Formalizing Emergence to Accelerate the Accretion of Embodied Intelligence

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Introduction

The emergence of spatially and/or temporally coherent structures is a basic phenomenon observed for interacting non-linear systems; and it is recognized that an understanding of emergent phenomena is of fundamental importance in the study of living organisms, and, the point made here, especially for the development of embodied intelligent systems.

Understanding intelligence in the sense of being able to deal with the physical properties of ones eco-niche in a life sustaining way [1], a higher level of intelligent or cognitive behavior can be expected to result from an emergent process, induced by the growing complexity of an agents internal composition, and the way it interacts (morphology, motor system) with its environment and perceives this interactions (sensor system).

Often the attempt to define emergence on the background of, and with reference to a particular theory is often assumed to be counter-productive because of its arbitrariness and limitations. Nonetheless, if one wants to make this concept a productive analytical tool for investigations, a formal definition may be of help, even if one approaches the problem only with regard to the limited applicability in the context of a specific theory.

Modular Neurodynamics and Evolutionary Robotics

Following a modular neurodynamics approach to cognitive systems [4] and applying it to Evolutionary Robotics [2], the realizable reactions and behaviors, as well as the capacity of cognitive abilities, like different types of memory, prediction, and planning, depend crucially on the richness of the attractor structure of the underlying neural control system.

Dynamical systems of this kind can in general not be constructed in terms of a fully connected neural system. It therefore is appropriate to start with specialized neuromodules developed already for specific sensor systems, motor configurations and tasks, and then using evolutionary fusion techniques [5] to generate enfolding structures by adding sensors (*sensor fusion*) and motors together with additional neurons and connections to solve a more comprehensive task. When applying such a fusion processes new qualitative behaviors can appear which are emergent in the sense that these – desired

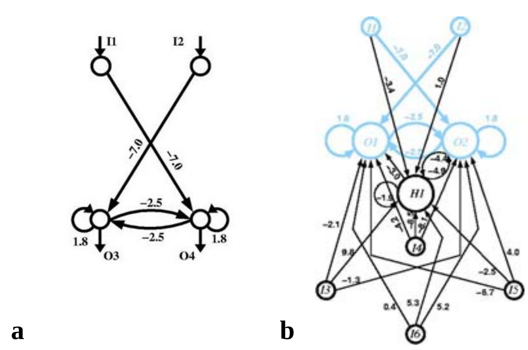

Fig. 1 a) A simple obstacle avoidance controller with two inputs and two motor neurons, **b)** light tropism (4 inputs one neuron) added by fusion (for a Khepera robot)

- properties (or solutions for a given task) are neither realizable by the original modules, nor can they be foreseen beforehand. The question then arises, if one can find general (mathematical) conditions for a fusion process, under which emergent properties or behaviors have to be expected. Or, what is almost as effective and perhaps more realistic to be achieved, is to characterize those coupling structures which will suppress emergent dynamical phenomena.

Measuring Behavior Relevant Dynamical Complexity

Concentrating on neural control systems (neuromodules) as parametrized discrete-time dynamical systems, a quantitative notion of emergence has to be based on a convenient behavior oriented measure of dynamical complexity. Like emergence, the term complexity is context dependent, and there are many different attempts to define this concept. But measures based on generalized dimensions, entropies, and Lyapunov exponents give rise to computational difficulties in high-dimensional systems, and other approaches based on local linearization, will probably miss the global character of emergent dynamical properties.

Here measures are discussed which seem to be appropriate for describing the power of a neuromodule **A** with respect to its possible contribution to the "cognitive" abilities of the whole system. They are based on a discrete-time variant of *topological complexity* introduced in [3]. After defining a convenient equivalence relation on attractor configurations (structural stability) of neuromodules, the measure describes the "distance" of an attractor configuration to a trivial one (globally stable fixed point attractor) by counting the minimal number of bifurcations one has to cross going along all possible paths in parameter space. Taken over all possible attractor configurations of the neuromodule **A** one derives its complexity γ(**A**).

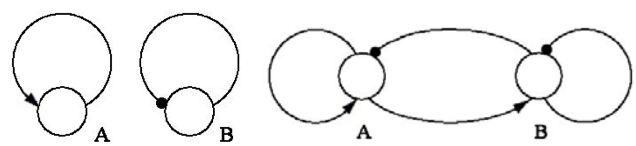

Fig. 2. A self-excitatory neuron **A** (hysteresis element) recurrently coupled to a self- inhibitory neuron **B** (period-2 oscillator) gives a parametrized 2-neuron system (**A**,**B**) capable of periodic, quasi-periodic and chaotic dynamics. Its dynamical complexity γ(**A**) is larger than that of the disjoint system A and B; i.e. γ(**A,B**) > γ(**A**) + γ(**B**).

References

1. Pfeifer, R. & Scheier, C. *Understanding Intelligence* (MIT Press, Boston, 1999).
2. Nolfi, S., & Floreano, D. *Evolutionary Robotics: The Biology, Intelligence, and Technologyof Self-Organizing Machines* (MIT Press, Cambridge, 2000).
3. Thom, R. *Structural Stability and Morphogenesis* (Benjamin, Reading, 1975).
4. Pasemann, F., Neuromodules: A dynamical systems approach to brain modelling, in: Herrmann, H., Pöppel, E. & Wolf, D. (eds.) *Supercomputing in Brain Research - From Tomography to Neural Networks* (World Scientific, Singapore, 1995), pp. 331 - 347.
5. Hülse, M., Wischmann, S. & Pasemann, F., Structure and function of evolved neuro-controllers for autonomous robots, *Connection Science*, 16:4, 2004, p.294 - 266.