A Survey of Information Driven Self Organizing Approaches

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Introduction

- In nature there are many kinds of loosely coupled networks of intelligent agents, largely varying in terms of quantity of agents and cognitive and adaptive capacity (i.e. of computational needs) of each agent.
- In the natural domain the most widely used method of 'intelligence', computation and 'cognition' are 'embodied' biological neural networks.

Introduction

A number of empirical and theoretical researches are investigating, on one side on the aspects and implication of 'embodiment', particularly interesting in the walking machine domain, on the other side on the 'emergence' of cognition from network interaction of physical agents

The (Shannon) entropy:

$$H(x) = -\sum_{x \in X} p_x(x) \log p_x(x)$$

Mutual Information

It is given by a function of the mutual information, between the sensors and the actuators connected to that node. The mutual information between two given variables is given by equation (4), where X and Y two random variables:

$$I(X,Y) = -\sum_i \sum_j P_{XY}(i,j) \log \frac{P_X(i) P_Y(j)}{P_{XY}(i,j)}$$

If X and Y are statistically independent eq above gives $I(X,Y)=0$

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Lungarella, Sporns (2006)

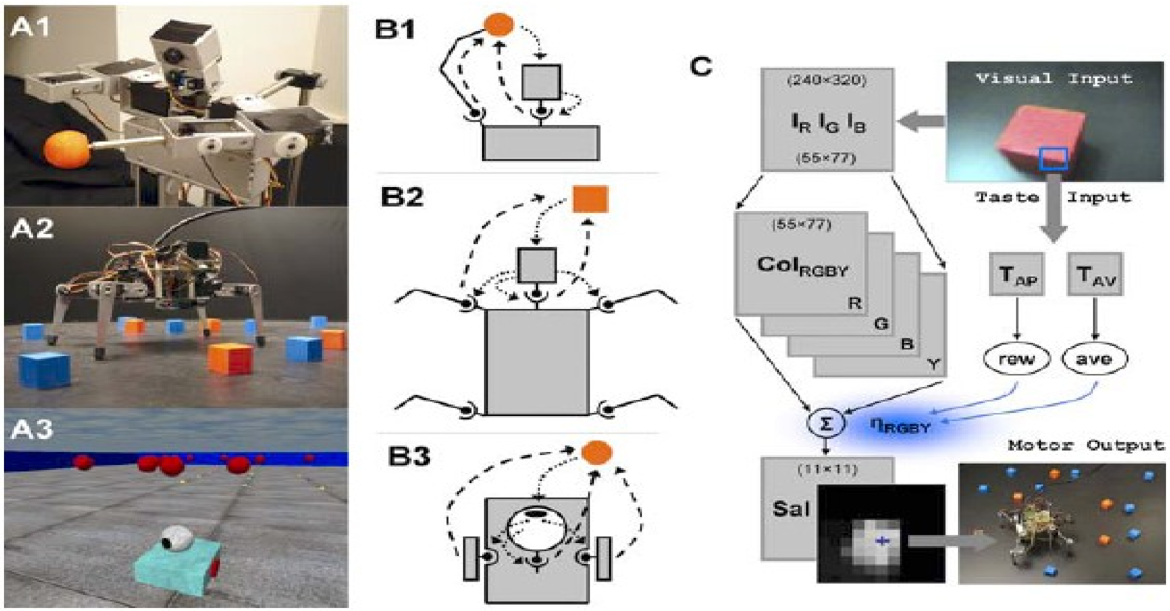

Figure 1. Robots, Sensorimotor Interactions, and Neural Control Architecture

(A1) *Roboto* has a total of 14 DOF, five of which are used in the current set of experiments. Note the head-mounted CCD camera, the pan-tilt head system (2 DOF), and the moveable left arm with shoulder, elbow, and wrist joints (3 DOF). The object is a red ball (1.25 inches diameter) attached to the tip of the last joint.

(A2) *Strider* has a total of 14 DOF, with four legs of 3 DOF each and 2 DOF in the pan-tilt head system. Objects are red and blue blocks (1 inch cubes). *Strider* is situated in an environmental enclosure with black walls.

(A3) *Madame* has 4 DOF, with 2 DOF in the pan-tilt system and 2 DOF for the wheels, which are both located on an axis vertical to the main body axis. The environment is a square arena bounded by blue walls containing 20 red-colored floating spheres.

(B1) *Roboto* engages in sensorimotor interactions via the head system and arm movements; sensory → motor (dotted arrows), motor → sensory (dashed arrows).

(B2) *Strider* engages in sensorimotor interactions via the head system, as well as via steering signals generated by the head and transmitted to the four legs.

(B3) *Madame*'s behavior consists of a series of approaches to colored objects and ovations. Fixations to the objects are maintained by independent action of head and body.

(C) Neural control architecture. The architecture common to all robots is composed of color image arrays I_R, I_G, I_B, color- intensity map $\mathbf{Col}_{RGBY}$, and saliency map *Sal* (see text for details). The peak of the saliency map (blue cross) determines the pan-tilt camera motion and body steering. In addition, *Strider*'s neural system contains a value system with taste sensory inputs relayed via a virtual taste sensor (blue square in visual image) to taste neurons ($T_{AP,AV}$), which in turn generates reward and aversiveness signals (rew, ave). These signals are used to modulate the strengths of the saliency factors η_{RGBY} (see text for details).

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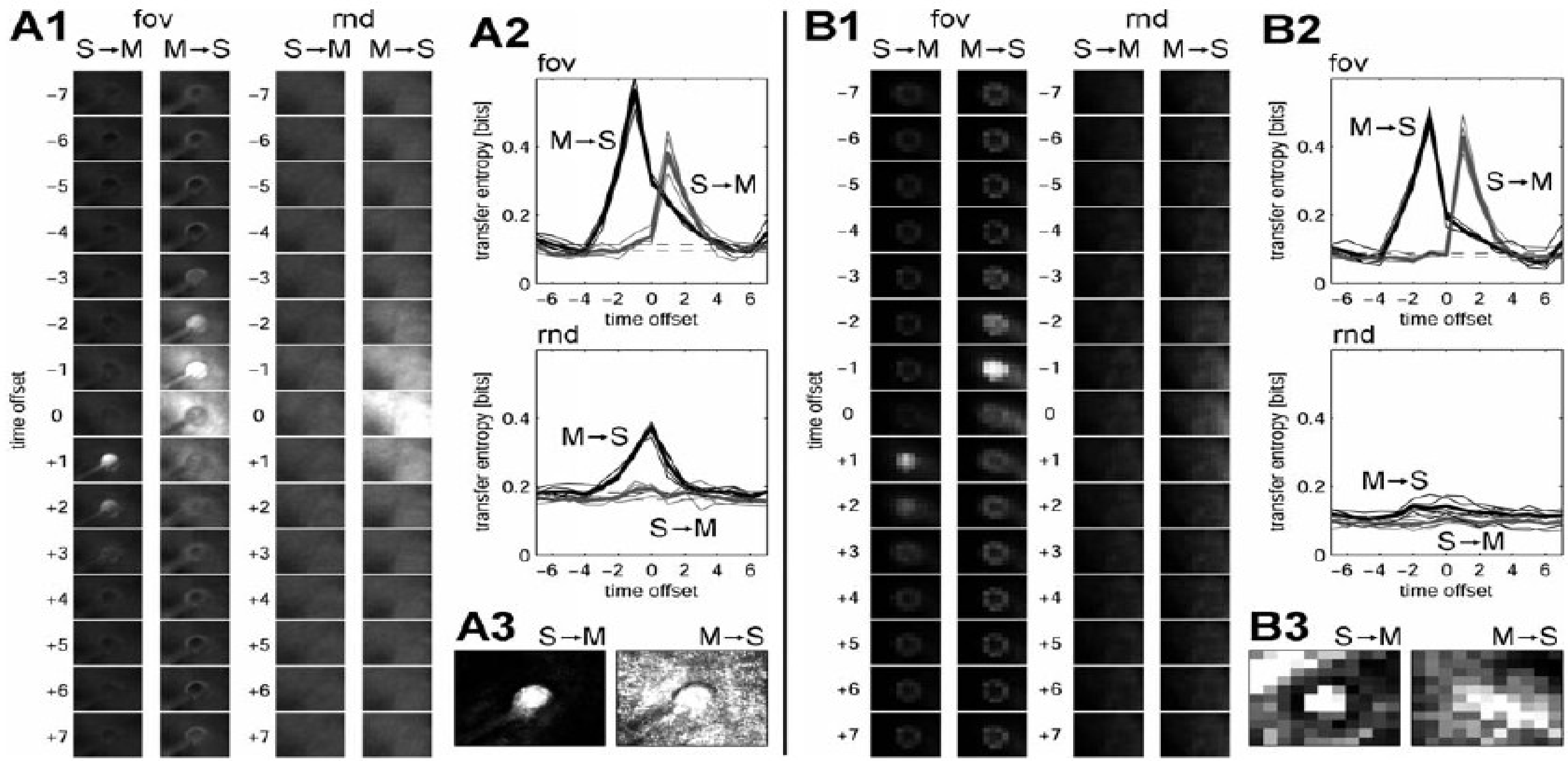

Figure 3. Information Flow (Transfer Entropy) between Sensory Input, Neural Representation of Saliency, and Motor Variables in *Roboto*

(A1) Transfer entropy between array I_R (variable S) and pan-tilt amplitude (variable M). Series of plots show maps of transfer entropy from S to M (S $\rightarrow$ M) and from M to S (M $\rightarrow$ S) over visual space (55 $\times$ 77 pixels), calculated for offsets between -7 ("M leading S") and $+7$ ("S leading M") time steps. Plots show data for conditions "fov" and "rnd." The gray scale ranges from 0.0 to 0.5 bits (for all plots in panels A1 and B1).

(A2) Curves show transfer entropy for five individual runs (thin lines) as well as the average over five runs (thick lines) between the single central pixel of array I_R (S) and pan-tilt amplitude (M), for directions M $\rightarrow$ S (black) and S $\rightarrow$ M (gray).

(A3) z-Score maps of significant image regions (plotted between $z = 0$ and $z = 6$). The z-scores are expressed as number of standard deviations above background at time offset +1 (S $\rightarrow$ M) and -1 (M $\rightarrow$ S). Mean and standard deviation of background is calculated from transfer entropy values at maximal time delays (-7,+7 time steps).

(B) All three panels have the same format as (A), but the neural activations of the saliency map *Sal* are substituted as variable S (11 $\times$ 11 neural units).

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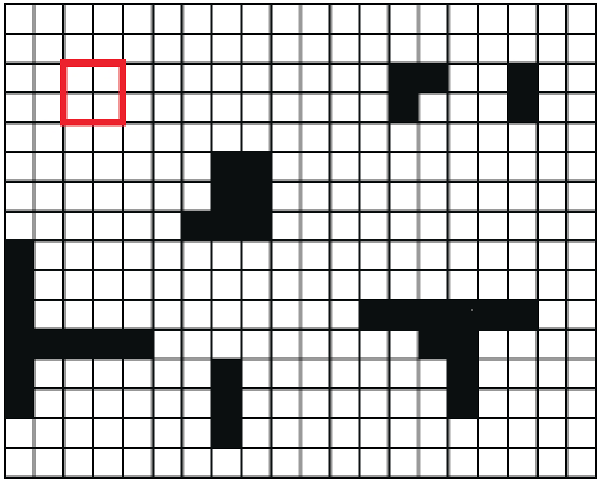
Lampe, Chatila (2006): Environment complexity

- H is defined as the entropy related to density of obstacles:

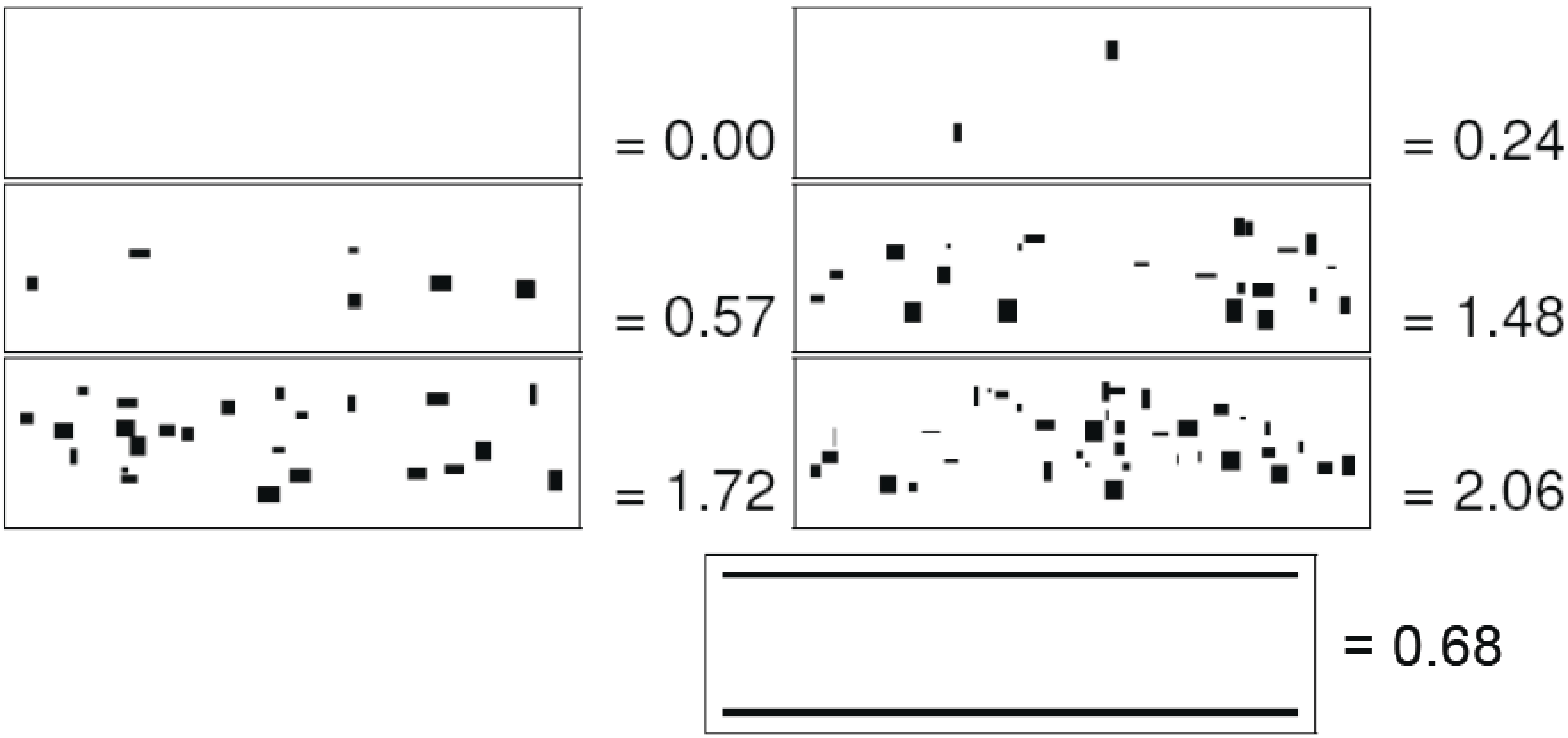


$$H = \sum_i -p(d_i) \log p(d_i)$$

$p(d_i)$ density of i-th density level in the occupancy grid,

with: $\sum_i p(d_i) = 1$

Lampe.Chatila (2006) : Entropy of cluttered environment



Information Driven Self Organization

- Several researchers have shown the importance of Information Driven Self Organization. IDSO (Information Driven Self Organisation) In particular Prokopenko , Ralf Der and other have shown simple demonstrators, mainly in simulation, with snake-bots, humanoids and grasping systems. These approaches seem very promising.

Information Driven Self Organization

Prokopenko have shown how evolutionary self-organisation can be simulated by optimizing the information-transfer within certain information channels, where 'information' is considered according to Shannon as a reduction in uncertainty.

Prokopenko, M., Gerasimov, V., and Tanev, I.: Evolving Spatiotemporal Coordination in aModular Robotic System. In Nolfi, S., Baldassarre, G., Calabretta, R., Hallam, J. C. T., Marocco, D., Meyer, J.-A., Miglino, O., and Parisi, D., editors, From Animals to Animats 9: 9th International Conference on the Simulation of Adaptive Behavior (SAB 2006), Rome, Italy, vol. 4095 of Lecture Notes in Computer Science, 558-569. Berlin, Heidelberg: Springer, (2006)

Information Driven Self Organization 'WEAK' form

Information metrics can be regarded as a quantitative criteria to compare the efficiency of different design for cognitive/intelligent/controlled systems.

“For instance, imagine a completely centralised modular robot, controlled from a single module/segment that regularly receives data from other segments, computes the best actions for every segment, and sends the instructions back. How would one systematically compare this design with other, more modular, designs? Measuring instructions' size, number of packets, memory usage, etc. would be prone to ambiguities. On the other hand, carrying out the analysis information-theoretically has the advantage of employing "the lingua franca" for multiple approaches.”

Information Driven Self Organization 'STRONG' form

Is maximization of information transfer through certain channels one of the main evolutionary pressures?

Information Driven Self Organization 'SNAKEBOT'

- Snakebot by Tanev is an example of a system built according to this principles.
- It can be shown that the amount of predictive information between groups of actuators (measured via generalised excess entropy) grows as the modular robot starts to move across the terrain. T
- The distributed actuators become more coupled when a coordinated side-winding locomotion is dominant.

Information Driven Self Organization 'SNAKEBOT'

Note that if the states of the remote segments are synchronised then some information has been indirectly transferred via stigmergy (due to the physical interactions among the segments, and with the terrain)

Information Driven Self Organization Issues

- In general the amount of information managed by the controller can be measured ex-post from the information measures computed on the variables of interest: the data stream coming from propio and exteroceptor (actuation generalized torques, encoders positions and video).
- These measures can derive from simulations models or they can come from a physical system.
- One of the major issues is to develop a formal method to predict them from a given system

Methods

Klyubin (2007, 2004) combines the Bayesian network formalism with both Pearl's causality theory* and information theory.

Kaplan, F., and Oudeyer, P.-Y.: Maximizing learning progress: an internal reward system for development. In Iida, F., Pfeifer, R., Steels, L., and Kuniyoshi, Y., editors, Embodied Artificial Intelligence, vol. 3139 of LNAI, 259-270. Springer, (2004)

Klyubin, A., Polani, D., and Nehaniv, C.: Representations of Space and Time in the Maximization of Information Flow in the Perception-Action Loop. Neural Computation, 19(9):2387-2432, (2007)

Methods
Linsker and Barlow

Linsker and Barlow: It seems of interest that the application of infomax principle (principle proposed by Linsker and Barlow) leads to structured mappings - on a stochastic base - of environmental ('external') states into an agent's internal state space in a self-organized way.

Linsker, R.: Self-Organization in a Perceptual Network. Computer, 21(3):105-117, , (1988)

Linsker, R.: How to Generate Ordered Maps by Maximizing the Mutual Information between Input and Output Signals. Neural Computation, 1(3):402-411, (1989)

Methods
Linsker and Barlow

To our purpose it is notable the Klyubin approach leads to fewer assumptions on the controller architecture. While Linsker's model requires an explicit neighbourhood notion to define receptive fields, in Klyubin's the structuring drive arises without particular hypotheses as a consequence of the embodiment of the agent in its environment. Does this show the potential of utilizing the embodiment of an agent in its environment to attain the emergence of structured information processing in an unsupervised way?

Methods
Relevant Information

The relevant information quantifies the informational cost for achieving a desired behaviour. This is estimated evaluating the difference between a given, a priori, utility function measuring the performance of an agent, and the relevant environmental information necessary to achieve this value. The agent's dynamic performance is modelled with this approach as a Markovian Decision Process. This has been shown to depend critically on the quality of the sensorimotor embedding into the environment.

Methods
Relevant Information

Different approaches to derive such an utility function have been proposed all making limited process assumptions,(Kaplan et al. 2004; Steels 2004; Der 2000; Klyubin 2008).

Methods
The autotelic principle

The 'autotelic' principle (Steels, 2004) proposes that agents can become self-motivated if their target is to balance challenges and skills. The referenced paper presents an operational version of this principle and argues that it enables a developing robot to self-regulate his development.

Methods

Kaplan, F., and Oudeyer, P.-Y.: Maximizing learning progress: an internal reward system for development. In Iida, F., Pfeifer, R., Steels, L., and Kuniyoshi, Y., editors, Embodied Artificial Intelligence, vol. 3139 of LNAI, 259-270. Springer, (2004)

Steels, L.: The Autotelic Principle. In Iida, F., Pfeifer, R., Steels, L., and Kuniyoshi, Y., editors, Embodied Artificial Intelligence: Dagstuhl Castle, Germany, July 7-11, 2003, vol. 3139 of Lecture Notes in AI, 231-242. Berlin, Springer Verlag, , (2004).

Der, R.: Selforganized robot behavior from the principle of homeokinesis. In Gross, H.-M., Debes, K., and Bohme, H.-J., editors, Proc. Workhop SOAVE '2000 (Selbstorganisation von adaptivem Verhalten), vol. 643 of Fortschritt-Berichte VDI, Reihe 10, 39-46. Ilmenau: VDI Verlag, (2000)

Klyubin, A. S., Polani, D., and Nehaniv, C. L.: Keep Your Options Open: An Information-Based Driving Principle for Sensorimotor Systems. PLoS ONE, 3(12):e4018. http://dx.doi.org/10.1371%2Fjournal.pone.0004018, , (2008).

Methods

- This relevant information will be limited if the sensorimotor adaptation of the embodied agent is good and larger if it is not: the acquisition of a minimal amount of relevant information requires a minimal information flow through the agent, following a basic law of a data processing chain.
- As a consequence minimizing relevant information, a quantity that can be measured from the system sensors will lead to a better sensorimotor coordination between the physical agent and the environment.

Methods

- The concept of relevant information allow the quantification for the offloading of information processing provided by the environment and physics of the agent.

Methods

- Ralf Der at MPI Leipzig: experiences with the so called time-loop error, a complexity measure derived from dynamical system theory, operationalized in a set of on-line learning rules run effectively on agents with up to 30 independent degrees of freedom in real time, and the videos which give an impression how the self-exploration of "bodily affordances" is emerging from this general approach.

Methods

R. Der. Self-organized acquisition of situated behavior. Theory in Biosciences, 120:179—187, 2001.

R. Der, F. Hesse, and G. Martius. Rocking stamper and jumping snake from a dynamical system approach to artificial life. J. Adaptive Behavior, 14:105 — 116, 2005.

R. Der, F. Hesse, and G. Martius. Videos of self-organized creatures. http://robot.informatik.uni-leipzig.de/videos/?lang=en

Methods

The predictive information concept, also known as excess entropy was introduced by Crutchfiled [Crutchfield 1989] and while Der use the above mentioned time loop error, an effective measure complexity [Der 2006], which is a most natural complexity measure for time series.

J. P. Crutchfield and K. Young. Inferring statistical complexity. Phys. Rev. Lett., 63:105—108, 1989.

R. Der, G. Martius, and F. Hesse. Let it roll — emerging sensorimotor coordination in a spherical robot. In L. M. Rocha, editor, Artificial Life X, pages 192—198. MIT Press, August 2006.

Methods

Embodied Statistical Learning

Burfoot, D., Lungarella M., Kuniyoshi,Y.: Toward a Theory of Embodied Statistical Learning, SAB2008, Osaka (2008)

Network growth model

- So far researcher interest has focused mainly on the structural properties of random complex networks in communications, biology, social sciences and economics.
- A number of giant artificial networks of such a kind came into existence recently. This opens a wide field for the study of their topology, evolution, and complex processes occurring in them.

Network growth model

- Such networks possess a rich set of scaling properties. A number of them are scale-free and show striking resilience against random breakdowns. In spite of large sizes of these networks, the distances between most their vertices are short, a feature known as the “small world” effect.
- It is known that growing networks self-organize into scale-free structures through the mechanism of preferential linking.

Network growth model

- Numerous networks, e.g., collaboration networks, public relations nets, citations of scientific papers, some industrial networks, transportation networks, nets of relations between enterprises and agents in financial markets, telephone call graphs, many biological networks, food and ecological webs, metabolic networks in cell etc., can be modeled in this way.
- It is thought that evolving self organizing networks can (could) model the collective knowledge of a network of intelligent (artificial) autonomous agents. the previous one, according to their 'fitness'.

Future Work

- Information related measures coming from Shannon entropy may help the understanding of intelligent cognitive controlled systems
- What we probably need to build 'real' artificial cognitive systems is a deep interchange of concepts, methods and insights between fields so far considered well distinct like information and control theory, non linear dynamics, general AI and psycology and neurosciences.
- Do we??? :-)

Thank you!

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