Introduction to Focus Issue: Nonlinear Dynamics in Cognitive and Neural Systems

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In this Focus Issue, two interrelated concepts, namely, deterministic chaos and cognitive abilities, are discussed. © *2009 American Institute of Physics*. [DOI: 10.1063/1.3106111]

Chaotic dynamics as loss of initial information affects, in general, any nonlinear system with three or more degrees of freedom. This finding by Poincaré was disregarded for some decades and then reconsidered by Lorenz in 1963.[1] Since then, deterministic chaos has been observed and analyzed in many physical systems, starting from simple laboratory situations as in, e.g., coupled pendula, nonequilibrium fluids, and lasers. In the case of large systems made of many components, it is crucial to discriminate chaotic motion from statistical effects due to the linear sum of uncorrelated causes; many indicators have been suggested and tested in this regard.

The distinctive feature of deterministic chaos is a positive rate of information loss called Kolmogorov entropy. On the other hand, cognition means extracting from the environment some features on the basis of which a living being reacts. This occurs at any level, starting from unicellular organisms that build decisions by processing the information provided by chemical and thermal gradients. In pluricellular organisms, a processing speed up is, in several cases, obtained by electrical rather than chemical mutual communication. This is not limited to animals but is now being observed in plants as well.[2]

As animals get more complex, the distributed processing networks specialize into a dedicated organ—the brain. A brain is made of huge networks of coupled units—the neurons—each one sufficiently rich in dynamics to have its own complex behavior if studied in isolation from other partners. It is, however, known that small neuron networks are stabilized against chaos by a combination of inhibitory mutual feedbacks. They can be considered as stable modules with a specific function, such as a stereotyped reaction to a stimulus as it occurs in central pattern generator or encoding mechanisms as explored in the olfactory system of insects.[3,4]

Encoding is just the first step, then how to read information and make good use of it. An attractive paradigm is that of fixed point attractors,[5,6] which allows a sound processing model. Any input is classified according to its resemblance to a template previously stored in the system; this fact endows an attractor network of a capacity scalable with its size. However, a stable attractor network has a strong limitation in its limited capacity. Recurring to the dynamical attractors associated with chaotic dynamics, one can build richer scenarios, flexibly adaptable to many situations rather than restricted to a fixed repertoire.

Here, the central cognitive issue emerges. In the presence of chaos, the information loss rate can be high enough to preclude a convenient reaction. In fact, the only operational way to attribute cognitive ability to an agent is to look at its reactions. A smart cognitive agent can compensate for chaotic information loss by recurring to memory resources that add extra signals perturbing the original input and, hence, recoding the original dynamical space. This provides a slowdown of the information loss rate. The strategy is called "control of chaos;" its introduction[7] signaled a breakthrough in chaotic scenarios. In the case of many coupled chaotic units, a way of displaying a coherent behavior, that is, holding some collective information for a time much longer than the chaotic decay rate of a single unit, is mutual synchronization.[8] A complete approach to synchronization strategies is provided in Refs. 9 and 10 and, more generally, for synchronization in complex networks in Ref. 11.

However, there remain several basic open problems in this topic, especially the following.

(1) How does chaos affect some brain areas? Do these areas behave as separate domains which maintain their individuality by holding inner correlations and yet elaborate global messages that they exchange at their boundary?
(2) Low resolution measurement techniques, such as EEG (electro-encephalography) and fMRI (functional magnetic resonance imaging), are unable to detect the single neuron electrical activity; they rather average out the behavior of a large number of neurons. On the other hand, sampling single neuron signals requires invasive methods as microelectrodes or inspection of calcium ion release by two-photon fluorescence. These microanalyses can be carried on sparse samples, and their connection toward the global behavior of a whole network remains an open problem.
(3) Consider a set of coupled neurons in an array acting globally as a feature detector; it is hypothesized that the interplay between bottom-up stimuli arriving from sensory areas and top-down signals fed from memory stores[11] yields collective synchronization.[12] How well do

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these attractive hypotheses match the observed types of behavior?

(4) The main cognitive problem is how a given sensorial input elicits a decision (motor response), which affects the same environment from where the input originated). Once some early neuron groups encode the sensory signals into specific sequences of neuron spikes,[3,4] is that code already driving an appropriate action, so that an external observer can establish that a cognitive act has occurred or is there a successive further recoding? Calling cognition the loop perception action, this can be fast (around 100 ms) and explained by the Bayes procedures[13] or slower (around, say, 800 ms) and mediated—in the case of humans—by processing in the prefrontal cortex.[14]

(5) In this second case, the cognitive agent makes use of its own resources, as modeled, e.g., by adaptive resonance theory[11] in order to reduce the original Kolmogorov entropy and be able to build an appropriate reaction on its environment. The amount of this reduction can change from an individual to another. Let us call *creativity*[15] the "best" recoding that lengthens the information loss (not too short, otherwise it would preclude an appropriate reaction, nor too long, otherwise it would make the agent blind to successive inputs). How do we measure creativity? How is it related to symbolic language? Is there creativity in nonhuman animals? Can we foresee a robot creativity? After these sparse considerations, we shortly introduce the 16 papers[16–31] collected in this Focus Issue.

This Focus Issue presents interdisciplinary approaches to these problems, including modern methods from nonlinear dynamics, statistical physics, and mathematical statistics, as well as from cognitive and neuroscience. New kinds of experimental data, but also traditional ones, are combined and confronted with new modeling approaches and new data analysis techniques. The main intentions are to understand functionality of brain dynamics but also spatiotemporal dynamics of brain disorders and their identification and forecasts.

Several model approaches are presented for understanding of brain functioning and of disorder. Rothkegel and Lehnertz[23] studied structure formation in a small-world network composed of rather simple model neurons (pulse-coupled nonleaky integrate-and-fire neurons) and find, in this nonregular network, multistable behavior, including local wave patterns, as well as global collective firing. This is an important first step to relate brain disorders (e.g., epileptic seizures) to the topology of synaptic wiring. Traveling pulses are of fundamental importance in neuroscience because they transmit information, but they are also related to cell depolarizations in migraine or stroke. They are investigated in Ref. 24 by means of a hybrid model which combines volume and synaptic transmission. Methods for control of pulse propagation via moderate manipulations are developed. Zamora *et al.*[31] presented a statistical analysis of cortico-cortical communication paths of a cat in order to understand how simultaneous segregation and integration of information is possible in the brain. It comes out that the modular structure and the presence of highly connected hubs are crucial for the multisensory and complex information processing capabilities. Komarov *et al.*[21] modeled the formation of slow brain rhythms with a minimal inhibitory circuit and investigate when it provides structurally stable solutions. Based on a subtle bifurcation analysis, it is shown that the condition for this is the existence of a stable heteroclinic channel. A neural network model for working memory is extended in Ref. 28 by a negative feedback. After decomposing the fast and slow dynamics and performing bifurcation analysis and simulations, they showed that this feedback is sufficient to explain the dynamics of reflex epilepsy. The influence of external stimuli on a network of chaotic oscillators was studied by Ciszak *et al.*[17] It is shown that shortly below the onset of collective synchronization, a stimulus operating on only one oscillator is sufficient to generate a stable regime of synchronization. This provides an explanation of sudden transitions in the brain and the occurrence of conscious states. In Ref. 27, the typical brain dynamics is regarded as transitory. This leads to new ideas for typical scenarios of such a nonrandom and nonchaotic behavior. Then, nine hypotheses on the formation of dynamic memory and perception are presented.

Next, various aspects of modeling cognitive and psychological phenomena are discussed. Each modeling is in the strong sense an inverse problem. This approach is consequently performed in Ref. 19 for cognitive modeling. The authors decomposed the model in three main steps and showed that the main problem—the determination of the synaptic weight matrices—is an ill-posed one. To overcome this serious problem, they designed an efficient regularization technique basing on Hebbian learning. Dynamic motor processes are a crucial element in various sensory systems to enhance perception; an outstanding case study for this is fixational eye movements.[26] These eye movements represent self-generated noise. The authors studied the influence of external noise and show the constructive role of noise in visual perception. This perceptual performance, found experimentally, is described in a mathematical model. A challenging question is how can physiological processes give rise to psychological phenomena (moods, cognitive modes, etc.). Allefeld *et al.*[16] proposed a Markov coarse graining, which relates physiologically characterized microstates to psychologically characterized macrostates. Additionally, they developed an analysis technique to identify stable macrostates from EEG data and demonstrated its potential for epilepsy patients. To describe associated memory functioning and to represent conscious and unconscious mental processes, a complex network model is developed in Ref. 30. In this model, consciousness is related with symbolic and linguistic memory activity in the brain.

As discussed in the previous contributions, brain activity is characterized by highly complex spatiotemporal dynamics. The measurements of this activity are usually noisy and nonstationary. These difficulties call for highly sophisticated techniques of data analysis. Vejmelka and Paluš[29] proposed a special filtering technique to extract nonlinear oscillations from broadband signals. This is an important first step for further analysis, especially phase synchronization analysis. This way, EEG data during sleep are analyzed. Romano *et al.*[22] derived a test statistics basing on twin surrogates to test for phase synchronization. Their new analytic expressions enable determination of the optimal parameters for the generation of twin surrogates, which is a highly relevant problem for analyzing experimental data. Applying this technique, it is shown that the left and right fixational eye movements are statistically significantly phase synchronized. The development of sleep is of fundamental importance in the maturation of brain functions. Based on *in utero* electrocorticogram data, different sleep states of fetal sheep are studied in Ref. 25 with a combination of a stability analysis and a bispectral analysis. This way, premature sleep states are clearly identified. Hamann *et al.*[20] studied sleep by means of a synchronization analysis of the cardiovascular system. Based on this synchrogram technique, they can clearly distinguish different main sleep stages. This offers a new way for assessing sleep and sleep disorders by simply analyzing Holter recordings. The concept of synchronization is in combination with the unscented Kalman filter used for parameter estimation of nonlinear neuron models in Ref. 18. This method yields robust estimates even for strongly noisy data.

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[1]E. N. Lorenz, J. Atmos. Sci. **20**, 130 (1963).
[2]E. Masi, M. Ciszak, G. Stefano, L. Renna, E. Azzarello, C. Pandolfi, S. Mugnai, F. Baluška, F. T. Arecchi, and S. Mancuso, Proc. Natl. Acad. Sci. U.S.A. **106**, 4048 (2009).
[3]M. I. Rabinovich, P. Varona, A. I. Selverston, and H. D. I. Abarbanel, Rev. Mod. Phys. **78**, 1213 (2006).
[4]M. I. Rabinovich, R. Huerta, P. Varona, and V. S. Afraimovich, PLoS Comput. Biol. **4**, e1000072 (2008).
[5]J. J. Hopfield, Proc. Natl. Acad. Sci. U.S.A. **79**, 2554 (1982).
[6]J. J. Hopfield, Scholarpedia J. **2**, 1977 (2007).
[7]E. Ott, C. Grebogi, and J. A. Yorke, Phys. Rev. Lett. **64**, 1196 (1990).
[8]L. M. Pecora and T. L. Carroll, Phys. Rev. Lett. **64**, 821 (1990).
[9]A. Pikovsky, M. Rosenblum, and J. Kurths, *Synchronization—A Universal Concept in Nonlinear Sciences* (Cambridge University Press, Cambridge, UK, 2001).
[10]A. Arenas, A. Diaz-Guilero, J. Kurths, Y. Moreno, and C. Zhou, Phys. Rep. **469**, 93 (2008).
[11]G. A. Carpenter and S. Grossberg, in *The Handbook of Brain Theory and Neural Networks*, 2nd ed., edited by M. A. Arbib (MIT Press, Cambridge, MA, 2003), pp. 87–90.
[12]W. Singer, Scholarpedia J. **2**, 1657 (2007).
[13]K. P. Kording and D. M. Wolpert, Trends Cogn. Sci. **10**, 319 (2006); W. J. Ma, J. M. Beck, and A. Pouget, Curr. Opin. Neurobiol. **18**, 1 (2008).
[14]E. Rodriguez, N. George, J.-P. Lachaux, J. Martinerie, B. Renault, and F. J. Varela, Nature (London) **397**, 430 (1999).
[15]F. T. Arecchi, Eur. Phys. J. Spec. Top. **146**, 205 (2007).
[16]C. Allefeld, H. Atmanspacher, and J. Wackermann, "Mental states as macrostates emerging from EEG dynamics," Chaos **19**, 015102 (2009).
[17]M. Ciszak, A. Montina, and F. T. Arecchi, "Control of transient synchronization with external stimuli," Chaos **19**, 015104 (2009).
[18]B. Deng, J. Wang, and Y. Che, "A combined method to estimate parameters of neuron from a heavily noise-corrupted time series of active potential," Chaos **19**, 015105 (2009).
[19]P. beim Graben and R. Potthast, "Inverse problems in dynamic cognitive modeling," Chaos **19**, 015103 (2009).
[20]C. Hamann, R. P. Bartsch, A. Y. Schumann, T. Penzel, S. Havlin, and J. W. Kantelhardt, "Automated synchrogram analysis applied to heartbeat and reconstructed respiration," Chaos **19**, 015106 (2009).
[21]M. A. Komarov, G. V. Osipov, J. A. K. Suykens, and M. I. Rabinovich, "Numerical studies of slow rhythms emergence in neural microcircuits: Bifurcations and stability," Chaos **19**, 015107 (2009).
[22]M. Carmen Romano, M. Thiel, J. Kurths, K. Mergenthaler, and R. Engbert, "Hypothesis test for synchronization: Twin surrogates revisited," Chaos **19**, 015108 (2009).
[23]A. Rothkegel and K. Lehnertz, "Multistability, local pattern formation, and global collective firing in a small-world network of nonleaky integrate-and-fire neurons," Chaos **19**, 015109 (2009).
[24]F. M. Schneider, E. Schöll, and M. A. Dahlem, "Controlling the onset of traveling pulses in excitable media by nonlocal spatial coupling and time-delayed feedback," Chaos **19**, 015110 (2009).
[25]K. Schwab, T. Groh, M. Schwab, and H. Witte, "Nonlinear analysis and modeling of cortical activation and deactivation patterns in the immature fetal ECoG," Chaos **19**, 015111 (2009).
[26]C. Starzynski and R. Engbert, "Noise-enhanced target discrimination under the influence of fixational eye movements and external noise," Chaos **19**, 015112 (2009).
[27]I. Tsuda, "Hypotheses on the functional roles of chaotic transitory dynamics," Chaos **19**, 015113 (2009).
[28]S. Verduzco-Flores, B. Ermentrout, and M. Bodner, "From working memory to epilepsy: Dynamics of facilitation and inhibition in a cortical network," Chaos **19**, 015115 (2009).
[29]M. Vejmelka and M. Paluš, "Detecting nonlinear oscillations in broadband signals," Chaos **19**, 015114 (2009).
[30]R. S. Wedemann, R. Donangelo, L. A. V. de Carvalho, "Generalized memory associativity in a network model for the neuroses," Chaos **19**, 015116 (2009).
[31]G. Zamora-Lópes, C. Zhou, and J. Kurths, "Graph analysis of cortical networks reveals complex anatomical communication substrate," Chaos **19**, 015117 (2009).