to approve a specialization modern dance course and workshop (KIM *Kosmos In Movement*, 2015).

EEG signal was recorded with the brain-interface device Emotiv Epoc® [38,39] at 128 Hz sample rate during 2 min performing the required task with the eyes closed.

The EEG system recorded from 14 channels/electrode location according to the standard system 10/20 (AF3, F7, F3, FC5, T7, P7, O1/O2, P8, T8, FC6, F4, F8, AF4). Electrodes were referenced bilaterally to the mastoid bone behind the ear. All subjects (N = 9; 6 *females* and 3 males; *CT*, *FA*, FCH, *JC*, *MB*, MP, *PL*, RA, *LC*), were young

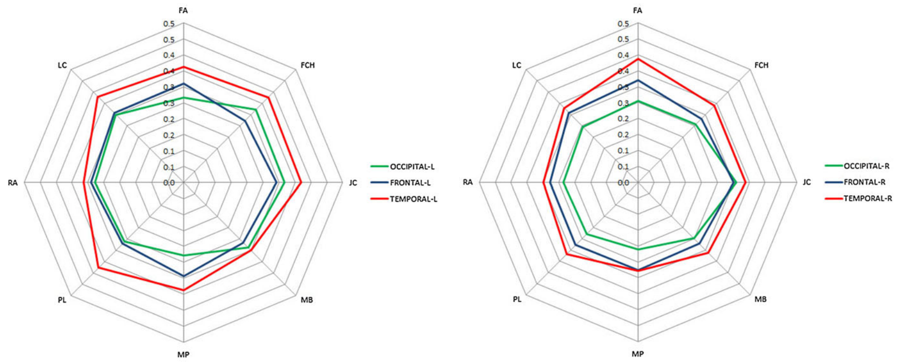

Fig. 6 Hurst exponent (H) estimation for the three brain areas depicted in color (blue = frontal; red = temporal; green = occipital), for 8 subjects (*FA*, FCH, *JC*, *MB*, MP, *PL*, RA, *LC*). *L* Left hemisphere, *R* Right hemisphere. (Color figure online)

adults between 20–30 years old, and rested during 5 min in comfortable relaxation previous to the experiment.

EEG data was then pre-processed for artifact cleaning in 1–64 Hz whole range filtering using EEGLAB [40] and ADJUST [41] toolbox, running on MatLab platform 2008a.

In the first step for this exploratory approach we integrated the whole frequency EEG range from 1 to 64 Hz, for both hemispheres left (L) and right (R) and for three dedicated brain areas: frontal (AF3–AF4), temporal (T7–T8) and occipital (O1–O2).

7 Results

7.1 Hurst Exponent Variation by Subject and Brain Location

All long-term (2 min) H estimation for 15,360 data points in the time series, for each channel rendered for frontal, temporal and occipital areas and for the eight subjects, gave results of $H < 0.5$ meaning that the signal moves in the range of anti-persistence and short-memory dynamics. It means that any high or low value of the data series will tend to be followed by values that counterbalance immediately any possible trend.

It is interesting that for all subjects, higher values of H were consistently obtained for the temporal region which shows the lower tendency to anti-persistence of the three areas. It also seem to be a slightly difference between frontal and occipital areas, being the latter the one that has the more short-memory processes going on.

7.2 The Chaos of the Data and the Chaos of the Chaos Oscillation (M-chaos)

When estimating the degree of self-similarity, long-memory tendency or persistence of a time series, this estimation, not been an average, is a better picture of the inner trend toward order or chaos that express the underlying mechanism in correlation with the oscillatory bio-electrical signal manifestation.

The value of H obtained for the whole duration of the experiment (2 min) were rather low for all subjects, as one expect to find when the brain is in a state of relaxed attention or daydreaming, not involved in nothing special, but kindly ready to face any experiential challenge.

As we indicated a precise projective visualization with a very specific goal (the mentally preparation of a dance performance), we went to look for more self-organizing processes at a different time scale.

We first study the Hurst exponent sensitivity to N (number of data points considered in the time series for the H estimation). We found that for many different data series a maximum H arise around processing between 160 and 320 data points, which in terms of time means around 1.3 ($\pm$0.5 s) seconds to then decrease slowly and gradually while N increase. We took then this consistent and also intuitive timeframe of around 1 s, which seems to be a good pace-marker for a moving time-frame window of 1 s length.

Cutting the entire EEG signal of 15,360 data points in shorter time series of 128 data points each (1 s duration), 120 new data set of 128 points each, allowing us to recalculate H' but this time over a time series containing a time series of H values.

Figure 7 shows five representative different time series oscillation of Hurst values for frontal brain area, over time, in 120 timeframes of 1 s duration each.

By revealing a new time series, now made of primary H values, in a very precise way, by looking at the oscillation of the chaos/order tendencies over time, we were looking at the chaos of the chaos. Individual differences in the trajectory of the chaos/no-chaos oscillation are evident for the three areas under study.

We could then compare two new, rather simple, but very informative modified H' values, obtained by averaging all 120 H (1 s duration each) values. This gave us a *proxy* linear indicator of the short-term timescale control process that must be at the root of chaos/no-chaos balance. As it was said, the other H' estimation was obtained by the recursive operation of to apply the Hurst exponent estimation over the time series of 120 (Fig. 7) short-term (1 s) data H values coming from the original time series of EEG data.

We used our approximations consisting in to operate linearly (by means of average, standard deviation, coefficient of variation, and linear correlation); and non-linearly (by mean of Hurst exponent estimation), over the same data set of 120 H values to obtain and compare three kind of chaos: (i) the chaos governing the primary long-term manifestation of the control process in the brain. This is based on the EEG data information; (ii) the chaos governing the secondary long-term manifestation of the chaos oscillation M-chaos (for meta-chaos) estimated by iterate the H function over the primary 120 H values of the chunked original EEG data by second; and (iii) the linear average of H values for chaos tendency in the short-term scale of 1 second.

In the figures, all this secondary approximations to estimate the chaos content variation coming from the analysis of the second order chaotic signal trajectory, are usually referred as H' or HH operations.

In resume, the estimation of short-term (moment-to-moment) control of data processing in the brain comes from averaging a set of consecutive H values obtained from EEG data time series of 1 second duration (128 data points). Two estimation of long-term control of the data process can also be obtained. The first one corresponding

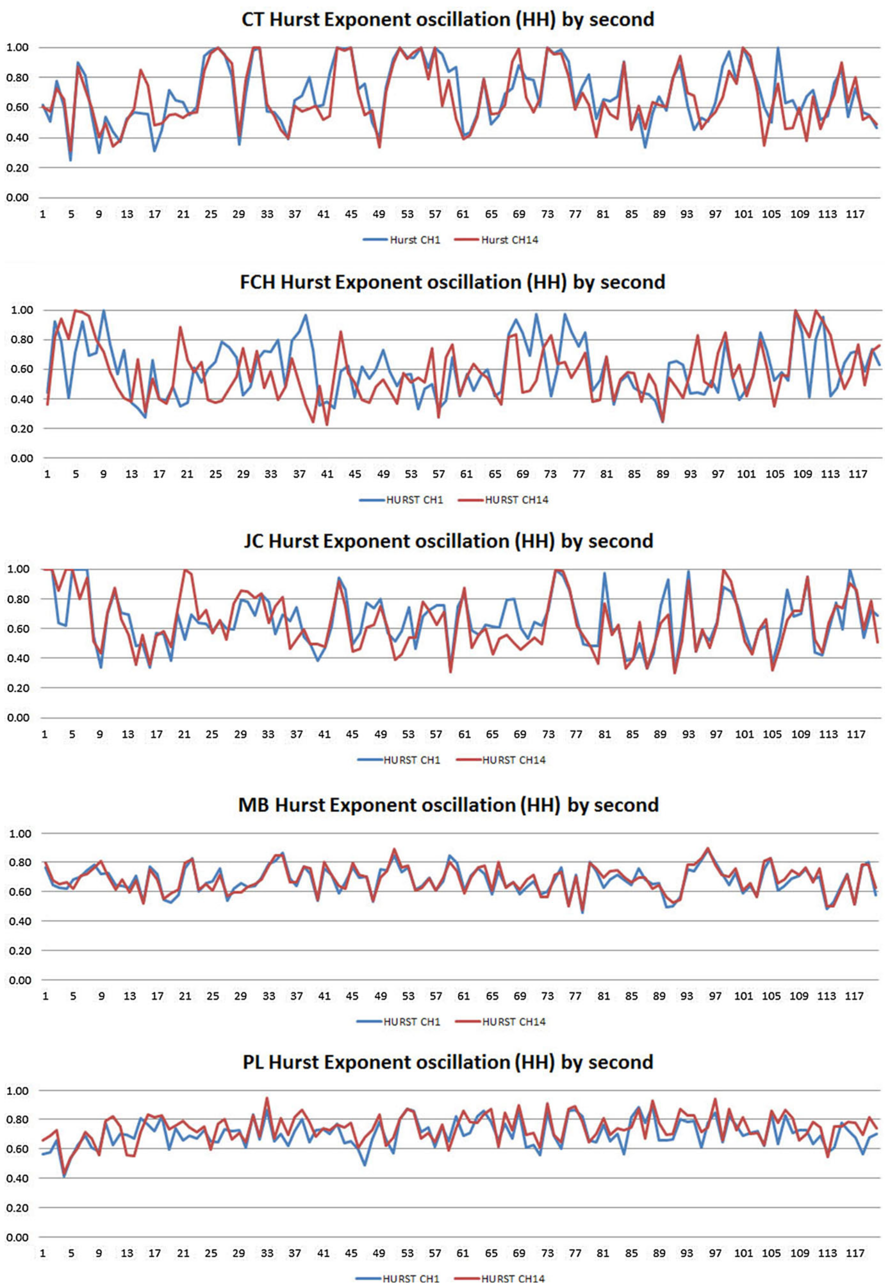

Fig. 7 Hurst exponent time series oscillation (HH) for frontal area, for five representative subjects (*CT,* FCH, *JC*, *MB*, MP, *PL*). Left and Right hemispheres for Hurst oscillation are indicted with color. *Red* Right and *Blue* Left. (Color figure online)

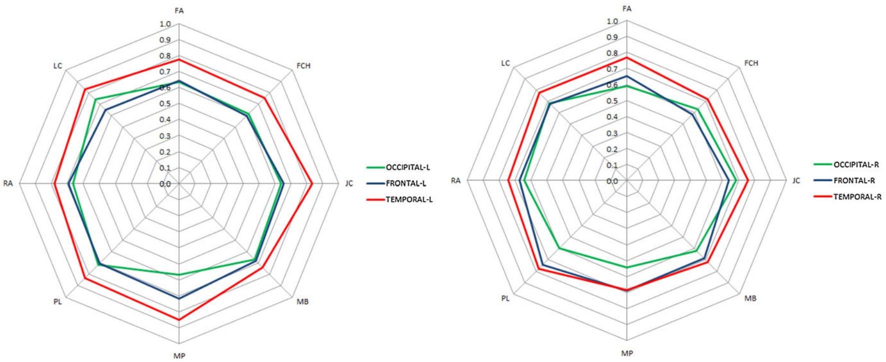

Fig. 8 HH short-term values comparison for eight subjects and three brain areas. *L* Left hemisphere and *R* Right hemisphere

to the primary long-term estimation of H calculated from the 15,360 data points covering the 2 min of EEG recording. The second correspond to the secondary long-term estimation o H (now also referred as H′), calculated from the 120 averaged values of the short-term (1 s) H estimations.

7.3 Quantitative Linear Descriptive Characterization of Non-linear Estimator of Chaos

Figure 8 compare HH short-term estimations (averages) for eight subjects and for the three brain areas. Similar to the individual differences distribution of long-term primary estimation in Fig. 6, HH short-term render high values of $0.6 < H' < 0.8$, reflecting strong trend for persistence, long/memory processes and self-organization. Among brain areas, comparative higher values of H′ appear again for temporal brain, while frontal and occipital differences are almost undistinguishable in the majority of the subjects for both hemispheres.

Figure 9 show the relationship between HH short- and HH long-term estimation of M-chaos. In this case more differences are appreciated among brain areas, but conserving interhemispheric consistency in its differences distribution. The graph depicts the values of (HH long-term / HH short-term) so when the plotted values are greater than 1, means that the control processing of the chaos/no-chaos balance is mainly modulated for the long-term control, prevailing over short-term fine tuning modulation. By the contrary, plotted values <1, mean that the control processing of the chaos/no-chaos balance is carried out by the short-term, moment-to-moment, fine tuning control, prevailing over long-term modulation. It is also observed that occipital (green) areas seems to have a preferred modulating control at the long-term scale of intervention, while temporal areas (red) tend to be the more fine tune, moment-to-moment, short-term modulated.

Figure 10 shows great differences observed in the values of H′ coefficient of variation (CV), reflecting the degree of individual variability. More specific individual differences cluster very clearly in frontal areas for subjects RA, *PL*, MP and *MB* with

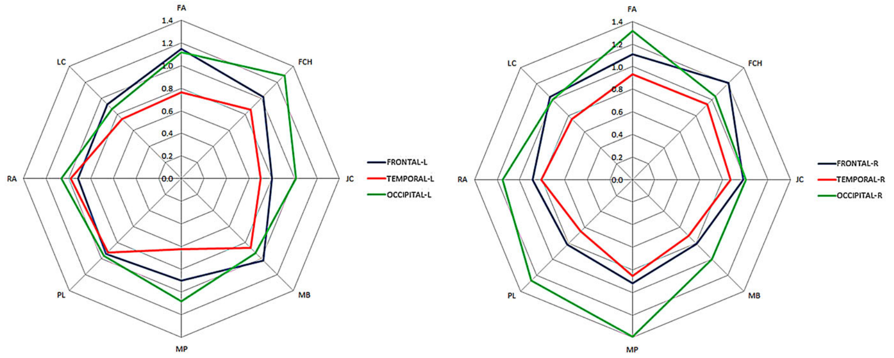

Fig. 9 HH short-term vs HH long-term values comparison for three brain areas and eight subjects. *L* Left hemisphere and *R* Right hemisphere

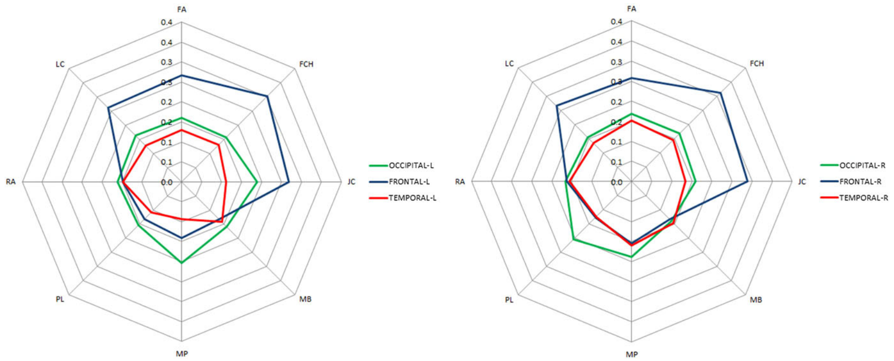

Fig. 10 HH Coefficient of variation ($CV = S.D./H'$ *short term AVERAGE*) comparison for three brain areas and eight subjects. *L* Left hemisphere and *R* Right hemisphere

low short-term M-chaos variability (CV ∼15 %); and subjects *LC*, *FA*, FCH and *JC*, showing higher values of variability (CV ∼ 25–30 %)

Figure 11 shows the HH short-term (H′ averages) interhemispheric (LEFT/RIGHT) linear correlation R values for frontal, temporal and occipital areas in the nine subjects. Frontal hemisphere show high values of interhemispheric correlation, while temporal and occipital areas are more individually variable but with less values of interhemispheric linear R correlation.

7.4 H, HH Short-Term and HH Long-Term for M-Chaos Comparison

Figure 12 depicts the relationship between primary and secondary operations used to characterize short- and long-term chaos trajectory estimated for chaos and M-chaos (HH). Comparing long-term (H) versus short-term (H′) timescales, short-term estimated values of H from 120 s of data points (M-chaos), has higher values of H′ than the long-term trend (H) estimated directly from the EEG whole data time series. The plot pattern is similar when comparing H versus HH long-term (data not shown)

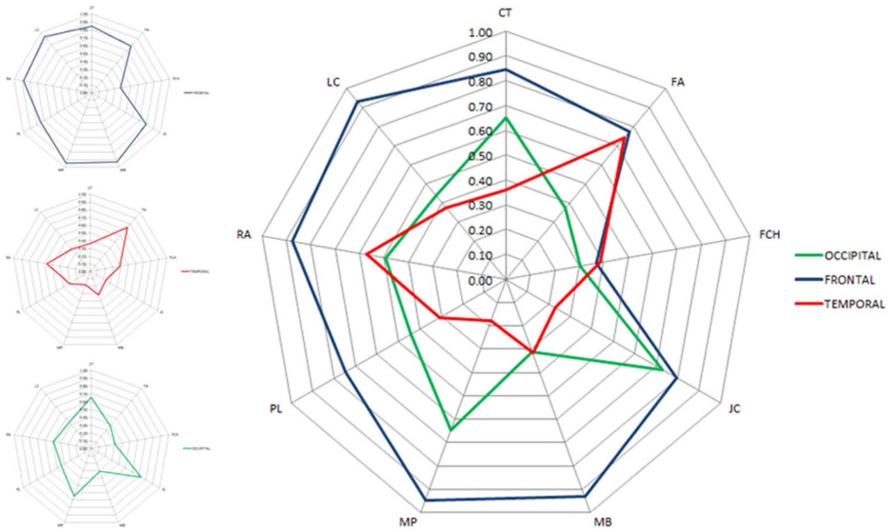

Fig. 11 Interhemispheric (Left/Right) linear correlation of HH short-term averaged values, for the three brain areas under study, and for the nine subjects

When comparing M-chaos (HH) short-term vs M-chaos (HH) long-term, there are reduced differences in the values of H′ for both hemispheres. Individual differences can be found in some brain areas and some subjects, which varies between tendencies in short- versus long-term control processing, and vice versa.

8 Discussion

The faculty to project our thoughts into the future, by means of create images in our brain while *imagination*, is maybe one of the pinnacles of human brain capacities evolution. Through this window toward the future, human beings has been able to create, emerging from an entirely abstract realm, a whole world of material entities, which has transformed our existence in a remarkable way.

Punctuated along the course of this human quest, remarkable men and women, by the only exercise of their minds, have driven the crucial inflections of our existence, and brought us now to the very present of our current human modern society. To use this interesting phenomenon that is commonly referred as *imagination*, we study some aspects of the linear and non-linear behavior of the electrical brain signal oscillation (EEG), during a projective mental task that consisted in to visualize body movements and choreography for an invented dance, which was actually going to be performed in the near future.

The experiment was executed by professional dancers as part of the requirement for the final exam of a specialization program in modern dance. We explore inter-individual differences in terms of functional fractal dimensions and Hurst exponent to look and describe the phenomenology of the chaos/no-chaos and competi-

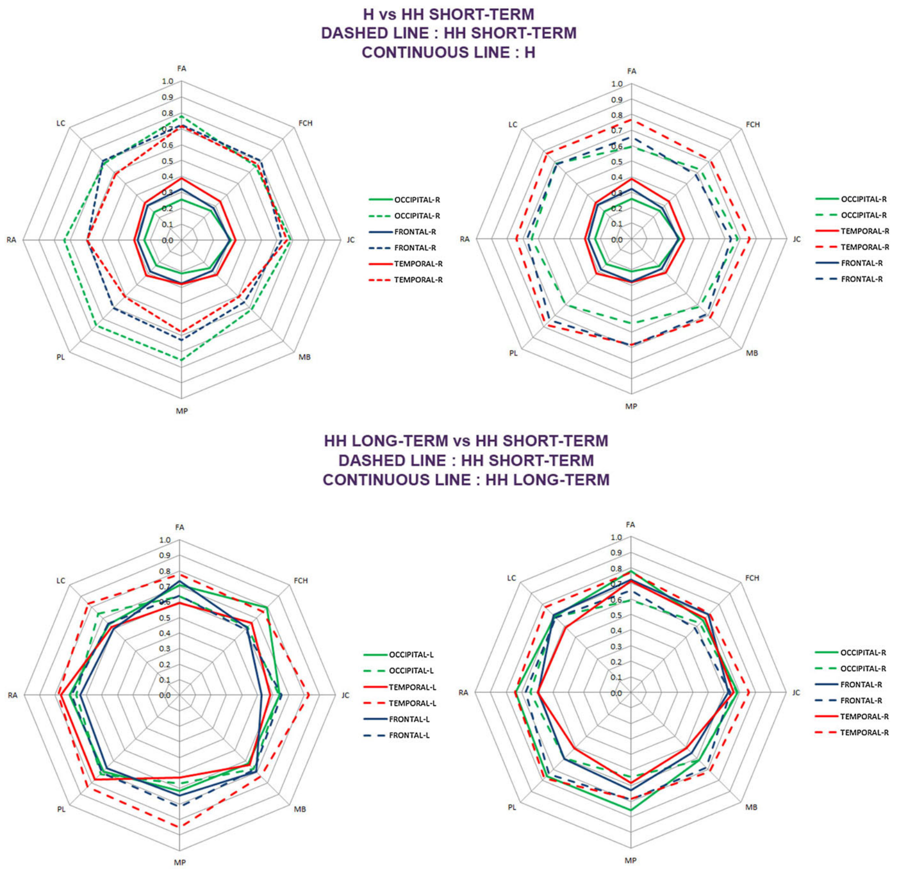

Fig. 12 H, HH short-term and HH long-term M-chaos comparison by brain areas and subjects. *L* Left hemisphere and *R* Right hemisphere

tion/cooperation balances of the brain working processes and the potential information content variation of the EEG data through time.

After to find rather discrete estimated values of H analyzing the complete sequence of 15,360 data points of the EEG time series, we found higher estimated H values when we took shorter segments of data (equivalent to 1 second length) along the time course of the experiment. In this new condition average H values 0.7 tell us another story about the persistence and long-memory process that must be operating at the short-term timeframe of one second.

In the long-term, seems to be that underlying process is working relaxed, maintaining anti-persistence and volatility. In this way, the brain could be using two different temporal scales to allocate different processes that require dissimilar phase space conditions to solve the question ahead. In our experiment, the brain of professional dancers was asked to work in the design of movements and choreography of a future performance. We can imagine at least two different aspects to take into consideration: (i) the creative part of the problem; and (ii) the technical part of the problem. For the first one we would prefer to work in a more unpredictable environment, where a mind state similar to daydreaming will be allowing the free interplay of possibilities with creative purposes. In the other hand, another part of the process may require the involving of more moment-to-moment, mid-analytical processing that will require more self-organization, long-memory and persistent activity.

Our preliminary results can suggest that brain could be able to modulate its ongoing processes by operating at two timescales ranges of modulation. The short-term modulation corresponding to a fine tune, moment-to-moment supervision, suggested by the high Hurst Exponent (H) average value around 0.7, indicating long-memory persistent processes in the working substructure. The second, long-term modulation, more relaxed, having short-memory and anti-persistent processes with similar values for H found recently in basal resting conditions for the EEG alpha band [31].

The fact that we were also able to study the oscillatory behavior through a 1 second windowed timeframe of the EEG signal, gave us the opportunity not only to see the chaotic general trend of the whole experiment during the total time length, but also the lot of information contained in the way that chaos/no-chaos balance (M-chaos) oscillate between certain numeric boundaries, opening a new time-space to explore and start the quest for finding fractal dynamic functional regularities as bio-markers for individual differences and groups' clustering.

Interhemispheric linear correlation of the M-chaos time series could be related to the competition/collaboration aspect of the brain functioning. In the classical linear way of thinking, we use to expect that collaboration be related to synchronization, and that the contrary will be expected for competition, say desynchronization. In this point we must be very careful because we have to remember that in the realm of non-linearity, many times things happen apparently counter-intuitively. For example, if we remember that synchronization is a phenomena rather spontaneous in nature (the only thing you need is to put in some kind of contact two or more oscillators in the proper arrange, and just wait for spontaneous synchronization), maybe some part of the brain must help avoiding extreme or out of range synchronization that in the long run will conduce inevitable to total temporal homogeneity. This will be equivalent to trivial, pathological information or no-information at all. So we need to explore this field more deeply to find, when and how the interhemispheric synchronization/desynchronization balance serves to specific brain tasks.

Even working with a wide EEG frequency range (1–64 Hz) for this exploratory utilization of non-linear analysis tools, we found considerable individual differences associated with brain location and processing modalities. Further research will be focused on specific EEG bands to dissect more precisely the range and the variability of these differences.

Finally, a great deal of information and future exploration arises when we start to apply a non-linear way of thinking to understand new and old aspects of long-lasting elusive questions about brain and human behavior. Changing gradually the paradigmatic starting points for scientific research and exploration, turning slightly to a better comprehension of complex systems like us, will be the wide-opening field of research that is it called to populate all the science and philosophy during the next following decades.

The study of the temporal multidimensionality of the brain processes manifested and visualized through the ongoing cortical brain electrical activity, continue opening new ways to increase our knowledge and understanding of the brain and how it works. The potential applications of all this new findings can help us to learn more precisely the complex and fascinating nature of the human brain, and through learning about it to achieve a better management and drive of our evolutionary brain faculties and human capacities.

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