Neurodynamics of Cognition and Consciousness

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Abstract. Dynamic aspects of higher cognitive functions are addressed. Dynamical neural networks with encoding in limit cycle and non-convergent attractors have gained increasing popularity in the past decade. Experimental evidence in humans and other mammalians indicates that complex neurodynamics is crucial for the emergence of higher-level intelligence and consciousness. We give an overview of research activities in the field, including dynamic models of consciousness, experiments to identify neurodynamic correlates of cognitive functions, interpretation of experimental findings, development of dynamical neural memories, and applications of dynamical approaches to intelligent system.

1. From Unconscious Chaos to Less Chaos and More Consciousness

A ubiquitous property of neurodynamics of consciousness is evolution from vague, fuzzy, and unconscious states to more concrete, and conscious. These neurodynamical processes are the essence of perception, cognition, and behavioral decision-making. More specific and conscious states correspond to recognized patterns and executed decisions. Neurodynamics proceeds from less knowledge to more knowledge and from less consciousness to more consciousness. Records of brain activity using EEG arrays and single-neuron evoked potential measurements indicate that brain states exhibit dynamic features of chaotic attractors [1, 2]. Vague and less conscious states are characterized by high-dimensional chaotic attractors. More concrete and conscious states are characterized by lower-dimensional "less chaotic" attractors.

Transitions from high-dimensional chaotic states to lower-dimensional and "less chaotic" states form a sequence of increasingly structured dynamics. Ultimately the dynamics leads to conditions facilitating conscious decision making and deliberate action by the individual [2, 3]. Following the action, a new situation is generated with modified internal states and goals and with changed environmental conditions. In this novel situation the neurodynamics starts again from high dimensional chaotic states and proceeds to lower-dimensional “less chaotic” states; this is called the intentional action-perception cycle.

In a cognitive cycle, neurodynamics evolves from less conscious to more conscious states, from vague and uncertain to more concrete knowledge, which is described at an abstract level of dynamic logic [4]. According to dynamic logic, brain states reflect the surrounding world and they are characterized by representations-models and by measures of similarity between the models and input signals. Vague, less conscious states are described by uncertain models with low similarity values. More conscious states correspond to concrete perceptions, cognitions, and decisions; they are described by concrete models and high similarity values. These more conscious models are better adapted-matched to input signals. Adaptation of models is driven by maximization of similarity. This drive is a mathematical representation of a fundamental instinct for more knowledge and more consciousness [5].

To summarize, chaotic neurodynamics and dynamic logic are equivalent descriptions of the dynamics of brain states. Dynamic logic-based modeling field theory provides the modeling framework, which evolves through the action-perception cycle. Dynamic logic can provide a cognitively-motivated model-based approach to describe the emergence of models of increasing clarity as the cognitive cycle progresses. Initial states are vague, uncertain, and less conscious. They are described by highly chaotic neurodynamics. They evolve into more concrete, certain, conscious states, described by less chaotic neurodynamics. Transitions from more chaotic states to less chaotic ones correspond to processes of perception, cognition, and decision making.

2. Neurocognition

Recordings of EEG activity in animals and humans demonstrate the spatial coherence of oscillations carrying spatiotemporal patterns, as described by Freeman in Chapter 2. The recordings reveal a shared oscillation in cortical potential over extended cortical areas within the beta band (12 Hz to 30 Hz) and gamma band (30 Hz to 80 Hz). These fluctuations serve as a carrier wave for perception information by means of spatial patterns with amplitude modulation (AM). The spatiotemporal patterns of the frequency of neural firing are correlated with the AM patterns. The shared carrier waveform is usually aperiodic and unpredictable, reflecting the chaotic dynamics of sensory cortices. These observations have been interpreted in terms of dynamic system theory [1, 6-9]. A complex brain state is characterized by a trajectory over a chaotic attractor landscape. The system dynamics may reside for a brief time period in a localized attractor basin, before it transits to another basin. The presence of a given sensory stimulus may constrain the trajectory to a lower dimensional attractor basin. Once the sensory stimulus is removed, the trajectory switches to a higher-dimensional dynamics (less concrete, less conscious state) until the next sensory stimulus constrains the dynamics again (to a concrete perception).

Experimental evidence indicates metastability of the dynamics, as described by Kelso and Tognoli in Chapter 3. Metastability is an inherent property of cortical dynamics, which is also manifested in coordination patterns of behaviors [10]. Metastability is the consequence of the competition of complementary tendencies of integration and fragmentation between cortical areas [11]. Intermittent oscillations, similar to those observed experimentally in metastable cortical states, have been mathematically described by chaotic itinerancy [12]. In chaotic itinerancy, the attractor landscape is characterized by attractor ruins. Accordingly, the trajectory is constrained intermittently to the neighborhood of the attractor ruin, but it never settles to the attractor. Rather it jumps from one attractor ruin to another and it generates a metastable dynamic pattern of spatio-temporal oscillations. Neuromodulatory effects through the hypothalamus and brain stem play role in the observed transitions (Chapter 2 by Freeman).

Experimental evidence of the formation of a global cortical neurocognitive state is provided by Bressler (Chapter 4). The cortex consists of a large number of areas profusely interconnected by long-range pathways in a complex topological structure. An important aspect of cortical connectivity is that each cortical area has a specialized topological position within the cortex, i.e. a unique pattern of interconnectivity with other cortical areas. To a large degree, the function of every cortical area is determined by its unique patterning of long-range connectivity. At the same time, the short-range interconnectivity of local circuits within cortical areas is generally similar throughout the cortex, implying that no area has a specialized monitoring function by virtue of its internal organization. These considerations suggest that cortical monitoring and integrative functions are the result of cooperative interaction among many distributed areas, and not the sole property of any one area or small group of areas [13]. Bressler shows that the cortex dynamically generates global neurocognitive states from interactions among its areas using short- and long-range patterning of interconnectivity within the cortex.

Various models address questions related to the hierarchies in neural systems. Dynamic models span from the cellular level to populations, including massively recurrent architectures with complex dynamics [14-16]. Biologically-motivated models of sensory processing have been successfully implemented in a wide range of areas [17, 18]. Clearly, dynamical approaches to neural modeling provide powerful and robust tools of solving difficult real life problems.

3. Cognition, Emotions, and Brain

Emotions were considered opposite to intelligence since Plato and Aristotle. Similar were attitudes to emotions during initial attempts to construct artificial intelligence; these attempts were based on logical-conceptual mechanisms. Recently, however, fundamental role of emotions in cognition have being recognized. What are the brain modules involved in interaction between emotions and cognition, and how these interactions can be modeled mathematically? In Chapter 5, Perlovsky analyses the interplay of conceptual and emotional mechanisms [5]. It is related to the role of prefrontal cortex, hippocampus, and amygdala in Chapter 8 by Levine [19]. The brain uses emotional memories to switch between appropriate sets of behavioral rules in various circumstances.

Special emotions accompany knowledge creation and improvement. Perlovsky (Chapter 5) describes our drive to learning, to improving understanding of the surrounding world, due to the knowledge instinct [1? Robert – is this the correct ref?]. Satisfaction of this instinct is experienced as positive aesthetic emotions. These emotions are the foundation for all our higher cognitive abilities. Mathematical technique describing these instinctual-emotional mechanisms of learning overcome difficulties encountered by previous artificial intelligence and neural network approaches, difficulties known as "curse of dimensionality," "exponential explosion," and "combinatorial complexity."

The relationship between emotional and rule-based aspects of decision making is analyzed by Levine (Chapter 8). The amygdala is closely connected with hypothalamic and midbrain motivational areas and it appears to be the prime region for attaching positive or negative emotional valence to specific sensory events. The amygdala is involved in emotional responses, from the most primitive to the most cognitively driven. The complex interplay of attention and emotion has been captured in various network models involving amygdala as well as various parts of the prefrontal cortex [19]. Emotional states of humans have been successfully identified using facial imaging based on neural network models [20].

In the dynamic brain model KIV introduced by Kozma (Chapter 7), amygdala plays an important role in its interaction with the cortico-hippocampal system. It gives an emotional bias to mechanisms from sensory cortical areas toward decision making and motor system [3, 21] (ROBERT – VERIFY IF MY CHANGES ARE OK). In a more general context, the role of the internal state of the sensory-motor agent is analyzed by Misra and Choe (Chapter 9). Instead of using a pure reactive agent, they develop an approach in which the sensory-motor agent has a long-term memory of its previous experiences (visual and skill memories) [22]. It has been demonstrated that especially skill memory leads to improved performance in the recognition task.

4. Hierarchy

The mind is not a strict hierarchy. Significant feedback exists between higher and lower levels. This architecture is sometimes called heterarchy. For simplicity, we will sometimes call it hierarchy. At lower levels of the hierarchy there are mechanisms of recognition and understanding of simple features and objects. Higher up are situations, relationships, abstract notions.

A hierarchy of structure, function, dynamics, within spatial and temporal brain scales are described by the K models by Kozma (Chapter 8). K sets are multi-scale models, describing increasing complexity of structure and dynamical behavior [3, 23]. K sets are mesoscopic (intermediate-scale) models introduced by Freeman in the 70's, and they represent an intermediate-level of hierarchy between microscopic neurons and macroscopic brain structures. The basic building block is the K0 set which describes the dynamics of a cortical micro-column with about 10 thousand neurons. K-sets are topological specifications of the hierarchy of connectivity in neuron populations in the 6-layer cortex. A KI set contains K0 sets from a given layer with specific properties. KII includes KI units from different populations, i.e., excitatory and inhibitory ones. KIII has several KII sets modeling various cortical areas. KIV covers cortical areas across the hemisphere. KV is the highest level of hierarchy describing neocortex. The dynamics of K sets has the following hierarchy: K0 has zero fixed point attractor; KI has non-zero fixed point attractor; KII has limit cycle oscillations; KIII exhibits chaos; and KIV shows intermittent spatio-temporal chaos. The function of KIII sets can be sensory processing and classification using a single channel; KIII may correspond to visual sensory system, olfactory system, hippocampus, midline forebrain, etc. KIV performs multisensory fusion and decision making. KV has components of higher cognition and conscious functions.

Werbos (Chapter 6) gives a careful, qualified endorsement to hierarchical brain models. The spatio-temporal complexity of cognitive processing in brains would benefit from a hierarchical partitioning and nature certainly exploits this opportunity [24-26]. He cites evidence for such temporal hierarchy in basal ganglia. The hierarchy in time, however, is not crisp, but apparently fuzzy. Recent research indicates that the connection from dorsolateral cortex to the basal ganglia proposes the "verb" or "choice of discrete decision block type" to the basal ganglia. It also suggests that the "hierarchy" is implicit and fuzzy, based on how one decision may engage others – but may in fact be forgotten at times because of limited computational resources in the brain.

Dynamic logic and neural modeling fields describe operation of the knowledge instinct within the mind hierarchy [4,5]. Aesthetic emotions related to improvement of knowledge, operate at every hierarchical level. At lower levels, where knowledge is related to everyday objects, aesthetic emotions are barely noticeable. At the top of the hierarchy, knowledge is related to purposes and meanings of life; improvement of this knowledge is felt as emotion of the beautiful. Operation of the knowledge instinct in the hierarchy is manifested as differentiation and synthesis. Differentiation refers to creation of diverse knowledge; it occurs at every level of the hierarchy. As more diverse knowledge is created, less emotional value is vested in every element of knowledge. Synthesis refers to connecting this diverse knowledge to more general concepts at higher levels. In these connections diverse knowledge acquires emotional value. This emotional value of knowledge is necessary for creating more knowledge, for differentiation. Thus, synthesis and differentiation are in complex relationships, at once symbiotic and oppositional.

5. Cultural Dynamics

Differentiation and synthesis, created in the individual minds, determine consciousness in individuals and also drive collective consciousness and evolution of entire cultures. Chapter 5 gives a mathematical description of this evolution. When synthesis predominates in collective consciousness, knowledge is emotionally valued, and more knowledge is created. However, more knowledge leads to reduced emotional value of every piece of knowledge; thus differentiation destroys synthesis, which is the condition of differentiation. This interaction describes cultural dynamics with alternating periods of cultural flourishing and destruction, which might characterize evolution of the Western culture during the last 4,000 years. An opposite dynamics is characterized by permanent predominance of synthesis. When every conceptual piece of knowledge is vested with high emotional value, differentiation is stifled, and limited knowledge is vested with more and more emotional value, while culture stagnates. Within each society levels of differentiation and synthesis can be measured and used to predict cultural evolution around the globe, including our own.

6. Overview of the Book

An important aspect of cognitive processing is the intermittent character of brain waves oscillating between high-dimensional spatio-temporal chaos and lower-dimensional more ordered states. Such an oscillatory dynamics is observed at the theta range, i.e., at a rate of approximately 5 cycles per second, as described in the cinematographic model of cognition by Freeman (Chapter 2). This process is characterized as metastability in the context of coordination dynamics by Kelso and Tognoli (Chapter 3). The formation of global neurocognitive states between mammalian cortical areas is documented and analyzed by Bressler (Chapter 4). A key property of neurodynamics is the evolution from less conscious to more conscious states, from vague and uncertain to more concrete knowledge, which is described at an abstract level of dynamic logic by Perlovsky (Chapter 5).

Cortical circuitries describing various aspects of the dynamics of cognitive processing have been analyzed by several authors. The capabilities of the mammalian brain are studied in the context of adaptive dynamic programming features by Werbos (Chapter 6). In particular, principles of adaptive critic systems are elaborated, and a roadmap is outlined toward artificially intelligent designs based on the thalamo-cortical circuitry. The role of the cortico-hippocampal system in intentional behavior generation and decision making is studied by Kozma (Chapter 7). This system also incorporates an internal motivation unit and amygdala as the emotional subsystem of the autonomous agent. The interplay of the hippocampus and amygdala in forming a context-dependent behavior balancing between goal-orientedness and emotional states is described by Levine (Chapter 8).

Dynamical models of cognitive functions, including categorization and pattern recognition gain popularity in a wide range of applications due to their robustness and biological relevance. The close link between visual recognition and motor representations is analyzed by Misra and Choe (Chapter 9). A computational model of the visual sensory system is used for object recognition based on dynamic programming principles by Iftekharuddin et al. (Chapter 10). Emotional states based on facial expression are successfully identified by Wong and Cho (Chapter 11). The dynamic KIII model, motivated by the olfactory system, is used successfully to solve difficult image recognition, voice recognition, and other classification problems by Li et al. (Chapter 12).

The chaotic oscillations identified in brains strongly motivate research in dynamic memories.. Hernandez in Chapter 13 studies the role of recursive connectivity in the neural circuitry for creating rich dynamics of cognitive functions. A rigorous study of cyclic attractors and their potential role as robust memory devices is given by Molter, Salihoglu, and Bersini (Chapter 14). Long-term memories modeled as self-reproducing communication networks by Charlton and Andras (Chapter 15). A novel dynamical model of the synaptic interaction in multiple vesicle pools is developed by Lu, Yamada, and Berger (Chapter 16).

Conclusions

This chapter provides an introduction to the volume on the neurodynamics of cognition and consciousness. Contributions from leading experts of the field provide a cutting-edge review of this challenging frontier of neuroscience and intelligent systems research. We hope it will help interested researchers to get familiar with research achievements and open new directions.

References

1. W. J. Freeman. Neurodynamics. An Exploration of Mesoscopic Brain Dynamics. London: Springer, 2001.
2. Nunez, R.E., Freeman, W.J. (1999) “Restoring to cognition the forgotten primacy of action, intention, and emotion,” J. Consciousness Studies, 6 (11-12), ix-xx.
3. Kozma, R., and Freeman, W.J. Basic Principles of the KIV Model and its application to the Navigation Problem, J. Integrative Neurosci., 2, 125-140, 2003.
4. Perlovsky, L.I. Neural Networks and Intellect. Oxford Univ. Press, New York, NY, 2001.
5. L. I. Perlovsky. Toward physics of the mind: Concepts, emotions, consciousness, and symbols. Physics of Life Reviews, 3:23-55, 2006.
6. W. J. Freeman. Origin, structure, and role of background EEG activity. Part 1. Phase. Clinical. Neurophysiology 115: 2077-2088, 2006.
7. W. J. Freeman. Origin, structure, and role of background EEG activity. Part 2. Amplitude. Clinical. Neurophysiology 115: 2089-2107, 2006.

8. W. J. Freeman. Origin, structure, and role of background EEG activity. Part 3. Neural frame classification. Clinical. Neurophysiology 116 (5): 1118-1129, 2005.
9. W. J. Freeman. Origin, structure, and role of background EEG activity. Part 4. Neural frame simulation. Clinical. Neurophysiology 117/3: 572-589, 2006.
10. J. A. S. Kelso. Dynamic Patterns: The Self-Organization of Brain and Behavior. Cambridge: MIT Press, 1995.
11. Kelso, J.A.S., Engstrøm, D.: The Complementary Nature. MIT Press, Cambridge, 2006.
12. Tsuda. I. Towards an interpretation of dynamic neural activity in terms of chaotic dynamical systems. Behavioral and Brain Sciences 24:793-810, 2001.
13. S. L. Bressler and J. A. S. Kelso. Cortical coordination dynamics and cognition. Trends in Cognitive Science 5:26-36, 2001.
14. J.S. Liaw and T.W. Berger. Dynamic synapse: a new concept of neural representation and computation. Hippocampus, 6:591–600, 1996.
15. Del-Moral-Hernandez, E.: Non-homogenous Neural Networks with Chaotic Recursive Nodes: Connectivity and Multi-assemblies Structures in Recursive Processing Elements Architectures, Neural Networks, 18, 532 – 540, 2005.
16. C. Molter and U. Salihoglu and H. Bersini, The road to chaos by time asymmetric Hebbian learning in recurrent neural networks, Neural Computation, 19(1), 100, 2007.
17. Li, X., Li, G., Wang, L., Freeman, W.J.: A study on a Bionic Pattern Classifier Based on Olfactory Neural System, Int. J. Bifurcation Chaos., 16, 2425-2434, 2006.
18. Iftekharuddin, K.M., Power, G.: A biological model for distortion invariant target recognition. In: Proc. of IJCNN, Washington DC, U.S.A., IEEE Press, pp. 559-565, 2001.
19. D. S. Levine. Angels, devils, and censors in the brain. ComPlexus, 2:35-59, 2005.
20. Wong, J.-J. and S.-Y. Cho, A Brain-Inspired Framework for Emotion Recognition. Neural Information Processing, 10(7), pp. 169-179, 2006.
21. R. Kozma and W. J. Freeman. Chaotic resonance: Methods and applications for robust classification of noisy and variable patterns. International Journal of Bifurcation and Chaos 10: 2307-2322, 2001.
22. Choe, Y., Bhamidipati, S.K.: Autonomous acquisition of the meaning of sensory states through sensory-invariance driven action. In Ijspeert, A.J., Murata, M., Wakamiya, N., eds.: Biologically Inspired Approaches to Advanced Information Technology. Lecture Notes in Computer Science 3141, Berlin, Springer, 176–188, 2004.
23. Kozma, R., Freeman, W.J., Erdi, P. The KIV Model - Nonlinear Spatio-temporal Dynamics of the Primordial Vertebrate Forebrain, Neurocomputing, 52-54, 819-825.
24. P.Werbos, Brain-Like Design To Learn Optimal Decision Strategies in Complex Environments, in M.Karny et al eds, Dealing with Complexity: A Neural Networks Approach. Springer, London, 1998.
25. J.Albus, Outline of Intelligence, IEEE Trans. Systems, Man and Cybernetics, 21(2), 1991.
26. P.Werbos, What do neural nets and quantum theory tell us about mind and reality? In K. Yasue, M. Jibu & T. Della Senta, eds, No Matter, Never Mind : Proc. of Toward a Science of Consciousness. John Benjamins, 2002.