SEMANTIC REPRESENTATIONS AND THE DYNAMICS OF SIMPLE COGNITIVE PROCESSES

Dimitris Stamovlasis[1] and Vassilis Tselfes[2]

[1]Education Research Center, Ministry of Education,
21 Lefkippou, Athens 116 33, GREECE, stadi@cc.uoi.gr
[2]Department of Early Childhood Education, University of Athens,
35 Hippocratous, Athens 16680, GREECE, tselfesv@ecd.uoa.gr

ABSTRACT

This study tests the nonlinear dynamical hypothesis in simple cognitive processes. Two experiments are presented. The first is related to mental "noise" experiments, where response time (RT) series in a simple decision-making process are recorded and analyzed. The analysis showed that these RT series possessed low dimensionality and $1/f^b$ dynamical characteristics. The second experiment was a decision-making process at the behavioral level, which consisted of the characterization of conceptual entities by ontological features with 'yes' or 'no' responses. The answers were converted to a symbolic sequence and mapped onto one-dimensional random walk. Nonlinear analysis showed that the sequences processed dynamical characteristics, which changed when the questions were asked in a different order. The results from the two experiments provided evidence for the dynamical hypothesis in cognitive processes. Moreover, a short literature review on dynamics of brain functioning is provided, which can explain the present findings.

1. INTRODUCTION

The computational approach to cognition, which has been dominated for decades, was based on the following assumptions [1]: The *representations* that refers to the internal structures, which encode states of the world are static structures, which could be reduced to discrete symbols and the cognitive operations are transformations from one static symbol structure to the other. On the other hand, *connectionism,* that is, modeling of cognitive processes using networks of neural units, brought changes in the traditional concept of representation. In connectionism the internal structure is referred as the *distributed representation* [2]. Neuroscience has attempted to investigate the materiale substratum changes for referential relationship for the representation. The discovery of the back propagating spikes in neurons suggests that an internal activated state feeds back on the input activation process, and thus the concept of a stable referential relation between input (environmental states) and internal activation states does not hold anymore. Computational neuroepistemology [3] suggests that the current internal state of representation can no longer be seen as a stable *repraesentandum* referring to a certain environmental state because it depends also on the previous internal states or activation patterns. Connectionism permits modeling cognition as the behavior of dynamical systems (NDS) providing the *dynamical hypothesis* as an alternative. It considers the cognitive processes as not discrete sequential manipulation of static representational structures (as the computer metaphor), but rather, it considers them as processes unfolding in real time, changing, interacting and coevolving with the environment. This approach provides a vast resource of tools, concepts and mathematical methods to model and explore the process of cognition.

One of the NDS approaches to cognition is the study of the irregular variation across repeated measurements of human performance. This background noise refers to intrinsic sources of variability, the intrinsic dynamics. Laboratory experiments have demonstrated $1/f^b$ scaling in simple reaction time series. Such interaction domain dynamics are found in systems that *self-organize* their behaviour. The first experiment in this paper refers to the mental 'noise' recorded in a simple decision-making process. The results revealed the dynamic nature of this process.

An interesting research question for cognitive science is whether the dynamical hypothesis could be tested in analogous processes at the behavioural level, and thus providing a connection between NDS and psychological science. The second experiment in this work aimed to test the dynamical hypothesis in a decision-making process, which consisted of categorizing *concepts* by a number of feature or attributes.

In the latest psychological theories knowledge is represented mentally in term of *concepts, categories* and *propositions* [4]. *Concepts* are the abstracted properties or attributes of objects or events; *categories* are the mental groups into which entities with common conceptual properties are placed; and *propositions* are entities that express relation among concepts. These theories attempt to provide the organization structures of mind and the processes by means of which elements within this structure are brought into contact with each other. Structurally, semantic memory could be viewed as a hierarchical associative network of concepts [5]. Within the Nonlinear Dynamical Systems (NDS) framework these associative networks of concepts has been proposed as complex, organized semantic entities, *semantic constellations* of meaning that are dynamic in nature [6]. Even a simple perception of a (concept) material object implies recognition of a category. Even though the lexical definition of a concept refers to recognition of a particular category, it appears that when relating to a concrete concept, one would be referring to a broader array of features or attributes many of which extended beyond the strict boundaries of the category. Ergo, *concepts* are not strictly circumscribed in theirs category definition. A way to include all feature of a concept in an aggregate entity is to provide a kind of mapping. Extended forms of these maps are made when network architecture is added to the semantic mapping of concepts, which codes relation between concepts. Concepts are nodes in a network and the links between nodes specify relations between concepts.

It is interesting that these semantic representations permit artificial neural networks to code and processes simple proposition. Experimental research in neural networks has shown that prepositional networks are able to simulate cognitive processes [7]. Learning is achieved when a specific weight attributed to links is modified by a given activation at the input nodes. The activation spreads though the whole network, modifies the weight of the links, and in addition renders the processing of subsequent inputs. In a neural network the neurons can activate or inhibit themselves. Thus, the network learns by means of a *self-organizing* mechanism.

On the other hand, in the human brain the creation process of such hypothesized hierarchical associative networks in memory and of course the manipulation of them in learning or the retrieval of them in thinking or communicating still remains a mystery.

Theoretical approaches have been pointed out that in processing the hierarchical semantic networks in the brain, natural language has an important role, since it determines to some extent the repertoire of categories in which the mind categorizes the environmental stimuli. The role of language in categorization of external world reveals a relation between language and the dynamic of thinking (information processing). It was suggested by Nicolis [8]: "*a dynamic modeling of the language about which experimental material from cognitive psychology abounds, can reveal the tip of the cerebral iceberg, that is, the software of biological information processing*".

The process of categorization of environmental stimuli on to a set of coexisting categories or (in the language of dynamics) attractors can be considered as a decision making process. From the information-processing point of view, the human processor is compressing or abstracting the environmental stimuli, so causing the external word collapse onto a set of 'categories' [8]. The 'meaning' can emerge after a number of judicious dichotomies (Yes/ No). Each concept in semantic memory associated with a number of features or attributes, and it can be determined or defined by a decision-making procedure of "Yes" or "No" responses. This process has been proposed as dynamical one performing at the 'edge of chaos', by giving a theoretical model but without providing any empirical evidence. This hypothesis is tested in the second experiment.

2. METHODOLOGY AND DATA ANALYSIS

2.1. Experiment I

In this experimental, the response time (RT) in mental tasks was measured. The subjects (*N*=5), education students, had to make simple decisions of '1' or '0' pressing the corresponding button on a computer keyboard (with no stimulus was present). In the language of dynamics, the cognitive system was let to oscillate between two attractors, '1' and '0' [9]. The recorded RT's (1000 points) were analysed as time series. The Singular Value Decomposition Method was applied as filter. The method is based on principal component analysis and removes 'white noise' from the raw data [10]. The filtered data were analysed for its nonlinear characteristics. The correlation dimension [11], which is the measure of dimensionality (provides the degrees of freedom of the system), was found to be lower that the corresponding measure of the *surrogate data*, which indicates low dimensionality. The surrogates are produced from the same data set by shuffling like a deck of cards, and they have the same distributional characteristic but all dynamics erased. In addition, the Hurst exponent, *H*, was calculated [12]. The values of *H* were between 0.15 and 0.30, indicating that the series exhibited long-range correlation with antipersisted behavior or that the $1/f^b$ dynamics of the RT series possess characteristics of *pink noise*.

This is evidence that the cognitive system demonstrated *self-organized* behavior, working at the 'Edge of Chaos' [13]. The results support the dynamic approach to cognition.

2.2. Experiment II

The subjects (*N*=5, different from those in the experiment I) completed a written questionnaire (Q1) where they were asked ontological questions about ten fundamental science concepts: Time, space, matter, energy, movement, force, light, sound, heat and pressure. Each questionnaire took the form of a grid, with ten scientific concepts across the top and a list of sixty-six features down the side. Subjects were asked to decide, for each concept, whether or not it possessed each feature. Examples of features-attributes used are of the type: 'You can move thing with it', 'You can touch it', 'You can see it', 'it is like a particle', etc. The answers were in the form of "Yes" or "No", and they sum up to six hundred sixty.

A week later, each subject was asked to complete a second questionnaire (Q2) containing the same questions in a different order. The answers from each questionnaire were converted to a symbolic sequence and the random walk methodology [14] was implemented:

A graphical representation of the sequence (Figure 1) was introduced, which is termed a *concept-random walk*.

We define the random walk function $\Psi(i)$ as follows:

$$\Psi(i) = -1, \text{ for decision "No";}$$

$$\Psi(i) = +1, \text{ for decision "Yes";}$$

For random walk RW ij, when i (1-*N*) refers to the subject and j (1 or 2) refers to the questionnaire, Q1 or Q2. For each subject then we created two sequences Q1 and Q2, and two random walk, RW1 and RW2 respectively.

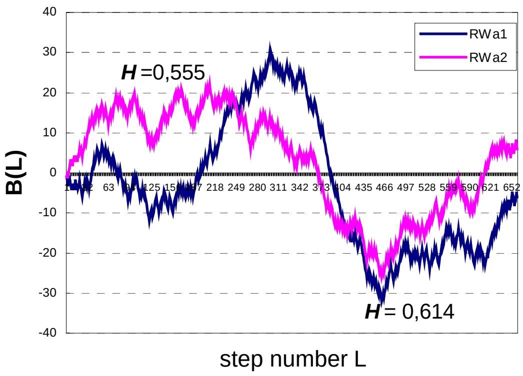

Figure 1. Random walks RWa1 and RWa2 for the subject A.

Consequently, the nonlinear correlation exponent, the Hurst (*H*) exponent was calculated by *rescaled range analysis* and *surrogate* method [10]. The value of *H* in these symbolic sequences depends: a) on the questionnaire ("input pattern") b) on the subject's answers (output). A sequence might posses by chance persisted or antipersisted characteristics due to factors (a) and (b). To make an essential comparison between RW1 and RW2 we created RW2 by taking the answers from questionnaire Q2 and placed them in the order appeared in the questionnaire Q1.

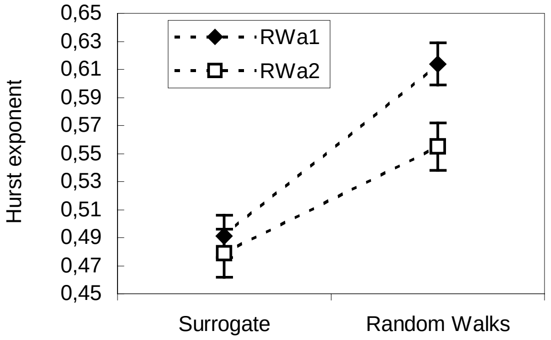

Figure 2. The Hurst exponent of the two random walks RWa1 and RWa2 for the subject A. The long-range correlations are statistically different (surrogate method).

By using the answers (decisions) given in the questionnaire Q2, in an order that of the questionnaire Q1, we remove the stochastic variability associated with random selection due to Q2. If the answers have not altered by the dynamics of Q2 then RW1 and RW2 must have similar nonlinear characteristic. These characteristics refer to $1/f^b$ dynamics [15]. The results showed that for all subjects the nonlinear characteristics for the two random walks, RW1 and RW2, had significantly changed. Figure 2 shows the values of the correlation exponent, *H*, for the two random walks of the same subject.

It is evident that the $1/f^b$ dynamics imposed by the patterns of input stimuli (Questionnaire) affects the intrinsic process of decision-making and alters the output (answers). The latter reflects the nature of the semantic network, which in this case refers to the identity of the fundamental- science-concept 'ontological space'.

3. DISCUSSION

The first experiment demonstrating $1/f^b$ scaling in simple reaction times added to the related literature, which provides support to the dynamic approach to cognition and to *self-organization* of cognitive performance.

On the other hand, the second experiment attempts to reveal the trace of the dynamic of brain functioning at the behavioral level by treating subject's responses with nonlinear tools and determining long-range correlations. These scale invariant long-range correlations characterize certain random walks in the students' 'ontological space' of scientific concepts, and they reveal a sequence effect on subject's responses related to dynamics of stimuli.

For a theoretical description one can evoke the dynamic modeling of language and the information processing approach [8] where the sequence of the judicious dichotomies (Yes/No) could 'decompress' concepts from semantic memory, which were collapsed onto a set of categories, and could cause the 'meaning' to emerge. In this processes one can distinguish two hierarchical levels in the role of language, the *Syntactical* and the *Semantic* level. At the syntactical level, from a given alphabet we produce stochastic sequence of symbols or words and we study the emerging syntactical rules. At the syntactical level the language carries no meaning because no correspondence between words and objects of the external word is established. At semantic level, which has been the subject of cognitive psychology we establish the "meaning", the correspondence between words or categories and stimuli of the external word.

The procedure in experiment II provides access to the students' associative network of conceptual representation by the interaction of two processes, the unfolding of the stimulus with a certain dynamics at the Syntactical level and the process of meaning creation at the Semantic level. According to the theoretical views mentioned earlier, students' semantic networks being non-static structures could be greatly affected by the dynamics of the stimuli during the accessing process (questionnaire). In other words, there is coupling between the dynamics of stimuli at *syntactical level* and the dynamics of meaning creation at *semantic level* (Figure 3). This happens because the decision-making process is a dynamical process, where each step has an impact on the future steps or at a given moment of time the state of the system is a product of the system' s history.

The coupling observed between the dynamic processes at the syntactical and the semantic level is not surprising if one consider resent advantages in neuroscience. It has been shown that the information procession in human brain differs substantially from the function of the Cartesian automaton or a Turing machine that follows stimulus response rules and has characteristics possessed by digital computers and by insects, such as honeybees.

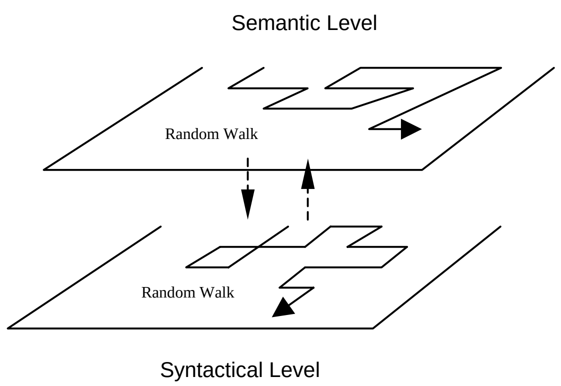

Figure 3**.** Random walks at the syntactical and the semantic level

A main difference of the human brain functioning is the brain does not directly respond to external stimuli. It responds to images (may be representations) and symbols created inside the brain. Electrophysiological studies [19] of visual, auditory, somatic & olfactory EEG's have shown that spatial patterns of neural activity emerge by construction with the act of perception and that they depend on the context of the present and equally on the past experience of each subject, not merely on the stimuli.

It is important to mention that NDS theory has offered significant contribution to neuroscience research on this history dependent response in the brain, which has been called an *interpretation* [16]. It has been proposed the notion of *chaotic hermeneutics* [17] [18] and introduced chaotic dynamics to interpretive role of brain activity. It was shown [19] [20] that spatiotemporal patterns of neural networks in the brains are chaotic and the observed chaos in these patterns underlies the correlated dynamics of brain and body. The above research has consolidated the dynamics of brain functioning and it is indirectly connected to the finding of the present study.

In conclusion, the present work implemented nonlinear methods and provided empirical evidence for dynamic effects in decision-making processes. Based on the latest advances of neuroscience the findings can support the dynamical hypothesis at the behavioural level. This could be seen as the **'tip of the iceberg'** of the dynamics of brain functioning.

4. REFERENCES

[1] T. Van Gelder and R. Port. "It's about time: An overview of the dynamical approach to cognition". In T. Van Gelder & R. Port (Eds.), *Mind as Motion, Exploration in the dynamics of cognition,*. MIT Press: Cambridge MA, 1995, pp 1-43.

[2] T. Van Gelder. "Distributed Representation," *Connection Science*, Vol. 4, pp 175-194, 1992.

[3] M. Peschl, "The representational relation between environmental structures and neural systems: Autonomy and environmental dependency in neural knowledge representation," *Nonlinear dynamics, Psychology and Life Science*, Vol. 1, pp 99-121, 1997.

[4] E. Tulving, "Episodic and semantic memory," In E. Tulving and W. Donaldson (Eds.), *Organization of memory*, Academic Press, 1972.

[5] A. Newell, *Unified Theories of Cognition*. Cambridge: Harvard University Press, 1994.

[6] Hardy, C. *Networks of meaning,* Praeger, 1998.

[7] D. Rumelhart and J. McClelland, *Exploration of the microstructure of cognition*: Vol. 1. Foundations, Cambridge, MA: MIT Press/Bradford Books, 1986.

[8] J. S. Nicolis, "Chaotic Dynamics as applied to information processing," *Rep. Prog. Phys*., Vol. 49, pp 1109-1187, 1986.

[9] G. Van Orden, J. Holden, and M. Turvey, "Self- organization of cognitive performance," *Journal of Experimental Psychology,* Vol. 132, pp 331-350, 2003.

[10] J. C. Sprott and G. Rowlands, *Chaos data analyzer*. Physical Academy Software, 1995.

[11] P. Grassberger and I. Procaccia, "Characterization of strange attractors," *Physical Review Letters,* Vol. 50, pp 346-349, 1983.

[12] H. Peitgen, H. Jurgens, and D. Saupe, *Chaos and fractal* Berlin: Springer, 1992.

[13] Haken, *Information and self-organization (a macroscopic approach to complex system).* Berlin: Springer, 1988.

[14] D. Stamovlasis and G. Tsaparlis, "An Application of Complexity Theory to an Information Model in Science Education," *Nonlinear Dynamics, Psychology and Life Science*, Vol. 5, pp 267-286, 2001.

[15] A. B. Cambel, *Applied Chaos Theory. A Paradigm for Complexity,* Academic Press, 1993.

[16] K. Kaneko and I. Tsuda, *Complex systems: Chaos and Beyond*, Springer, 1996.

[17] I. Tsuda, "A hermeneutic process of the brain," *Prog. Theor. Phys. Suppl.* Vol. 79, pp 241, 1984.

[18] J. S. Nicolis and I. Tsuda, "Chaotic dynamics of information processing: The 'magic number seven plus-minus two' revisited," *Bulletin of Mathematical Biology*, 47, pp 343-365, 1985.

[19] W. J. Freeman, *Societies of Brains: A study in the Neuroscience of Love and Hate*. Lawrence Erlbaum, 1995.

[20] W. J. Freeman, *How Brains Make Up Their Minds*. Columbia University Press, 2000.