

## **In the search of principles underlying cognitive phenomena**

Martin Hülse<sup>1†</sup>, Keyan Zahedi<sup>1</sup>, Steffen Wischmann<sup>2</sup>, Frank Pasemann<sup>1</sup>

<sup>1</sup>Fraunhofer Institute for Autonomous Intelligent Systems,  
Schloss Birlinghoven, Sankt Augustin, Germany

e-mail: [ martin.huelse | keyan.zahedi | frank.pasemann ]@ais.fraunhofer.de

<sup>2</sup>Bernstein Center for Computational Neuroscience,  
University Göttingen, Germany  
e-mail: steffen@chaos.gwdg.de

### **Introduction**

The dynamical system approach to natural cognitive systems is formulated as an empirical hypothesis, that can only be validated “if in a long run, the best theories of cognitive processes are expressed in dynamical terms.”<sup>1</sup> From this point of view scientists emphasize the importance of concrete examples of minimal cognitive systems developed or demonstrated with autonomous robot systems<sup>2</sup>. The formal analysis of such minimal systems are the prerequisites for dynamical explanations and “abstracting general principles” of artificial cognitive systems, and might also give us the right tools and experience for the study of complex natural cognition as dynamical systems.<sup>2,3</sup>

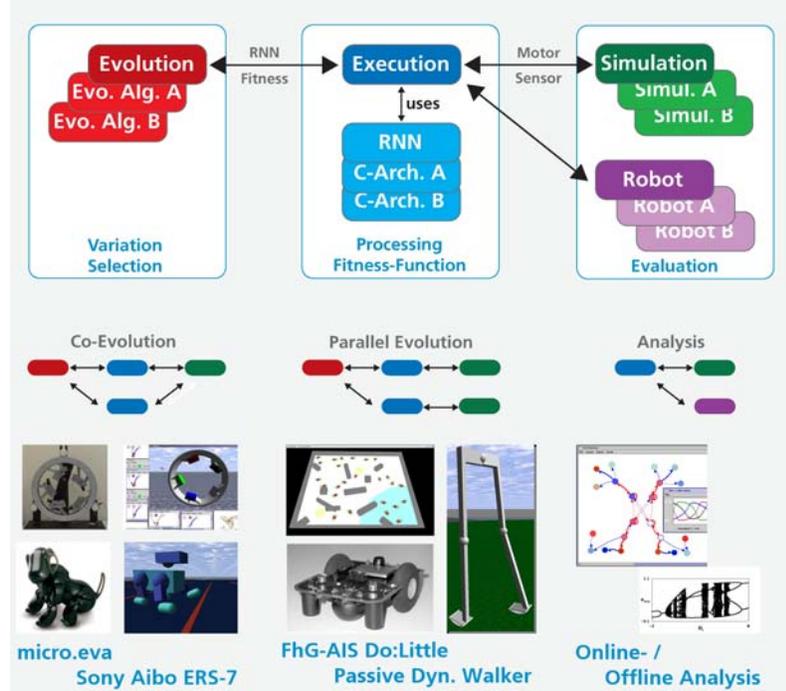
### **Offering minimal solutions and new questions**

Applying the approach of evolutionary robotics<sup>4</sup> and artificial life<sup>5</sup> we are able to evolve recurrent neural networks (RNNs) of general type. They serve as neuro-controllers for autonomous robots that act successfully in an open, noisy and changing environment. Due to the stochastic character of the applied evolutionary algorithm<sup>6</sup> the development of small, but complex RNNs can be forced. The minimality of the resulting RNNs allows us the study of their behavior relevant dynamics in a reasonable depth. Many examples demonstrate the utilization of complex phenomena for behavior control, like bistability<sup>6</sup>, quasi-periodic<sup>7</sup> and chaotic attractors<sup>8</sup>. But minimal control structures of autonomous systems support also the study of embodiment<sup>9</sup>. Finally, the “embedding” of complex neurodynamics into the sensorimotor-loop can also offer interesting questions in the field of dynamical systems theory. Within this theory neuro-control for autonomous robots can be formally described as parameterized dynamical systems that underlie specific boundary conditions. These boundary conditions are represented by the characteristics of the system’s parameters. Specific parameter characteristics, like the time scale on that a parameter is operating, can evoke interesting transient effects. Such transient effects can, for instance, create adaptive low-pass-filter<sup>10</sup>.

### **ISEE: A structure evolution environment**

All the above mentioned examples suggest the strong interdependency of synthesis and analysis of complex behavior control in order to get new insights into the neuro-dynamical effects and phenomena underlying cognitive phenomena. Our integrated structure evolution environment (ISEE) provides a unified framework for the evolution and analysis of RNNs. The evolution is open to diverse robot platforms and experimental setups due to a general interface that enables the connection to each reasonable robot simulation.

The activities of a RNN can be analyzed during the robot-environment interaction, but also off-line to simulate the RNNs as isolated dynamical systems, e.g. computation of bifurcation diagrams and iso-periodic plots, etc. The versatility of ISEE is sketched in the figure, where the general architecture and some sample applications are given, like the evolution of complex control for sensor-driven walking machines, co-evolution of different populations of cooperating controllers, co-evolution of morphology and control of a simulated bipedal walker and finally the evolution of swarm behavior.



**Fig.1.** Some applications of the ISEE package

Among others, these examples indicate that evolution and analysis of minimal, but complex neural control provide a promising framework for further studies of cognitive phenomena.

## References

1. Port, R. F. & Gelder, v. T. *Mind as Motion* (MIT Press, Cambridge 1995).
2. Beer, R. D. A dynamical systems perspective on agent environment interaction. *Artificial Intelligence*, **72**, 173-215.
3. Pasemann, F., Neuromodules: A dynamical systems approach to brain modeling, in: Hermann, H., Pöppel, E. & Wolf, D. (eds.) *Supercomputing in Brain Research – From Tomography to Neural Networks*.
4. Nolfi, S. & Floreano, D. *Evolutionary Robotics* (MIT Press, Cambridge 2000).
5. Langton, C. G. *Artificial Life* (MIT Press, Cambridge 1995).
6. Hülse, M., Wischmann, S. & Pasemann F.: Structure and function of evolved neurocontrollers for autonomous robots. *Connection Science*, **16**, 294–26.
7. Wischmann, S., Hülse, M., Knabe, J. & Pasemann F.: Synchronization of internal neural rhythms in multi-robotic systems. *Adaptive Behavior*, in press.
8. Pasemann, F.: Evolving neurocontrollers for balancing an inverted pendulum, *Network: Computation in Neural Systems*, **9**, 495-511.
9. Pfeifer, R. & Scheier, C. *Understanding Intelligence* (MIT Press, Boston, 1999).
10. Manoonpong, P., Pasemann, F., Fischer, J. & Roth, H. : Neural Processing of Auditory Signals and Modular Neural Control for Sound Tropism of Walking Machines. *International Journal of Advanced Robotic Systems*, **2**, 223-235.