Trends in Dynamic and Embodied Cognition

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The dynamical systems approach is becoming increasingly important in cognitive science and robotics. In this perspective an agent and its environment are modeled as two coupled dynamical systems and cognitive activity arises from the history of interactions between the agent's internal dynamics, its body morphodynamical properties and its environment [1, 2]. Recent advances in this field were presented in a September 2006 workshop on Dynamic Brain Models organized by Stefano Nolfi in Roma. In this short letter, we give a highlight of the approaches presented there and also include additional work by other groups that could not attend the workshop.

In their seminal work, Beer and colleagues carried out rigorous analysis of the performance, behavioral strategy, and psychophysics of a model agent capable of minimally cognitive behaviors [3]. Such behaviors include active object discrimination and hexapod walking. The language of dynamical systems significantly contributes to their understanding of the complex, dynamic agent-environment interaction. The authors have consistently adopted continuous-time recurrent neural networks (CTRNN) as the controller of those robots. The emphasis on continuous dynamics is motivated by the fact that the dynamics of both nervous systems and the macroscopic physical world are continuous in nature [2].

Evolutionary Robotics [4] is an ideal framework to explore rich dynamics between robots and their environment. Researchers at the University of Sussex, EPFL, and CNR Roma investiagted the evolution of various types of dynamic neural networks as well as CTRNN embedded in autonomous robots [5, 6, 7, 8]. These dynamic networks have been widely applied to various behavioral and cognitive tasks including bipedal walking [9], multiple and sequential problem solving [7, 10, 11], obstacle avoidance [12, 13], predator-prey coevolution [14, 15, 16], and T-maze navigation [17, 18] to mention a few.

Der and colleagues used a different approach where robots develop sensory-motor coordination by means of self-exploration [19, 20]. Robot congnition is defined as the ability to predict the future consequences of the action undertaken by the robot. As concrete examples, they demonstrated that wheeled and spherical robots can develop dynamic sensory-motor coordination from scratch to purposive actions by self-exploration. Their control systems are often implemented as small fully-connected neural networks with Hebbian learning.

Pasemann and colleagues studied structure and function of a extremely small but effective neural controller of autonomous robots [27, 28, 29]. The development of minimal networks is based on their former intensive studies of the rich dynamics in a single neuron and a single loop network [30, 31]. They have shown that temporal sequences of the attractors formed in their recurrent neural network can be used to characterise the robot-environment interaction.

Tani and colleagues explored higher cognitive abilities of autonomous robots with the language of dynamical systems. They developed hierarchical dynamic neural networks and analyzed the dynamics of agent-environment interaction in their robotic experiments [32, 33]. Each module of the network is essentially predicting the sensory consequences of the motor actions. In recent work, they use a self-organizing clustering of the neural modules according to the similarity in their prediction values. In other words, whenever a discrepancy occurs between predicted and perceived sensory values, a new module attempts to take over or learn the sensory motor mapping. They argue that this mechanism may underly the difference between automated and conscious behavior. They also argue that symbols can be realized in the neuronal dynamical systems and hence they can be grounded to the sensory-motor experiences [35].

Another attempt to understand higher cognitive abilities has been given by Ikegami and colleagues; they have aimed at understanding communication between two agents as a chaotic itinerant phenomenon [36, 37, 38]. Chaotic itinerancy is a shifting dynamic process that continually creates and destroys a temporal structure in a deterministic manner [39]. In the coalition and turn-taking games, they have shown that the communication between two agents can be sustained only when both agents are driven by nonconvergent, unstable dynamics.

Inspired by aperiodic, chaotic processes in dynamic brain activity observed in mammalian perceptual systems, Freeman, Kozma and colleagues have developed K-set neurodynamical population models capable of reproducing these biological properties [21]. These models have been used to demonstrate perceptual categorization by aperiodic attractors [22, 23] and cognitive map formation in autonomous agents [24, 25]. More recently they have attempted to evolve the neural architectures based on their neurodynamic model for controlling autonomous robots [26].

A great majority of the researchers in dynamic and embodied cognitive systems have traditionally been very critical of representations and symbols, arguing that those items were not necessary to understand cognition. Over the very recent year, we witnessed a progressive shift of interest from complex –but reactive– to simple –but cognitive-style– control systems. Often, these cognitive-style systems include structures and mechanisms for expectation, prediction, and multi-task operation. This shift stems most likely from a better understanding of the behaviors emerging from reactive systems and the readiness to apply the same tools to study more complex phenomena. Symptomatic of this trend was the comment by Randall Beer in Roma that we may have to shift from being *against* representations to being *skeptical* of representations. The difference is less subtle that you may think!

Readers further interested in a collection of very recently published papers in this field may read, e.g., the Special Issue on the Dynamical Systems Approach to Cognition of the journal Adaptive Behavior [40].

References

[1] E. Thelen and L. Smith. *A dynamical systems approach to the development of cognition and action.* The MIT Press, Cambridge, MA, 1994.

[2] R. D. Beer. A dynamical systems perspective on agent-environment interaction. *Artificial Intelligence*, 72:173–215, 1997.

[3] R. D. Beer. The dynamics of active categorical perception in an evolved model agent. *Adaptive Behavior*, 11(4):209–243, 2003.

[4] S. Nolfi and D. Floreano. *Evolutionary Robotics: Biology, Intelligence, and Technology of Self-Organizing Machines.* MIT Press, Cambridge, MA, 2000.

[5] P. Husbands, T. Smith, and M. Jakobi, N. O'Shea. Better living through chemistry: Evolving gasnets for robot control. *Connection Science*, 10:185–210, 1998.

[6] E. A. Di Paolo. Homeostatic adaptation to inversion of the visual field and other sensorimotor disruptions. In *Proceedings of IEEE International Joint Conference on Neural Networks*, 2000.

[7] J. Urzelai and D. Floreano. Evolution of adaptive synapses: Robots with fast adaptive behavior in new environments. *Evolutionary Computation*, 9:495–524, 2001.

[8] D. Floreano, M. Suzuki, and C. Mattiussi. Active Vision and Receptive Field Development in Evolutionary Robots. *Evolutionary Computation*, 13(4):527–544, 2005.

[9] T. Reil and P. Husbands. Evolution of central pattern generators for bipedal walking in real-time physics environment. *IEEE Transactions on Evolutionary Computation*, 6(2):10–21, 2002.

[10] D. Floreano and J. Urzelai. Evolution of plastic control networks. *Autonomous Robots*, 11(3):311–317, 2001.

[11] J. Blynel and D. Floreano. Levels of dynamics and adaptive behavior in evolutionary neural controllers. In B. Hallam, D. Floreano, J. Hallam, G. Hayes, and J.-A. Meyer, editors, *From Animals to Animats 7: Proceedings of the seventh international conference on simulation of adaptive behavior*, pages 272–281, Cambridge, MA, 2002. The MIT Press.

[12] D. Floreano and F. Mondada. Active Perception, Navigation, Homing, and Grasping: An autonomous Perspective. In P. Gaussier and J.-D. Nicoud, editors, *From Perception to Action Conference (PERAC'1994)*, pages 122–133, 1994.

[13] F. Mondada and D. Floreano. Evolution of neural control structures: Some experiments on mobile robots. *Robotics and Autonomous Systems*, 16(2-4):183–195, 1995.

[14] D. Cliff and G. F. Miller. Tracking the red queen: measurements of adaptive progress in co-evolutionary simulations. In F. Morán, A. Moreno, J. J. Merelo, and P. Chacón, editors, *Advances in Artificial Life: Proceedings of the Third European Conference on Artificial Life*, pages 200–218, Berlin, 1995. Springer Verlag.

[15] D. Floreano and S. Nolfi. Adaptive Behavior in Competitive Co-Evolutionary Robotics. In P. Husbands and I. Harvey, editors, *Proceedings of The 4th European Conference on Artificial Life*, 1997.

[16] S. Nolfi and D. Floreano. Coevolving predator and prey robots: Do "arms races" arise in artificial evolution? *Artificial Life*, 4(4):311–335, 1998.

[17] J. Blynel and D. Floreano. Exploring the T-maze: Evolving learning-like robot behaviors using CTRNNs. In G. R. Raidl, J.-A. Meyer, M. Middendorf, S. Cagnoni, J. J. Romero Cardalda, D. Corne, J. Gottlieb, A. Guillot, E. Hart, C. G. Johnson, and E. Marchiori, editors, *Proceedings of EvoWorkshops*, volume 2611 of *Lecture Notes in Computer Science*, pages 593–604. Springer Verlag, 2003.

[18] J. Blynel. Evolving reinforcement learning-like abilities for robots. In A. Tyrrell, P. C. Haddow, and J. Torresen, editors, *Proceedings of The 5th International Conference on Evolvable Systems*, volume 2606 of *Lecture Notes in Computer Science*, pages 320–331. Springer Verlag, 2003.

[19] R. Der, F. Hesse, and G. Martius. Rocking stamper and jumping snakes from a dynamical systems approach to. *Adaptive Behavior*, 14:105–115, 2006.

[20] R. Der and G. Martius. From motor babbling to purposive actions: Emerging self-exploration in a dynamical systems approach to early robot development. In S. Nolfi, G. Baldassarre, R. Calabretta, J. Hallam, D. Marocco, O. Miglino, J.-A. Meyer, and D. Parisi, editors, *From Animals to Animats 9: Proceedings of the Ninth International Conference on Simulation of Adaptive Behaviour*, volume 4095 of *Lecture Notes in Artificial Intelligence*, pages 406–421, Berlin, Germany, 2006. Springer Verlag.

[21] R. Kozma, W. J. Freeman, and P. Erdi. The KIV model – nonlinear spatio-temporal dynamics of the primordial vertebrate forebrain. *Neurocomputing*, 52(4):819–826, 2003.

[22] R. Kozma. Chaotic resonance – methods and applications for robust classification of noisy and variable patterns. *International Journal of Bifurcation and Chaos*, 11(6):1607–1629, 2001.

[23] W. J. Freeman. Basic principles of the KIV model and its application to the navigation problem. *Journal of Integrative Neuroscience*, 2(1):125–145, 2003.

[24] R. Kozma and P. Ankaraju. Learning spatial navigation using chaotic neural network model. In *Proceedings of the IJCNN 2003: International Joint Conference on Neural Networks*, pages 1476–1479, Portland, OR, 2003.

[25] D. Harter and R. Kozma. Chaotic neurodynamics for autonomous agents. *IEEE Transactions on Neural Networks*, 16(3):565–579, 2005.

[26] D. Harter. Evolving neurodynamic controllers for autonomous robots. In *Proceedings of the International Joint Conference on Neural Networks*, pages 137–142, Montréal, Canada, 2005.

[27] F. Pasemann, U. Steinmetz, M. Hülse, and B. Lara. Robot control and the evolution of modular neurodynamics. *Theory in Biosciences*, 120:311–326, 2001.

[28] M. Hülse and F. Pasemann. Dynamical neural schmitt trigger for robot control. In J. R. Dorronsoro, editor, *Proceedings of International Conference on Artificial Neural Networks*, volume 2415 of *Lecture Notes in Computer Science*, pages 783–788. Springer Verlag, 2002.

[29] M. Hülse, K. Zahedi, and F. Pasemann. Representing robot-environment interactions by dynamical features of neuro-controllers. In M. V. Butz, O. Sigaud, and P. Gérard, editors, *Proceedings of the Workshop of Anticipatory Behavior in Adaptive Learning Systems*, volume 2684 of *Lecture Notes in Artificial Intelligence*, pages 222–242, Berlin, Germany, 2003. Springer-Verlag.

[30] F. Pasemann. Dynamics of a single model neuron. *International Journal of Bifurcation and Chaos*, 3:271–278, 1993.

[31] F. Pasemann. Characterization of periodic attractors in neural ring networks. *Neural Networks*, 8:421–429, 1995.

[32] J. Tani and S. Nolfi. Learning to perceive the world as articulated: an approach for hierarchical learning in sensory-motor systems. In R. Pfeifer, B. Blumberg, J.-A. Meyer, and S. W. Wilson, editors, *From Animals to Animats 5: Proceedings of the Fifth International Conference on Simulation of Adaptive Behaviour*, pages 270–279, Cambridge, MA, 1998. The MIT Press.

[33] R. W. Paine and J. Tani. Motor primitive and sequence self-organization in a hierarchical recurrent neural network. *Neural Networks*, 17:1291–1309, 2004.

[34] S. Harnad. The symbol grounding problem. *Physica D*, 42:335–346, 1990.

[35] Y. Sugita and J. Tani. Learning semantic combinatoriality from the interaction between linguistic and behavioral processes. *Adaptive Behavior*, 1:33–52, 2005.

[36] T. Ikegami and G. Morimoto. Chaotic itinerancy in coupled dynamical recognizers. *Chaos*, 13(3):1133–1147, 2003.

[37] H. Iizuka and T. Ikegami. Simulating turn-taking behaviours with coupled dynamical recognizers. In Standish, Abbass, and Bedau, editors, *Proceedings of Artificial Life VIII*, pages 319–328, Cambridge, MA, 2002. The MIT Press.

[38] H. Iizuka and T. Ikegami. Adaptive coupling and intersubjectivity in simulated turn-taking behaviours. In Banzahf, editor, *Advances in Artificial Life: Proceedings of the 7th European Conference on Advances in Artificial Life*, pages 336–345. Springer Verlag, 2003.

[39] I. Tsuda. Toward an interpretation of dynamic neural activity in terms of chaotic dynamical systems. *Behavioral and Brain Sciences*, 24:793–847, 2001.

[40] F. Almeida e Costa and E. Izquierdo-Torres. Special issue on the dynamical systems approach to cognition. *Adaptive Behavior*, 14(2):101–185, 2006.