UNIVERSITY „ALEXANDRU IOAN CUZA" IASI
DOCTORAL SCHOOL OF THE FACULTY OF PHYSICS

STUDY OF VISUAL SYSTEM THROUGH EXPERIMENTAL AND COMPUTATIONAL METHODS

PhD THESIS ABSTRACT

SCIENTIFIC COORDINATOR

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CHAPTER I: Motivation of the study and the current state of the research in the analysis of saccadic eye movements in terms of non-linear dynamics

Motivation of the study:

In this thesis we proposed a new approach for studying the visual system through a full analysis of the saccadic eye movements from the view point of nonlinear dynamics. This type of analysis combines several qualitative and semi-quantitative computational tests, applied to temporal data series - obtained following the recordings of saccadic eye movements on human subjects in two experimental conditions, in order to establish the type of dynamics (periodic, random, chaotic) which governs the neural system underlying the execution of these movements. Another important aspect of this thesis is the interpretation of saccadic signals from the neuropsychological point of view, by analyzing the temporal coupling between the action of executing a saccadic movement and the conscious perception of the visual stimulus that determine this eye movement - which has not been studied so far.

CHAPTER III: Saccadic eye movements recording and analysis of primary data

Eye movements helps us to explore the environment, but visual areas that determines the location of where to look (action) are different from those that determine what we see (perception). It is not known whether or how action and perception are temporal coordinates.

To obtain the time series used in the dynamic analysis of neuro-motor system underlying the execution of saccadic eye movements, I recorded this kind of movements in well-defined experimental conditions.

III.4. Temporal coupling of action and perception

To observe the gap effect and its influence on the action and perception in saccadic data series, we analyzed the saccadic reaction time, decision reaction time and also the perceptual response as a function of temporal asynchrony.

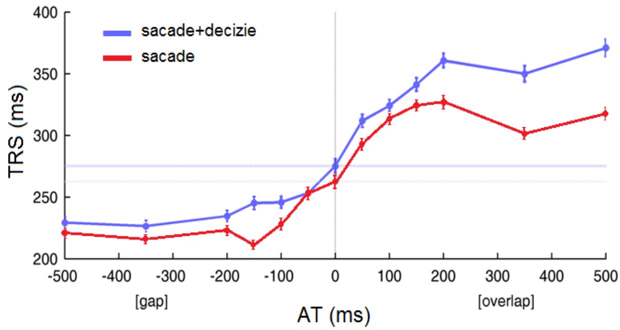

Fig.III.6: Dependence of saccadic reaction time (TRS) on temporal asynchrony (AT), for all the subjects [1]

In fig.III.6 is the saccadic reaction time dependence on the temporal asynchrony in two conditions: main experiment - saccade and decision and control experiment - simple saccades. One can observe that the saccadic reaction time is higher in saccades and decision condition in comparison with simple saccades execution in response to eccentric visual stimuli appearance. This might be determined by the cognitive load caused by the two tasks that have to be accomplished simultaneous. While the dependence of saccadic reaction time has been studied before by Saslow, in this experiment we showed that the reaction time for decision (perception) has the same dependence on temporal asynchrony.

In fig.III.7 is the decision reaction time dependence on the temporal asynchrony in the main experiment - saccades and decision and control experiment - decision only. The values for decision reaction time (fig.III.7) are higher than those for the saccadic reaction time (fig.III.6) due to the organization of the experiment, which involves decision (by pressing a button) after saccade execution towards the eccentric stimulus. Also in this case one can observe the same effect of decreasing the decision reaction time as the time length between the appearances of the two visual stimuli increases.

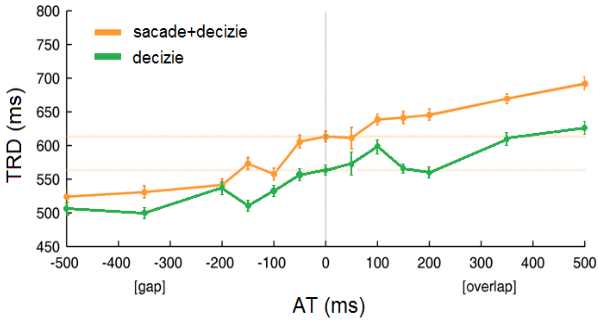

Fig.III.7: Dependence of decision reaction time (TRD) on temporal asynchrony (AT), for all the subjects [1]

Thus, we assumed that the decision reaction time dependence of temporal asynchrony between visual stimuli could be the basis of erroneous perception, but we cannot say exactly how this happens. The results were accepted for publication in a professional journal [1].

CHAPTER IV. Complexity analysis of saccadic eye movements

Analysis of neural system that coordinates saccadic eye movements from the computational point of view was achieved by processing and interpretation of saccadic data series using the strategy proposed by Sprott and Rowlands [2], designed based on the graphical and numerical tests, both linear and nonlinear.

IV.2.1. Dynamical complexity analysis of saccadic eye movements using the probability distribution test

Representation of data distribution histograms showed repetitive geometric character of component peaks for all analyzed subjects (fig.IV.17), for simple saccades execution (fig.IV.17, green) and also for saccades and decision (fig.IV.17, red) - this result is specific to signals extracted from highly complex systems (deterministic chaos).

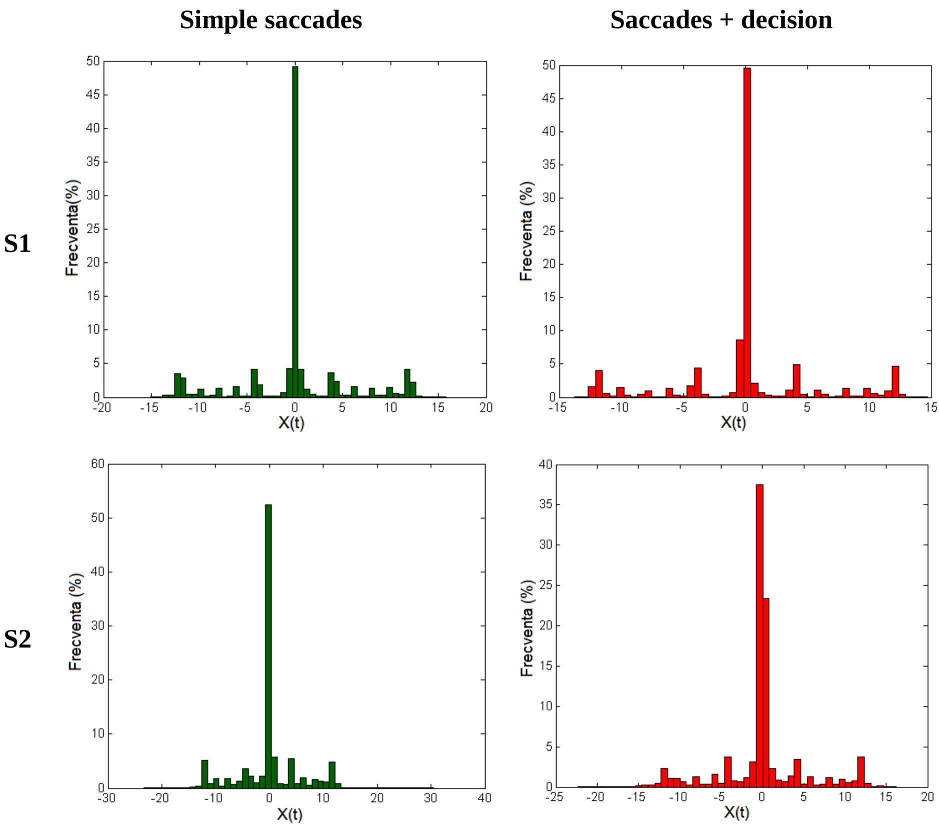

Fig.IV.17: Probability distribution of data for simple saccadic task data series (green) and saccades-decision task data series(red), for two of the analyzed subjects (S1 and S2)

Also, it can be observed the presence of extreme points in distribution shape, determined by the subject's involuntary blinks while performing the saccadic eye movements towards the eccentric target. The fact that subjects had to execute the additional task of making a decision did not influenced in any way the shape of probability distribution of data, so the visual perception of events was not affected by the cognitive load of the subject.

IV.2.2. Dynamical complexity analysis of saccadic eye movements through power spectrum test

From the power spectrum representation in a double-logarithmic scale (fig.IV.18), for the data obtained from saccades registration in simple conditions of execution (fig.IV.18 - green) and also for increased brain activity (fig.IV.18 - red) one can be observe the decrease of power logarithm with the increasing of frequency logarithm, indicating the presence of complex dynamics, chaotic component that characterizes the studied neuro-visual system.

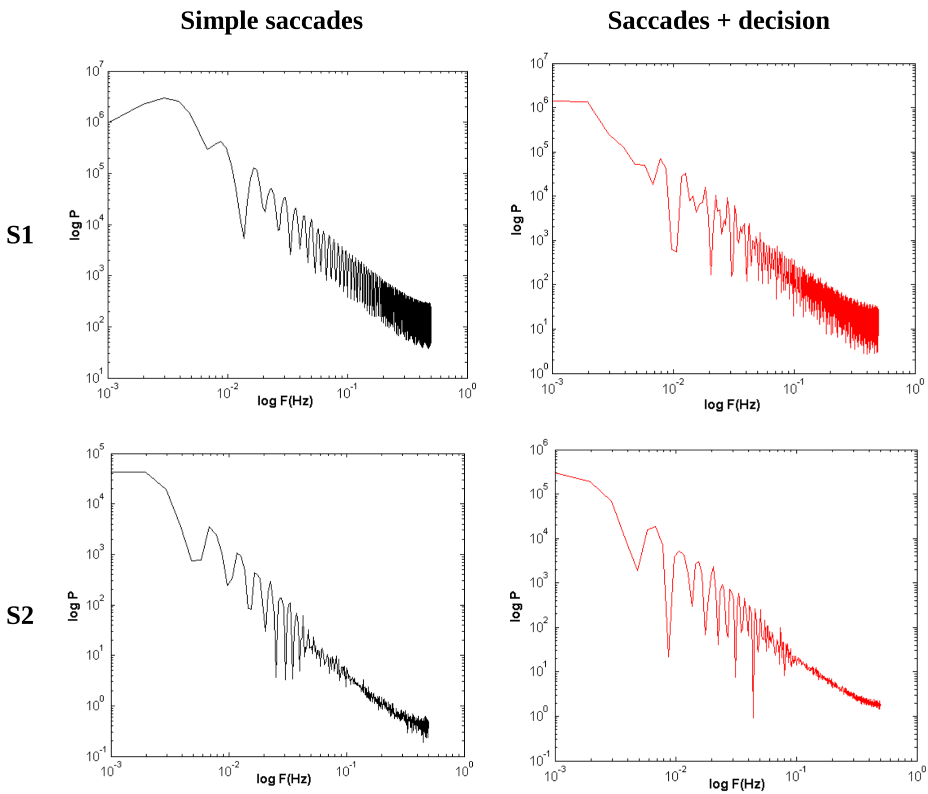

Fig.IV.18: Log-log power spectrum representation for simple saccadic task (green) and saccades- decision task (red), for two of the analyzed subjects (S1 and S2)

As it can be seen, the cognitive load of the subject has not changed significantly the shape of power spectrum.

IV.2.3. Complexity analysis of saccadic eye movements using the autocorrelation function

The correlation is a mathematical relation between two variables or two random signals. The correlation of two identical signals is called autocorrelation [3]. Autocorrelation function measures the correlation of a signal *X(t)* with itself at an appropriate time delay, τ [4].

Autocorrelation function shape is shown in fig.IV.19 (for only one subject, since the shape does not changes significantly from one subject to another), for saccadic data series obtained in the two experimental conditions. Thus, it can be seen slowly decreasing of autocorrelation function in time, this behavior being specific to data series obtained from systems with a high degree of complexity. High values of autocorrelation time show an increased degree of correlation between the data, for all the studied subjects. As one can observe, cognitive load increase leads to a decrease of autocorrelation time, suggesting the diminution of predictability in neuro-motor saccadic system, when the subject is subjected to a cognitive load.

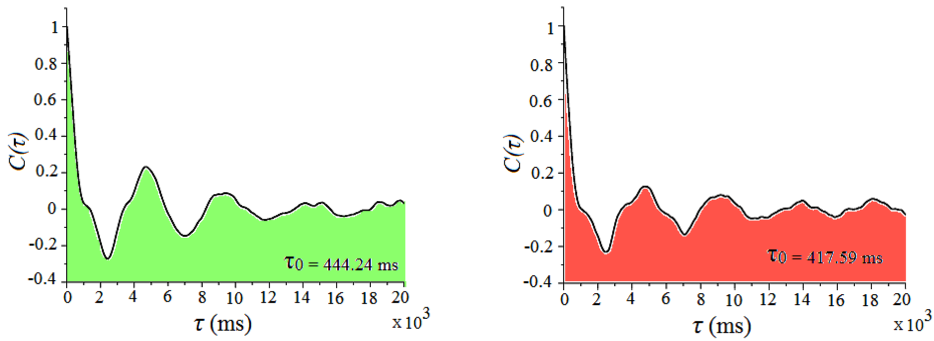

Fig.IV.19: Autocorrelation function for simple saccadic signals (green) and cognitive loaded ones (red), where C(τ) *is the correlation coefficient and* τ *is the time delay*

So, the signal obtained by recording the saccadic eye movements shows a high degree of correlation which is probably due to a linear dynamic component coexisting with dominant chaotic dynamic one.

IV.2.4. Complexity analysis of saccadic eye movements through phase-space portrait representation

Phase-space portrait analysis is based on the studied system's attractor shape interpretation [5].

Simple saccades **Saccades + decision**

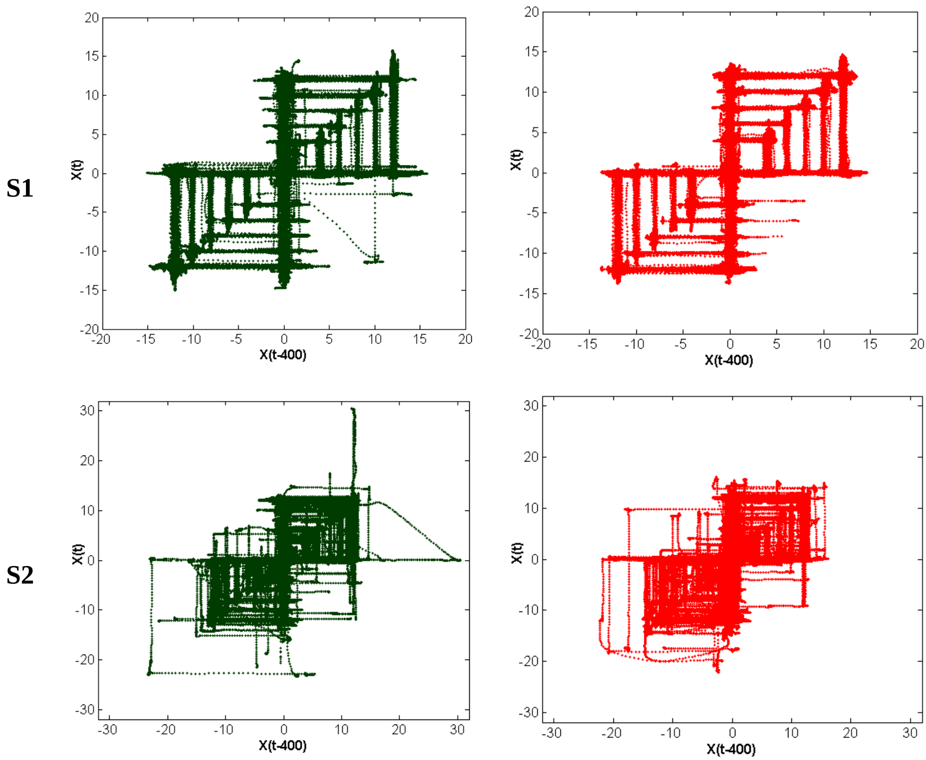

Fig.IV.20: Phase-space portrait for simple saccades (green) and saccades with decision (red), in delay coordinates, for two of the analyzed subjects (S1 and S2)

Comparing the saccades executed in simple conditions with those executed under increased brain activity conditions based on phase space portrait reconstruction is presented through the system attractor in delay coordinates, $X(t)$ and $X(t-\tau)$ where τ = 400 ms. Simple saccades execution made in response to the presentation of visual stimuli led to a form of attractor with symmetrical lobes, for all analyzed subjects (fig.IV.20, green). Comparing the graphs in fig.IV.20 (red), it can be seen that increased brain activity did not lead to a major change in the attractor shape, symmetry of the object is evident also in these conditions, with the presence of large amplitude fluctuations caused by involuntary blinking, so the additional task has not resulted in an increased level of attention from the subject and did not lead to a higher degree of complexity in the analyzed series.

IV.2.5. Nonlinear dynamical analysis of saccadic eye movements estimating the correlation dimension

Estimation of the correlation dimension for the signal obtained in the case of simple saccades execution, and for cognitive loaded saccades, led to similar low values of this parameter, in both cases for all the analyzed subjects.

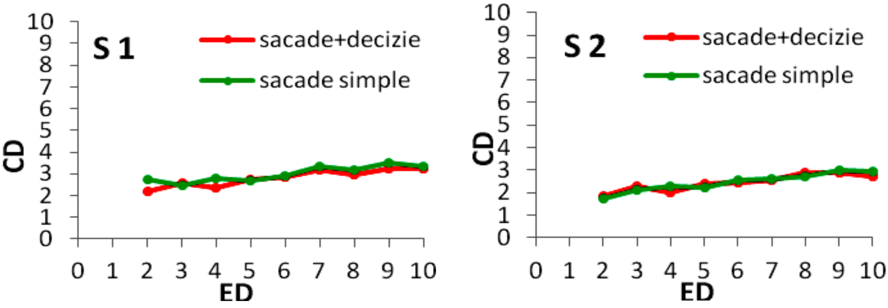

Fig.IV.21: Correlation dimension (CD) as a function of embedding dimension (ED) for simple saccades (green) and cognitive loaded saccades (red), for two of the analyzed subjects

Plotting the correlation dimension as a function of the embedding dimension (fig.IV.21) in all subjects, it can be seen a tendency of saturation of the correlation dimension value for an embedding dimension between 6 and 8, both for simple saccades and cognitive loaded saccades.

IV.2.6. Complexity analysis of saccadic eye movements estimating the Hurst exponent

Hurst exponent is a measure of long-term correlation in temporal series [6], a dimensionless estimator for the self-similarity in temporal series. To compute the Hurst exponent, one represents the ratio *R/S* in a logarithmic scale, as a function of *T*, where *R/S* is the rescaled range corresponding to the range of duration *T* of the data series; the slope of this representation is the Hurst exponent [7]. Following the application of this algorithm one obtained values of this parameter higher than 0.5 for both simple saccadic data series and for cognitive loaded saccades. This result suggests the persistent tendency of the values in the analyzed data series, typical to systems with a high degree of complexity.

IV.2.7. Study of nonlinear dynamics in saccadic eye movements estimating the largest Lyapunov exponent

Lyapunov exponents quantify the sensitivity to initial conditions of a system and describe how small perturbations grow exponentially in the state system and eventually come to dominate the system behavior [8]. They show us the rate of divergence of neighboring trajectories [9], a key component of chaotic dynamics.

Estimation of largest Lyapunov exponent led to low values of this parameter for both simple saccades and cognitive loaded saccades execution. However, since these values are positive, we can say that the series of analyzed data show a complex behavior, chaotic character of the neural system underlying the saccadic eye movement execution, being more pronounced in the case of simple saccades where the exponent values Lyapunov are higher than those obtained for saccades and decision.

CHAPTER VI. Multifractal analysis of saccadic eye movement's velocity fluctuations

Multifractal analysis of the fluctuations in shuffled data obtained from temporal saccadic (MF-DFA) was applied in accordance to Kantelhardt et al. [10] and Ihlen and Vereijken [11].

VI.3. Multifractal detrended fluctuation analysis

The generalized Hurst exponent for each moment order, *h(q)* is a measure for the degree of correlation of the analyzed dimension as *q* changes its value, i.e. small fluctuations for *q<0* and large fluctuations for *q>0*. Main Hurst exponent corresponds to *q=2* (*h(2)*). Monofractal time series are characterized by *h(q)* independent of *q*, while for multifractal time series *h(q)* is a nonlinear function of *q*.

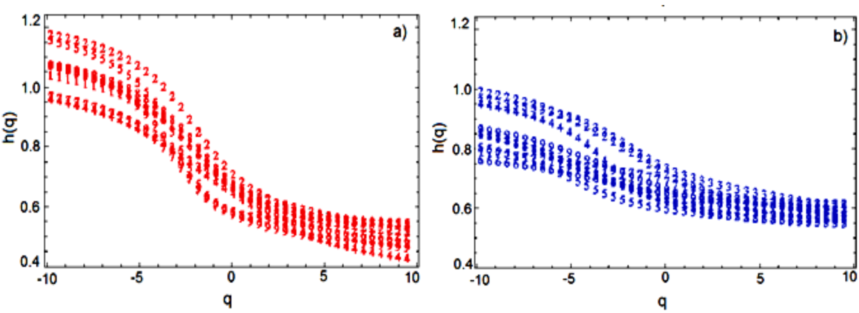

Fig.VI.5: Generalized Hurst exponent spectra: (a) simple saccades; (b) saccades and decision [12]

According to fig.VI.5, multifractality is present in both experiments, since *h(q)* dependence shows nonlinear decrease. These graphs show that both saccadic data series are persistent data series, with long-term positive autocorrelation. One could say that in the second experiment, when the dual-task involves a higher cognitive load, *h(q)* tends to depend less on *q*.

To get a deeper insight into the origin of multifractality in the two saccadic data types, the shuffling procedure was applied. Statistical approach of data shuffling effect can be analyzed using box-plot representation of data distribution (fig.VI.6).

Box-plot representation of the Hurst main exponent for the initial and shuffled data (fig.VI.6, a) show some differences for simple saccades and cognitive loaded saccades data series. For initial data, the box size is approximately the same (0.035) and the median value moves non-significant from 0.586 for simple saccades to 0.630 for cognitive loaded saccades.

a) **b)**

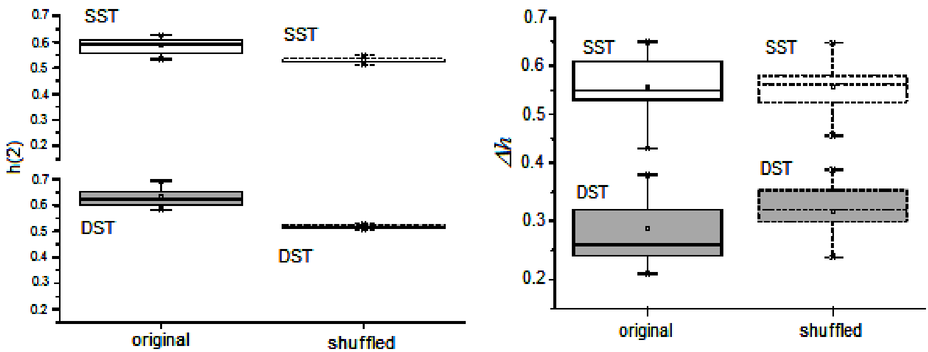

Fig.VI.6: Box-plot representation for: (a) Hurst main exponent and (b) multifractal strength for initial and shuffled data (SST- simple saccadic task; DST- decision saccadic task) for all the analyzed subjects [12]

A wider view is given by statistical analysis of the difference Δh between the Hurst exponents corresponding to the lowest and highest moment order, quantifying the multifractal strength (fig.VI.6, b). The original data for simple saccadic task (SST) has significantly higher multifractality (median equal to 0.55) than for decision saccadic task (DST) (median equal to 0.26) which suggests that the additional task simplifies the fractal character of recorded time series data so the complexity in saccadic data series decreases. Thus, one can say that for decision saccadic task, increased cognitive load results in a more homogeneous distribution of fluctuations.

According to Coey et al. [13], since the shuffled data show multifractality, this can only be the result of a power law distribution of the signals, i.e. a $P(f) = 1/f^{\beta}$ relation, where f is the frequency of the Fourier transform for the considered signal.

VI.4. Lempel-Ziv (LZ) complexity method

LZ complexity measure proposed to evaluate the randomness of a finite sequence is based on the estimation of a number of different patterns obtained by decomposing a symbolic sequence when scanned from left to right [14].

In general, LZ complexity for infinite random sequence is 1, but for a finite random sequence, LZ complexity can be considerably greater than 1. The shorter the sequence, the greater than 1 LZ complexity will be. In computational experiments performed on binomial data series (known as typical multifractals) it has been observed that for a number of length n = 10,000 the theoretical value is obtained with very good accuracy. Since the series analyzed in this thesis are not long enough to give with accuracy the values of LZ complexity, we used the correction method proposed by Hu et al [15]; usually a normalized LZ complexity index is considered which gives the complexity of a string relative to that of a purely random one.

One could observe that for all subjects LZ complexity index (fig.VI.9, a) for simple saccades is greater than the corresponding value for the saccades with decision. Moreover, in both cases, LZ complexity index basically follow the same dependence on the transition from one subject to another, as the multifractal strength for the two experimental conditions (fig.VI.9, b). Lower values obtained for decision saccadic task, when involved both action and perception, confirms the presence of deterministic dynamics with a high degree of correlation.

We believe that this observation could be used as an indicator of specific characteristics of each subject in particular for pathological cases where different variations are expected. This idea is also supported by the multifractal strength's subject dependence. As it can be seen in fig.VI.9 b, this dependence is similar for the two experimental conditions. The results were published in an international ISI journal.

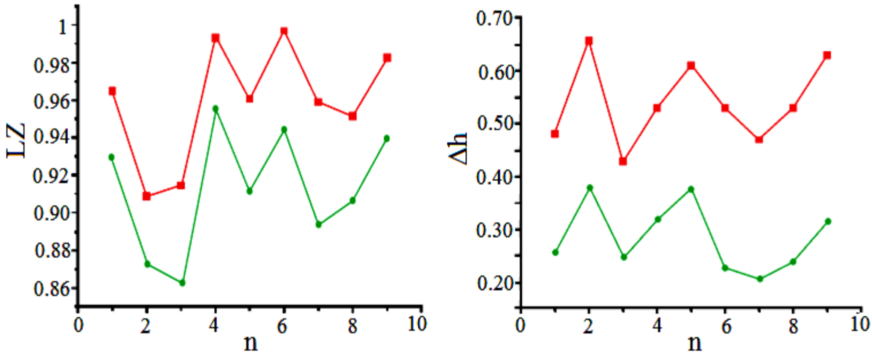

Fig.VI.9: (a) LZ complexity index; (b) multifractality strength Δh - for simple saccadic task (red) and decision saccadic task (green) [12]

CONCLUSIONS

The data obtained from fast eye movements recording were analyzed with computational methods and the results are the following:

- From the graphical analysis of saccadic eye movement data, one could observe that saccadic reaction time and decision reaction time have shown almost parallel graphics to increased temporal asynchrony. This similar behavior and also the assumptions published in literature have suggested the presence of a common neural substrate for the two neural circuits involved and the most likely source of this coupling is the superior colliculus located in the cerebellum, which is responsible for saccades generation.
  - The difference between the saccadic response for cognitive load conditions and the response for simple saccades was estimated by the corresponding reaction times. Averaging the values for all the analyzed subjects, this

difference in reaction times was 21.3 ± 4.5 ms (statistically significant, relative to the threshold of $p < 0.001$).

- Application of computational tests based on chaos theory showed the presence of dynamic chaotic component in the neural system underlying the preparation and execution of visually guided saccades, putting the studied system in the category of high complexity biological systems;
  - The tests that made the difference between the two psycho-physiological conditions (simple saccades and decision saccades) were: autocorrelation time which decreased significantly ($p < 0.05$) for saccades with decision (from 543 ms to 511 ms for simple saccades); largest Lyapunov exponent showed the greatest differences from 0.09 for simple saccades, decreasing to 0.07 for saccades with decision ($p < 0.05$).
- Analysis of velocity fluctuations in the series during saccadic movement showed multifractal character of the analyzed data series given by the variation of Hurst main exponent and also a high degree of complexity - studied through Lempel-Ziv complexity method.
  - Hurst main exponent differs significantly only for shuffled data series but not for the initial ones.
  - For all the subjects LZ complexity index is lower for saccades with decision comparing to the simples ones (the average values for all the subjects differs significantly relative to the threshold $p<0.005$, from 0.96 to 0.91).

The results were validated by publication in ISI journals with significant influence score, two BDI articles and two articles in ISI proceedings volume.

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