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Time series of closed and open eyes EEG conditions reveal differential characteristics in the temporality of linear and non-linear analysis domain

Hernán Díaz M.[a,b,*], Fernando Maureira[c], Felisa Cordova[d]

[a,b]University of Santiago de Chile, Department of Industrial Engineering, Av. Ecuador 3769, Santiago 9170124, Chile.
[b]*University of Santiago de Chile, Department of Mathematics and Computer Science, Las Sophoras 173, Santiago 9170020*
[c]*Universidad Católica Silva Henríquez,Escuela de Educación en Ciencias del Movimiewnto y Deportes. Lo Cañas 3636, Santiago 8280354, Chile*
[d]*School of Industrial Engineering, University Finis Terrae, Av. Pedro de Valdivia 1509, Santiago 7501015, Chile*

Abstract

The basal states defined by the closed (EC) and open (EC) eyes conditions are revisited using linear and nonlinear analysis approaches. We compared EO and EC control states using standard Spearman R correlation between pairs of EEG electrodes. We also performed a moving correlation coefficient (MCC) analysis to explore the short-term (1-second) timeframe scale behavior of the synchronous/asynchronous dynamic of paired brain regions, and compared these results with the long-term correlation coefficient rendered from the complete 2 minutes EEG time series. In these two different (long- and short-) time scales, we also explored the nonlinear domain of chaos/order dynamic fluctuation. Using Hurst exponent as an estimator of the chaos/order balance of a time series, we studied the chaotic and self-organized (persistent) trends of the EEG signal coming from 8 subjects in closed and open eyes basal resting conditions.

* Corresponding author.
E-mail address: hernan.diaz@usach.cl.

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1. Introduction

Progressively, our understanding of biological phenomena in general and of the brain in particular has shown that linear models, which are operational under restricted and controlled environmental conditions, lose their predictive effectiveness when the phenomena move away from the ideal models under which they are characterized, study and understand.

During the last decades, a great effort has been devoted to the integration of dynamic systems [1], chaos theory [2], fractal mathematics [3], thermodynamics [4] and the sciences of the complexity [5] with the intention of providing a broader frame of reference that allows us to understand the phenomena in a multidimensional perspective [6-8].

In 1951 (9), Harold Edwin Hurst is studying the oscillatory dynamics of the floods and droughts experienced by the Nile river, he noticed a certain periodicity of self-similar patterns of this behavior that could be used to evaluate the degree of spontaneous self-organization of the phenomenon and approximate a prediction of future behaviors with a certain degree of persistence.

The Hurst exponent (H) corresponds to a balance indicator between chaos and order that can be used to evaluate time series [10] as the EEG signal [11]. The range of H has extremes of 0 and 1. Values H = 0.5 indicate a completely random trend of the fluctuations of the system, equivalent to brown noise or Brownian motion. While values H<0.5 reflect a short-term memory and an anti-persistent tendency. Conversely, H values> 0.5 reflect a long-term memory where system oscillatory trend tend to continue repeating the previous more recent dynamics [12,13].

From the linear point of view, the study of the EEG has been mainly focused on the characterization of the power spectrum of the electroencephalographic signal, the domains of intensity variation and frequency spectral oscillation over time [14]. The second approach, focused on the study of synchrony through numerous researches aimed at finding patterns of synchronous connectivity reflecting the integrative functionality of the brain [15-17]. Depending on the timescale of the processing, different areas of the brain will be synchronized or desynchronized, conditional to the processing requirements. Resting; baseline; perceptual; integrative; and executive loads have specific and different resources recruitment needs and operational management, to achieve in maintaining (or dissolving) emergent organizing patterns. Alpha waves synchrony manifests itself with the regular or continuous appearance of wave trains whose frequency oscillates between 8-12 Hz, during one or more seconds of duration, and with amplitude of 2 to 3 times the size of the background wave [18].

The characteristic pattern of alpha wave synchronicity when eyes are closed is abolished when the subject is asked to perform some mental operation such as a mathematical calculation [19-20]. In other words, the alpha wave would obey to a spontaneous synchronization after to be freed from a state of perceptual and integrative processing load, leaving the oscillatory system unrestricted to be attracted into a saving-energy mode of functioning. Considering that the mass of an average brain of 1,125 g consumes 20% of the energy produced by of a 70 Kg body, it is expected that energy saving will be one of the priorities of the system to ensure proper management of resources when they are needed.

For the states of open and closed eyes conditions the difference in the alpha wave has been the most studied to characterize the dissimilarities between these two states [21]. The rest of the brain waves remain virtually unchanged, except for the higher energy of the power spectrum accompanying the closed eyes state.

Most studies with healthy subjects with eyes open (EO) and eyes closed (EC) conditions have been focused on alpha waves [21]. It shows a dominant activity during the condition of EC, and an immediate decrease in the intensity and structure of the signal in the occipital region, when eyes are opened [22]. It is also considered that the cortical activity during the EO state is oriented towards external perception, while in EC condition it is oriented towards internal perception [23]. A study conducted with 50 college students showed that alpha waves (8-12 Hz) had lower mean powers during EOs (in all brain regions) compared with ECs. The beta waves (13-30Hz) of the prefrontal area (Fp1 and Fp2) were found to be higher during the EO. Theta waves (4-8 Hz) recorded in the prefrontal area had higher powers during AO, but in the parietal area (P3 and P4) and occipital area (O1 and O2) the power was higher during the EC condition. On the other hand, delta waves (1-4 Hz) presented higher power during the EO in the prefrontal and frontal areas (F3 to F8). In the rest of the brain no significant differences were observed [21]. In another study it was observed that the average power of the alpha waves in the frontal, parietal and occipital regions is stronger during the EC condition than during the EO state, and that the theta and beta waves did not show significant differences between the two states [24].

The EO/EC paradigm has also been used to study biomarkers in the EEG that allow identifying various levels of severity in brain dysfunctions [25] such as Alzheimer's, where global connectivity was observed with an increase in beta 2 waves (20-30 Hz) and gamma waves (30-45 Hz); and a decrease in alpha 2 waves (10.5-13Hz) in EC with respect to the state of EO [26].

In a previous paper [27] using linear and nonlinear analysis tools, we explored the electroencephalographic signal coming from a database of 8 people in basal conditions with closed eyes to evaluate the effectiveness of these analyzes (linear and nonlinear), when exploring the EC conditions on three timescales.

In the present work, using the same tools, we review the study of the basal conditions of closed eyes vs open eyes conditions to look for differences and similarities at the level of the global functioning of the brain in the domain of the predictability of the chaos/order balance, and in the domain of the synchronous/asynchronous functional connectivity of the brain.

2. Method

We explored EEG data sample coming from 8 subjects with ages between 15 and 20 years. In the total sample, six (75%) are men and two (25%) are women.

Standard 10/20 EEG recording was supplied to be tested under linear and non-linear mathematical methods of description. We selected channels (electrodes) FPZ1, FPZ2, F3, F4, T3, T4, T5, T6, O1, and O2 to perform our analysis. The EEG recording was taken during three (6) minutes under basal conditions: eyes closed (3 minutes) and eyes open (3 minutes), From which we obtained the 2 minutes of EEG artifact-cleaned recording. The EEG band data range was 1-64 Hz. Data pre-processing and artifact rejection was assisted complementary with automatized methods using the EEGLAB toolbox, ADJUST and ICA, running in MATLAB 2008.

To study functional correlations between EEG channels in two temporal scales we used the standard test for Spearman R coefficient applied to the whole data sample by each electrode, which render the R value that describes the degree of correlation (synchronization) between the two time series compared during the whole 2 minutes of EEG recording. To explore the phenomena at a smaller time scale we used moving correlation coefficient (MCC) method (Figure 1) which renders us one R value between the two channels for each second of recording. This gives us a visualization of the small 1second timescale dynamic behavior of the functional synchronization between two or more EEG channels [27].

$$R_n = \frac{\sum_{i=t-n+1}^{t} (x_i - \overline{x_i})\ (y_i - \overline{y_i})}{\sqrt{\sum_{i=t-n+1}^{t} (x_i - \overline{x_i})^2 \cdot \sum_{i=t-n+1}^{t} (y_i - \overline{y_i})^2}} \qquad \text{Where,} \qquad \overline{x_i} = \frac{1}{n}\sum_{i=t-n+1}^{t} x_i, \quad \overline{y_i} = \frac{1}{n}\sum_{i=t-n+1}^{t} y_i,$$

Fig. 1. Moving correlation coefficient.

We used a similar approach to reveal the internal structure of the order/chaos balance variation in time. We selected 1s-epoch segments (128 data points recorded at 128Hz frame rate) of the EEG signal and estimated the successive 120 (2 min) Hurst exponents (Figure 2).

$$\mathrm{E}\left[\frac{R(n)}{S(n)}\right] = Cn^H \text{ as } n \to \infty,$$

Where,
$R(n)$ is the range of the first n cumulative deviation from the mean, and $S(n)$ is their standard deviation.
E[x] is the expected value
n is the time span of the observation or number of data points in a time series.
C is constant.

Fig. 2. Hurst Exponent estimation.

We differentiate three Hurst parameter indicators:

i) T-Hurst: The total-Hurst exponent who is estimated from the total 15,360 data points (2 min) of the original EEG time series.
ii) M-Hurst: The meta-Hurst [13], which is the Hurst exponent estimated for the new time series obtained from the successive 120 sequential 1s-Hurst exponents obtained from each 128 data points (1 second) during the 2 minute recording.
iii) µ-Hurst: The average H calculated over the 120 1s short-time Hs obtained to estimate M-Hurst.

3. Results

3.1. Correlation analysis

Figure 3 shows the cross-correlation maps with high functional synchronization (0,5<R<0,8) for the whole time EEG recording (2 min) between scalp/brain areas in the two conditions studied: Eyes Closed (EC) and Eyes Open (EO).

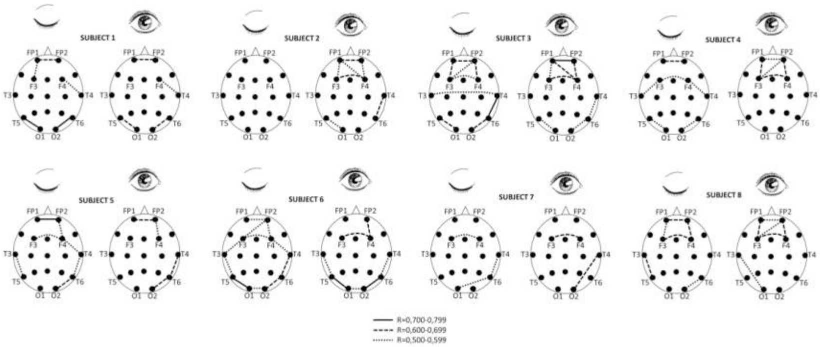

Fig.3. Spearman R cross-correlation maps of highly synchronized (0.5<R<0.8) brain areas. Basal condition closed and open eyes.

Figure 4 shows the cross-correlation map of low functional synchronization (0<R<0.5) for the whole time of EEG recording (2 min) between scalp/brain areas for the two conditions EC and EO.

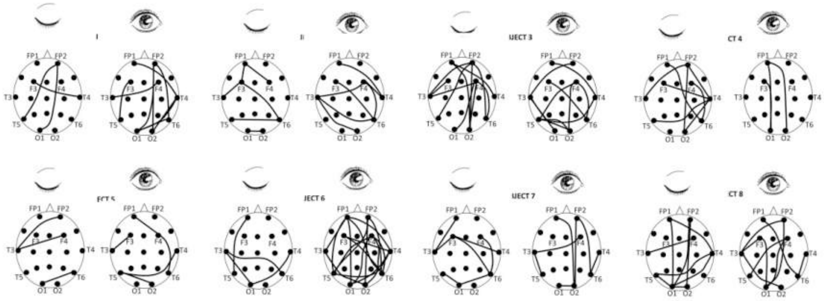

Fig.4. Spearman R cross-correlation maps of low synchronized (0<R<0,5) brain areas. Basal condition closed and open eyes.

The total number of high R correlations ranged from 0 to 11 with an average of 5.5. We found no evident differences in the number of high correlated pairs of electrodes between EO and EC states, but a reconfiguration of several parts of the network come together with the change between states EC↔EO. Together with the individual differences, a default basal network predominates on both states almost in all subjects. This network comprises mainly symmetrical frontal and temporal/occipital areas, with the latter slightly asymmetric to the right hemisphere in the EO state.

The slightly correlated network (0<R<0.5) showed in figure 4, is more complex in structure and in the inter- and intra-individual variation. A slight difference in the number of pairs of electrodes slightly correlated can be seen in the EC condition (52 correlations) and EO condition (60 correlations).

As expected [27], when applying MCC to both EC and EO states for the whole recording, those low correlated regions across the long-run (whole 2 min recording) behavior of the time series, appears to be very active when it is studied at short 1-second timescale. At this short-term magnification, any of the two paired areas of the brain displays a dynamic of fluctuating behavior composed by transient high correlations (positive and negative) that can reach very high values of R (-0,5<R<+0,75).

To explore in more detail the variability of the synchronic/asynchronous fluctuation measured through MCC method, we compared the frequency distribution of the two data sets: i) the long-run 10x10 matrix of data that renders the R values for the 45 combinations of pairs of electrodes; and ii) the short-time (1-second) 45x120 matrix of data that renders the 120 R values, one second each, for the 45 combinations of pairs of electrodes.

Figure 5 shows the comparison between EC and EO for these two frequency distribution histograms labeled as MCC (short-time) for the former; and Rs (long-time) for the latter.

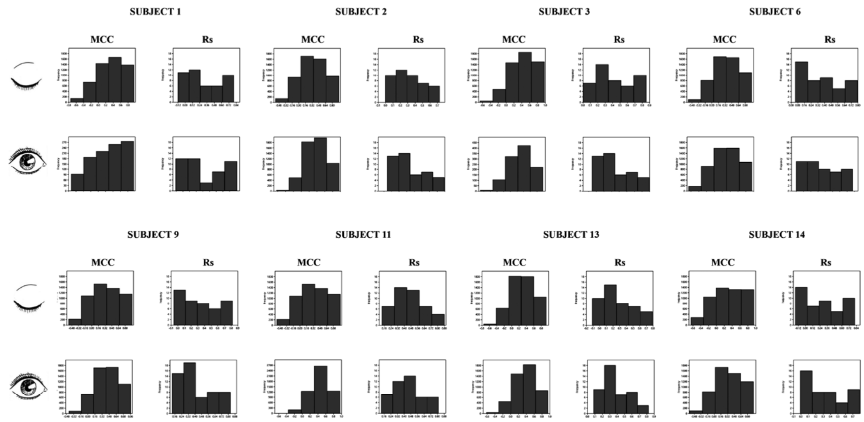

Fig.5. Comparison of frequency distribution histograms of Spearman's R data. .CE vs OE and MCC vs Rs

When comparing EC and EO states, the general shape of the frequency distribution (skewness and kurtosis) doesn't change very much in the majority of the sample with some minor variations in few subjects. A major difference is observed when comparing the shape of the short-time representation (MCC) against the long-term (Rs) description of the temporal relationship of the EEG channels.

While MCC histograms look more Gaussian shaped, Whole data Rs histograms are different. Many of them look bi-modal, and of those that are uni-modal, some show an opposite distribution skews compared with the MCC distribution. In the majority of the cases of the sample, the central tendency measurement of Rs is underscored by the long-time (Rs) frequency distribution histogram.

3.2. Hurst exponent analysis

To study the EEG in the nonlinear domain looking for differences between closed and open eyes conditions, we evaluated the three parameters of chaos dynamics (T-Hurst, M-Hurst, and μ-Hurst) allowing us to estimate the tendency of the chaos/order balance in the long- and short- timescales. Figure 6 shows the plot of the T-Hurst, M-Hurst, and μ-Hurst along the fronto-occipital axes from FP1-FP2 to O1-O2 electrodes, for the two conditions (EC and EO). A linear trend line was calculated and depicted together in the figure.

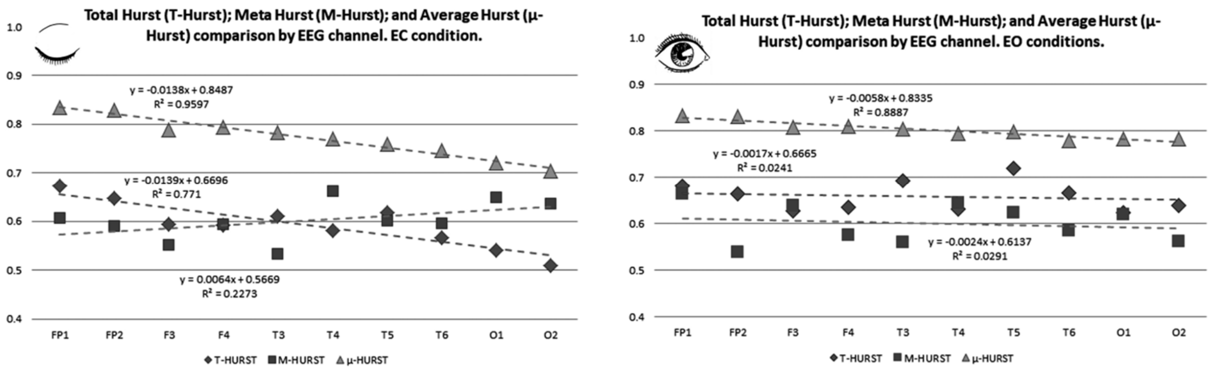

Fig.6. T-Hurst, M-Hurst, and µ-Hurst by EEG channel, averaged across the eight subjects. EC and EO conditions.

A general decreasing trend along the fronto-occipital axis is observed in two of the estimators (µ-Hurst and T-Hurst) during eyes closed condition, These trends revert in the eyes open condition where the three curves turn to be almost parallel with slope values close to zero. At the scale of 1-s chaos/order balance, the parameter estimator M-Hurst shows the higher variability and a slightly increasing tendency of H values along the frontal-occipital axis, in EC state. This slight trend is also abolished when changing from EC to EO condition. Figures 7 depict this change represented as the variation of the slope value of the three estimators' trend lines, when shifting from EC to EO state.

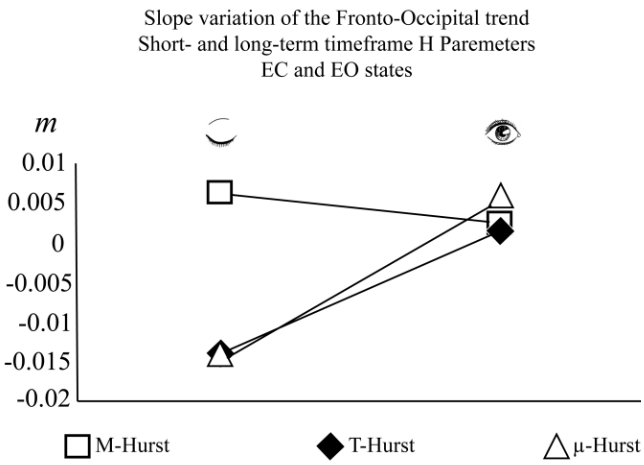

Fig.7. Slope variation of the fronto-occipital trend for the three chaos estimators: M-Hurst, T-Hurst and µ-Hurst. Open Eyes vs Close Eyes conditions.

4. Discussion and conclusions

Eyes closed and open conditions have been systematically used to establish basal comparative states against who to contrast experimental results in EEG experimentation. In other words, nonetheless its simplicity, these two conditions are the only basal-control states that during the waking period give us some information about the brain in its default vigil resting states of functioning.

Through the use of linear and non-linear analysis tools, we gathered knowledge about these two basal states, especially in which concern to: i) the notion of functional synchrony between brain areas at short- and long-term timescales during EC and EO situations; ii) the basal chaos/order fluctuating dynamics at different (short- and long-) timescales during EC and EO states; and iii) the possible relationship between these linear and non-linear descriptors of the EEG phenomenology.

In the correlation domain we found that those pairs of electrodes that render high values of correlation during the total recording are more stable, both in EC and EO conditions. They can work together as a default anchoring network, restricted only by this anchoring network. As a default mode, which it is assumed to be reached spontaneously, it can be compared with a basal homeostatic attractor which must reflect both, a general and more conservative functional structure, common among subjects, and a subject-dependent set of conditional networks attractors. This must reflect the particular personal history as a personal default network operating over individually-learned homeostatic responses.

The short-term 1-s fluctuating balance (M-Hurst) between chaos and order in the brain seems to have a general trend to reach more organized values of H (minimizing unpredictability) in EO conditions. M-Hurst slightly decrease in the fronto-occipital axis. Chaos estimators, T-Hurst and μ-Hurst show a tendency to a phase state toward more chaotic states in the same fronto-occipital axis. This reverts to equilibrium when shifting from EC to EO conditions. To the general well known observation that during EC conditions increase the brain EEG spectral power in the whole range of frequencies compared with EO conditions [28], we conclude here that in our sample, during EC condition, and in the long- timescale estimation, the brain tends to be more unpredictable and chaotic in the fronto-occipital axis. This condition reverts toward a more unified equilibrium state along the axis, after shifting from closed to open eyes state. At the short- (1-s) time scale, the chaos/order trend seems to fluctuate toward more organized phase states.

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