Complexity Analysis of the Visual-Motor Cross-Modalities Using the Correlation Dimension Parameter

Monica C Serban, Dan M Dobrea

"Gh. Asachi" Technical University, Iasi, Romania

Abstract

This paper focuses on the tremor signal as a window to observe and analyze the central nervous system's functions and organization. In this idea it is proposed a custom system and some methodologies that reveal the cross-modalities influences, specifically, the increased complexity of the neuro-motor system generating the tremor as a result of photic driving activation method. The correlation dimension is used as a measure of system's complexity change and the behaviour of the physiological system is modelled using the Hindmarsh-Rose neuronal model. The proposed system includes: three neurons and their unidirectional coupling – considered to be a possible way the system changes its complexity –, the dynamical noise and the photic driving action. The correlation dimension (CD) analysis was performed on the real tremor signal and on the output signal of the modelled system. The global behaviour of the CD parameter proved to be similar in both cases. Thus, the results are promoting the idea of a complex and structured system that is accounting for the photing driving induced tremor.

Keywords:
Tremor; Correlation dimension; Central nervous system (CNS)

1. Introduction

In two previously papers it was investigated the dependence between the tremor signals and the visual stimuli [1], [2]. It was proved the existence of a direct relation between basic motor activity and the external visual stimuli. The observed changes in the frequency characteristics of the tremor signal due to visual stimuli demonstrated a significant connection between visual pathways in the central nervous system (CNS) and the regions basically governing tremor [1], [2]. In this context, given a multidimensional dynamical system (CNS – its efferent pathways, the motor units) and its one-dimensional output (a series of scalar observations represented by the tremor signal), it appeared the following question: can it be inferred any characteristics of the original CNS system given only its output? In order to answer this question, the complexity of the system was considered as a key feature to be analysed.

The major theoretical contributions for complexity measurement of one system have been resulted so far from the tools of nonlinear dynamics and those of the information theory. Among these, the methods usually used to assess biological complexity were: correlation dimension [3-5], approximate entropy [6], detrended fluctuation analysis [7], false nearest neighbours [5], recurrence plot analysis [4], [8] and point wise correlation dimension [9-10].

In this paper, in order to characterize the systems involved and to get an insight of the process of visual influence on the tremor movement, the correlation dimension was used. More, the system was modelled using for this the Hindmarsh-Rose neuronal model.

2. Methodology

There were admitted four subjects for this study, three males and one female. All subjects were aged between 26 and 29 years. All subjects were healthy, with no known neurological or endocrine pathology, and no known Ca^{2+} or Mg^{2+} deficiency that could influence the tremor characteristics. In addition, they had been taken no medication in the week previous to the recordings. The experimental protocol was explained to the subjects and they gave written consent regarding the participation in this study. The entire procedure of tremor acquisition was unobtrusive for the subjects, without any physical contact, due to the acquisition system capability [11]. In order to isolate them from the surrounding stray stimuli, other than the stimuli supplied by using a computer display, all the recordings took place in a quiet room without any source of light. Also, they were particularly asked to think at nothing.

It has been made 20 recordings for each subject. Each recording had 98.4 s, but only the first 32.8 s and the last 32.8 s of hand tremor were kept. After the first time segment of 32.8 s a visual stimuli was presented to the subject. The seating subjects were asked to maintain the hand in the same postural position. Moreover, the subject's elbow was fixed in order to avoid the fatigue influence. In the first part of the recording, the display was a uniform black background. The stimuli consisted in a circle of 2 cm radius, placed in the middle of the display, changing its luminosity between a black background and a white flash. The stimuli changes' pattern was a symmetric rectangular wave of 5Hz frequency. The subjects had no visual control of their hand position. The sampling rate was 250 samples per second and they had been 8.200 samples per each acquired segment of a recording.

3. Correlation dimension

Correlation dimension (CD) is a parameter able to describe the global complexity degree of a system based on only one of its outputs [12]. The method proposed by Grassberger and Procaccia [13] was used here to estimate the CD parameter. The CD's algorithm is based on the computation of integral correlation, a parameter that makes no assumption regarding the embedding dimension. In this article, the integral correlation was computed for different embedding dimensions (from 1 up to 10), by using the formula:

$$C(R) = \frac{1}{M(M-1)} \sum_{i=1}^{M} \sum_{i \neq j}^{M} H\left(R - d\left(x_i - x_j\right)\right) \quad (1)$$

where: H is the Heaviside function and M is the space dimension; xi and xj are two vectors constructed from the original time series by using the time delay method; R is an arbitrary radius and d is the distance computed by using the Takens norm.

The CD is taken as the average slope of the cumulative curve generated by the integral correlation function obtained for different values of the hyper-dimensional sphere R. Both, the radius R and the integral correlation were plotted in log-log coordinated. When the embedding dimension increases the CD should increase but eventually saturate at the correct value. Due to the variability of the psychological influences in the time series (e.g. the level of subject's concentration) and to the continuous dynamics of the CNS, this kind of behaviour was not confirmed in all time series. Consequently, in order to correctly estimate the CD parameter, the embedding dimension was computed for each time series. The particular value thus obtained was then used for the selection of the correct CD value.

Prior to this, it was established the optimal time delay parameter value needed for the state space reconstruction. It has been used the mutual information function [14], the optimal time delay value being chosen for that point where the average mutual information reached its first minimum. For all tremor series the time delay parameter was within the interval [3÷6]. In Figure 1(a) it can be observed a typical characteristic for average mutual information versus time lag. The mutual information reached its first minimum at a time delay value of 5. This value should be considered, in this particular case, the "optimal" value for the time delay parameter.

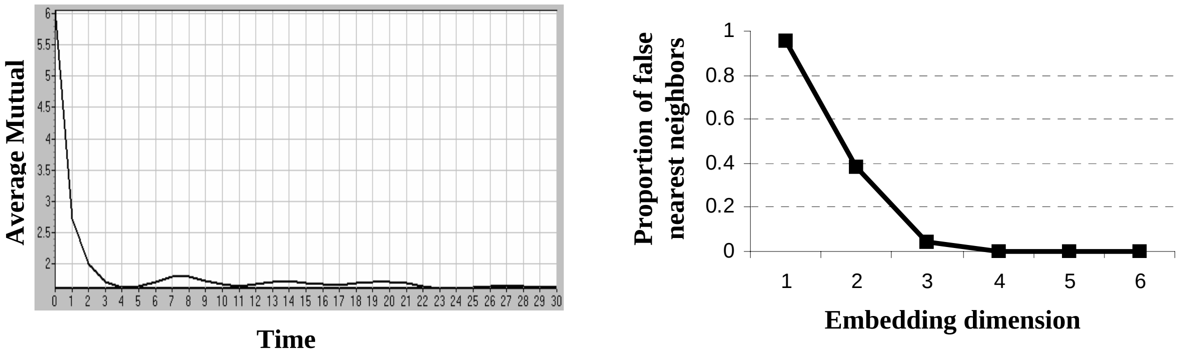

Figure 1 – (a) The average mutual information (b) False nearest neighbours calculation for one time series with an embedding time delay of 5 (R_{tol} = 15)

Having the time delay information it is possible to calculate for each one dimensional time tremor series the corresponding minimum embedding dimension. To calculate this last parameter in has been used the false nearest neighbours method [15]. Figure 1(b) presents one of the results obtained for a randomly chosen tremor time series. The proportion of false nearest neighbours drops to 0 when the correct embedding dimension is reached (6, in this case). For almost all time series the obtained embedding dimensions reside within the range from 5 to 8; only for few time series the embedding dimension was greater then 10. The threshold parameter for the embedding criterion (distance tolerance Rtol) was 15 for all determinations [15]. Finally, the CD estimations were calculated for all time series and for all subjects. In the pre-processing step all time series were digitally low-pass pre-filtered, using a cut off frequency of 40 Hz. The aberrant data series were eliminated.

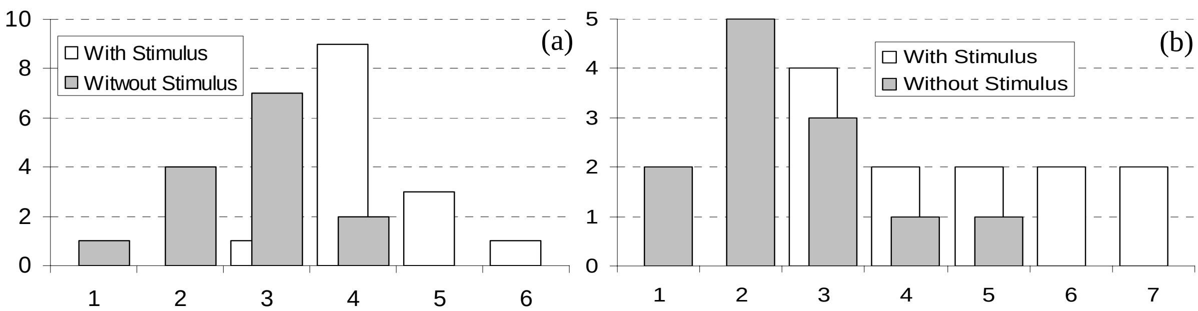

Figure 2 – The histogram distribution for CD parameter based on the time series recorded with and without external visual stimulus for (a) subject 1 and (b) subject 2

In 78.3% of the recordings it was observed an increase of the CD value for the series with stimuli in comparison with the series recorded without any kind of stimuli. For two of the subjects the results are presented in Figure 2. The histogram distributions of the CD parameter for both types of time series (with and, respectively, without stimuli), shown in Figure 2, confirm through their displacement the same global trend. In both graphics the bins' width was 0.275. For subject 2, Figure 2 (b), there are more bins (seven) mainly because the value range of the correlation dimension for this subject was larger. For subject 1 the bins intervals were: [2.4, 2.675), [2.675, 2.95), [2.95, 3.225), [3.225, 3.5), [3.5, 3.775), [3.775, 4.05). For subject 2 the first bin (spanning the range [2.4, 2.675)) had zero elements and the added bins were [4.05, 4.325) and [4.325, 4.6), corresponding to bins 6 and 7.

The correlation dimensions for all time series varied between 2.82 and 4.46. As a consequence, the class of dynamic model that could replicate the complexity of the recorded time series must have at least five independent control variables to account for the system's complexity. The increased complexity of the system, this could be seen as an effect of some underlying structural modifications (new components are added) and/or as an effect of some functional (coupling) changes in the system.

4. Model simulation

As it was shown, data sets analysis reveals that the CD parameter increases from the signals without stimuli to the case with stimuli. Thus, the "measure of complexity" shows that the visual stimulation phase modifies the physiologic system's complexity that becomes a greater one.

It is known that the control of the muscle force can be obtained: (a) by varying the number of recruited motor units (MU) and (b) by varying the activation rate of the motoneurons. In general, MUs fire asynchronously. Moreover, MUs synchrony produces tremor [16]. In our case it was proved [1], [2] that the synchrony was due to external/tuned synchronization that primarily reflects a common driving oscillation, namely the CNS oscillations. The origins for these driving oscillations are still unknown. They could be cortical – even if there is no evidence of sensorimotor induced visual stimuli frequency (this was proved only for primary visual cortical area [17]) –, and/or subcortical (e.g. thalamus, brainstem etc.). Also, from the experimental data there is no evidence for "pure" sensory pathways (dashed line in Figure 3a).

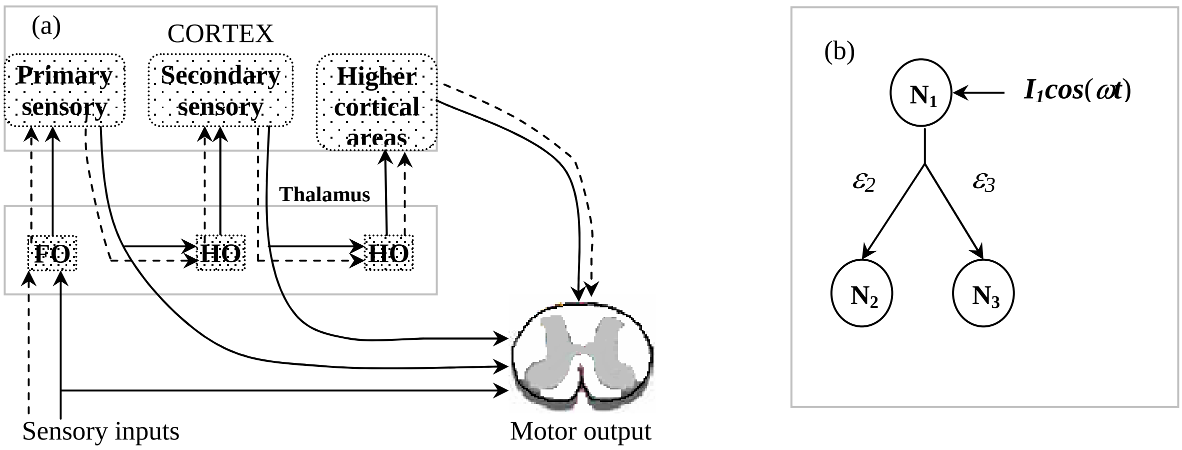

Figure 3 – (a) Sensory processing pathways (b) The proposed model

In [18] it can be found a review on the evidence that many of the afferent sensory inputs reaching the thalamus and then passed on to the cerebral cortex come from axons that branch, sending one branch to the thalamus (namely, to the "first-order" thalamic relays) and the other directly to centres in the brain stem or spinal cord (motor outputs), see Figure 3(a). This pattern is also true for the axons that arise in the layer five of the cortex and pass to "higher-order" thalamic relays (HO). The axons that give off branches to lower motor centres and also innervate the thalamus are crucial for an immediate and completely different behavioural role (e.g. the fast motor actions needed for animal's survival). In terms of complexity this means that the system complexity primes the organism for an adaptive response, making it ready and able to react to sudden physiologic stresses.

Under repetitive visual stimuli the system's complexity can increase at the CNS level as a result of a change in the coupling strength between structural components (cortical/subcortical centre/visual path and, on the other hand, spinal motoneurons) and by recruiting new spinal motoneurons. In order to test these hypotheses a very simple model of the visual influence was proposed and analysed. The proposed system was designed with 3 neurons, all of Hindmarsh-Rose (HR) neuron model type [Figure 3(b)][19]. The HR model, eq. (2), is one with minimal complexity (i.e., three variables only), replicating the main dynamical regimes of regular spiking and chaotic spiking-bursting activity observed in living neurons. One neuron (N1) mimics the central pattern generator; the other two neurons (N2, N3) model two distinct MUs.

$$\begin{cases} \dot{x}_i = y_i - x_i^3 + 3x_i^2 - z_i + I_0 + \xi_i + \varepsilon_i(x_i - x_j) \\ \dot{y}_i = 1 - 5x_i^2 - y_i \\ \dot{z}_i = 0.006[4(x_i + 1.6) - z_i] \end{cases} \tag{2}$$

The x variable represents the membrane potential, y is a recovery variable, z is the internal mechanism which regulates the patterns of discharges, ξ represents the background Gaussian white noise (synaptic, dendritic, axonic noise etc.) that is important in the stochastic resonance phenomena (its absolute value ≤ 1.5) and ε is the coupling strength parameter, (i= 1..3, j=1). The I0 parameter denotes the intensity of a constant (tonic) signal that is delivered to the neuron from the external world and its values were chosen as: 14 for N1 and 20 for N2 and N3. Further, we implemented the following four cases: (1) No coupling, ε1 = ε2 = ε3 = 0; (2) Light coupling, ε1 = 0, ε2 = ε3 = 0.005; (3) Strong coupling, ε1 = 0, ε2 = 0.5, ε3 = 0.4; (4) Strong coupling + a forcing term, I1cos(ωt), as input for N1 neuron, ε1 = 0, ε2 = 0.5, ε3 = 0.4, I1 = 22, ω = 5. On successive trials the noise components and the initial state variables were varied for all three neurons, the other parameters of the model being maintained constants. For all cases, there were generated the signals as a sum of N1 and N2 outputs, cut out the first samples corresponding to the transition phase and then, it was applied to them the same CD analysis that was applied to the original tremor data set. The results are summarized in Table1.

Tabel 1: Estimations of the correlation dimension parameter for N_1+ N_2 outputs

	Case 1	**Case 2**	**Case 3**	**Case 4**
N_1+ N_2	**3.1954**±0.3988	**3.13505**±0.2917	**3.3765**±0.2688	**3.4402**±0.2210

5. Conclusions and further direction

The global complexity of the system increases, fact that is revealed by the tremor signals recorded during a photic driving process. This confirms the emerging coupling strength that appears in the moment of stimuli presentation between the visual CNS pathways and the motor centres generating tremor. With a very simple formal model it has been replicated this behaviour by coupling a HR neuron, modelling the visual CNS input origin, with two other HR neurons that are modelling two independent motor units. The greatest enhancement was observed in case 4, where a new dynamic variable, $I_1 cos(\omega t)$, was introduced. The periodic driving force models the visual repetitive stimuli, also retrieved from the N_1+ N_2 outputs' spectra. The mean growth in the complexity parameter obtained within the model was 0.3052. This represents the difference between strong couplings with driving force and light coupling without any external force. This value is similar with the value obtained for real tremor signals, 0.3717 for subject 1 and 0.5584 for subject 2. This fact shows that, although the proposed model is a very simple one, it still succeeds to capture the main dynamics of the real system. The small increase of only 0.0637 obtained in case 4 compared to case 3 is due to only one new independent dynamic variable $I_1cos(\omega t)$ introduced at N_1's input. The increase of 0.2415 obtained in case 3 compared to case 2 is due to the strength of couplings. These facts can lied to the idea that the greater values achieved with the real data sets (0.3717 and, respectively, 0.5584) beside those achieved with the simulated ones (0.3052) could be explained by a more complex and structured system directly responsible for the photing driving induced tremor. It has to be stressed that these results are only preliminary ones. There is one major drawback in the approach: the length of the real data set is relatively small for this kind of analysis. In order to get sufficient data samples, as a further direction we aim to reshape the acquisition part of our system. Obviously, on the model proposed will be performed further improvements for perfection it.

6. References

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Address for correspondence

Dan-Marius Dobrea, Faculty of Electronics and Telecommunications, Iasi, Romania, Bd. Carol I, No. 11, Iasi, Postal Code: 700506, mdobrea@etc.tuiasi.ro, http://www.etc.tuiasi.ro/cin/Members/Dan/dan.htm