4th International Conference on Cognitive Systems
CogSys 2010
January 27 & 28, 2010, ETH Zurich, Switzerland

Information Driven Self Organisation of Physically Embedded Controllers

How the information driven self organization paradigm may help the development of emergent sensory motor controllers more flexible than current ones.

Fabio P. Bonsignorio, fabio.bonsignorio@uc3m.es, fabio.bonsignorio@heronrobots.com
Ceo,Heron Robots s.r.l.,Genova, Italy
Prof, Santander Chair of Excellence in Robotics, UC3M, Madrid, Spain
Board Member Euron 3

To take robots out of the factories in everyday life is not a free lunch.
Have we the science or even the concept framework to deal with open ended unstructured environments?

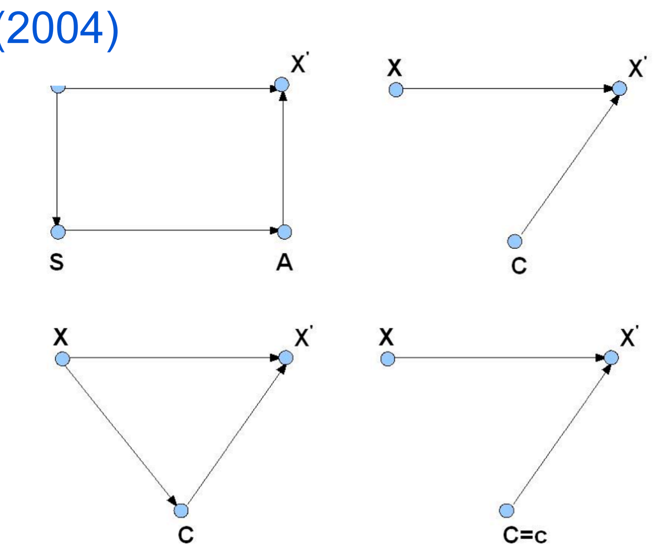
In nature there are many kinds of loosely coupled networks of intelligent agents, largely varying in terms of quantity of agents and cognitive and adaptive capacity (i.e. of computational needs) of each agent.
In the natural domain the most widely used method of 'intelligence', computation and 'cognition'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

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

(Just) a point of view :-)

Information related measures coming from Shannon entropy may help the understanding of intelligent cognitive controlled systems
What we probably need to be able 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.

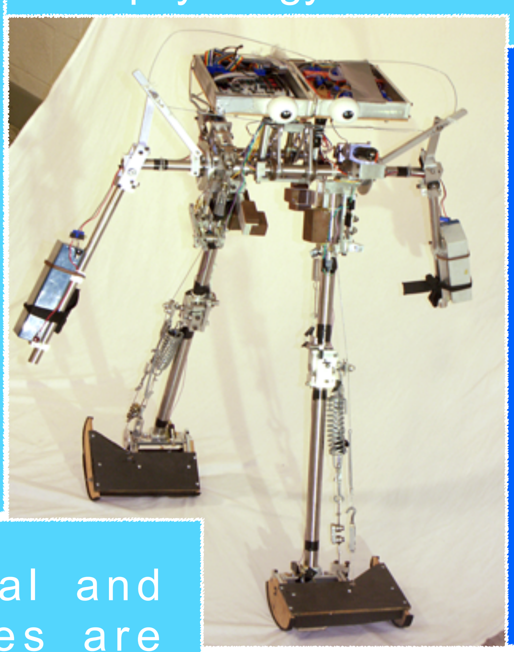
Touchette,
Lloyd (2004)



Directed acyclic graphs representing a control process. (Upper left) Full control system with a sensor and an actuator. (Lower left) Shrinked Closed Loop diagram merging sensor and actuator, (Upper right) Reduced open loop diagram. (Lower right) Single actuation channel enacted by the controller's state C=c.

Probabilistic Modeling of Control

Although it may seem strange only in recent times the classical results from Shannon theory, have been applied to the modeling of control systems.
As the complexity of control tasks namely in robotics applications lead to an increase in the complexity of control programs, it becomes interesting to verify if, from a theoretical standpoint, there are limits to the information that a control program must manage in order to be able to control a given system.



Cornell's passive walker

(see Garcia, Chatterjee, Ruina, Coleman, 1998)

$$K(X) \overset{+}{\leq} \log \frac{W_{closed}}{W^{\max}_{open}} \qquad \mathbf{I}$$

$$\Delta HN + \sum_i \Delta H_i - \Delta I \leq I(X;C) \qquad \mathbf{II}$$

$$K(X) = \Delta HN + \sum_i^n \Delta H_i - \Delta I \qquad \mathbf{III}$$

$$\Delta HN = \log \frac{\Omega_{closed}}{\Omega_{\max}} + \Delta I \qquad \mathbf{IV}$$

$$\Omega_{closed} = \frac{W_{closed}}{\prod_i^n W_{closed(i)}} \qquad \Omega^{\max}_{open} = \frac{W^{\max}_{open}}{\prod_i^n W^{\max}_{open}}$$

Information metrics and phase space: preliminary relations

With some rough cut hypotheses you can derive the left side relationships.
Relation (I) links the complexity ('the length') of the control program of a physical element to the state available in closed loop and the non controlled condition.
This show the benefits of designing stuctures whose 'basin of attractions' are close to the desired behaviors in the phase space.
Relation (II) links the mutual information between the controlled variable and the controller to the information stored in the elements, the mutual information between them and the information stored in the network and accounts for the redundancies through the multi information term ΔI.
Relation (III) links the program complexity of the controller to the information stored in the elements, the mutual information between them and the information stored in the network.
Relation (IV) links the program complexity of the controller to the information stored in the elements the mutual information between them and the information stored in the network.
(see Bonsignorio, 2009, 2007)

The (or ... some :-)) big questions

How the new paradigms in AI, from swarm intelligence to morphological computation and complex adaptive systems theory applications, (could) help robotics?
Is robotics the science of embodied cognition?

Is there a need to extend computation theory to manage the interaction with the physical world?

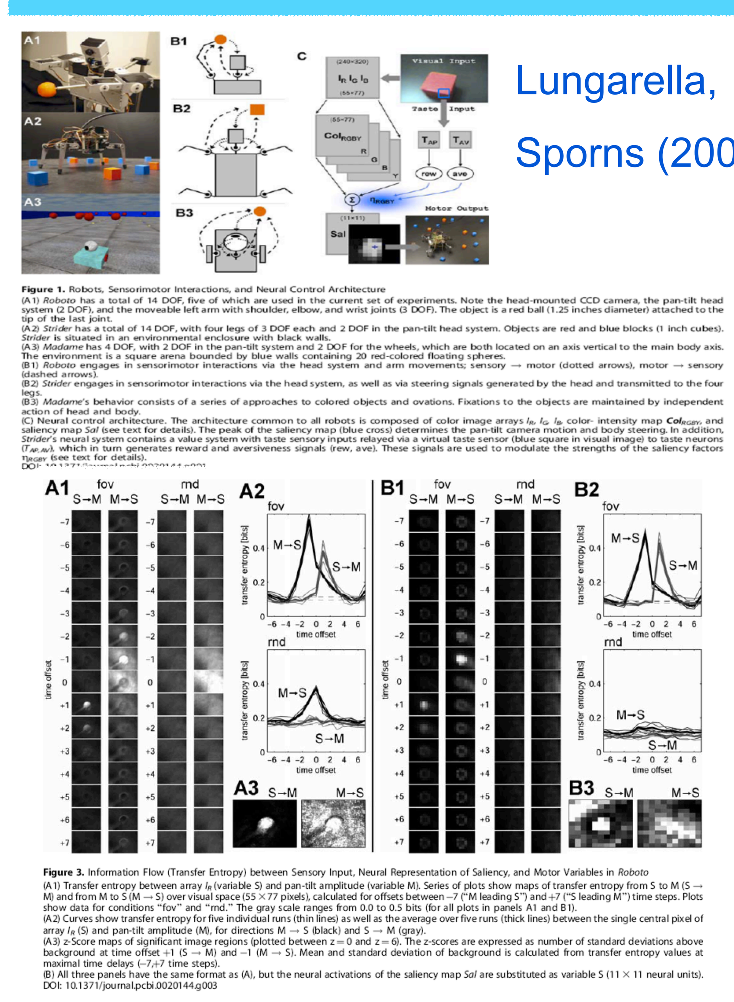
Does robotics needs a 'paradigm change' from top-down symbolic processing to emerging self-organized cognitive behaviors of complex adaptive dynamical systems?

Which relations are there between new AI, the US NSF idea of CyberPhysical Systems Science, and the concepts of embodied and situated cognition popular in European cognitive sciences community and a significant part of the robotics community?

What does it mean in this context to be 'biomimetic'?

How to quantify? ex-post...

as in:
Lungarella, M., Sporns, O. (2006)



Lungarella,
Sporns (2006)

IDSO (not complete) Survey

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.
This is called Information Driven Self Organization.

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)

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.
The distributed actuators become more coupled when a coordinated side-winding locomotion is dominant.

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)

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)

Der, Ay et al. (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.

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

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

Ay, N., Bertschinger, N., Der, R., Güttler, F., Olbrich, E.: Predictive information and ex- plorative behavior of autonomous robots. In: European Conference on Complex Systems, Dresden (2007)

Embodied Statistical Learning

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

Quantifying Sensory-Motor Coordination

Lungarella, M., Sporns, O.: Mapping Information Flow in Sensorimotor Networks. PLOS Computational Biology 2(10), 1301–1312 (2006)

IDSO and 'embodiment'

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: 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

Steps Forward?

- IDSO in the 'real' world: (SE(3) with tan-gent space se(3): information metrics should be computed on Lie groups with Lie algebra - alike what it happens in rela world? - more than on 'flat' Rn spaces?
- networks of chaotic oscillators: should we exploit explicitly the results of statistical physics of networks and go forward?

General References

Bonsignorio,F.P., Preliminary Considerations for a Quantitative Theory of Networked Embodied Intelligence. In M. Lungarella et al. (Eds.): 50 Years of AI, Festschrift, LNAI 4850, pp. 112–123, Springer-Verlag Berlin Heidelberg, 2007
Bonsignorio,F.P.,Steps to a Cyber-Physical Model of Networked Embodied Anticipatory Behavior.In G. Pezzulo et al. (Eds.): ABiALS 2008, LNAI 5499, pp. 77–94, Springer-Verlag Berlin Heidelberg, 2009
Shannon, C.E.: The Mathematical Theory of Communication. Bell Sys. Tech. J. 27, 379, 623 (1948)
Pfeifer,R.:Cheap designs: exploiting the dynamics of the system-environment interaction. Three case studies on navigation. In: Conference on Prerational Intelligence ,Phenomonology of Complexity Emerging in Systems of Agents Interacting Using Simple Rules, pp. 81–91. Center for Interdisciplinary Research, University of Bielefeld (1993)
Lungarella, M., Iida, F., Bongard, J., Pfeifer, R. (eds.): 50 Years of AI. Springer, Heidel- berg (2007)
Touchette, H., Lloyd, S.: Information-theoretic approach to the study of control systems. Physica A 331, 140–172 (2003)
Gomez, G., Lungarella, M., Tarapore, D.: Information-theoretic approach to embodied category learning. In: Proc. of 10th Int. Conf. on Artificial Life and Robotics, pp. 332–337 (2005)
Philipona, D., O' Regan, J.K., Nadal, J.-P., Coenen, O.J.-M.D.: Perception of the structure of the physical world using unknown multimodal sensors and effectors. In: Advances in Neural Information Processing Systems (2004)
Olsson,L.,Nehaiv,C.L.,Polani,D.:InformationTrade-OffsandtheEvolutionofSensory Layouts. In: Proc. Artificial Life IX (2004)
Garcia, M., Chatterjee, A., Ruina, A., Coleman, M.: The Simplest Walking Model: Stability, Complexity, and Scaling, Transactions of the ASME. Journal of Biomechanical Engi- neering 120, 281–288 (1998)
Albert, R., Barabasi, A.L.: Statistical physics of complex networks. Rev. Mod. Phys. 74, 47–97 (2002))
Kopell,N.,Ermentrout,G.:Phasetransition and other phenomena in chains of coupled oscillators. SIAM J. Appl. Math. 50, 1014–1052 (1990)
Rus, D.L.: Robotics as Computation for Interaction with the Physical World. In: Special Session on CyberPhysical Systems, IEEE/RSJ 2008, Nice (2008)