Logic Systems Laboratory (EPFL):

Roadmap in Artificial Neural Network technologies

The Logic Systems Laboratory, School of Computer and Communication Sciences, Swiss Federal Institute of Technology-Lausanne (EPFL) conducts research along three primary lines: (1) bio-inspired systems, (2) development and analysis of innovative hardware architectures, including new microprocessor architectures and custom processors based on reconfigurable logic, and (3) biologically inspired robots.

Artificial Neural Network technologies play an important role in these different research directions. In this document, we summarize the state of the art and our vision for the future in five specific research areas: 1) the POEtic project, 2) Developmental approaches in hardware, 3) Neural networks for locomotion control in animals and robots, 4) Neural networks for modular robotics, and 5) Implementing hybrid intelligent methodologies in hardware.

1) The POEtic project

State of the art

The development of bio-inspired systems [1], like artificial neural networks, evolvable hardware, embryonic cellular arrays [2], or genetic algorithms, has increased in the last years. Field Programmable Gate Arrays (FPGAs) are interesting tools for prototyping such systems since they allow rapid prototyping, but these circuits are not fit for the implementation of cellular and growing systems. No actual circuit is currently general enough to implement different kinds of neural networks or other learning mechanisms, and specialized enough for the development of efficient multi-cellular systems.
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[1] D. Mange and M. E. Tomassini. Bio-Inspired Computing Machines. PPUR, Lausanne, 1998.
[2] D. Mange, M. Sipper, A. Stauffer, G. Tempesti. Towards Robust Integrated Circuits: the Embryonics Approach. *Proceedings of the IEEE* 88(4):516-541.

Vision for the future

The POEtic [1] project [2][3][4], in collaboration with the universities of Barcelona (UPC), York, Glasgow and Lausanne, plans to realize an electronic tissue for efficiently implementing bio-inspired applications, following the 3 life-axis: Phylogenetic (evolution), Epigenetic (learning) and Ontogenetic (growth and development). This tissue is presented as a programmable electronic circuit. It is based on a grid of molecules similar to standard FPGA cells, containing a look-up-table and a D flip-flop. A second plane composed of dynamically reconfigurable connections allows the creation of long distance connections. Molecules are used to implement different types of cells, like artificial neurons, and the reconfigurable connections are used for inter-cellular links. Finally, an on-chip micro-controller manages the input/output, and the evolution process (phylogenetic axis).

[1] M. Sipper, E. Sanchez, D. Mange, M. Tomassini, A. Pérez-Uribe, A. Stauffer. The POE Model of Bio-Inspired Hardware Systems: A Short Introduction. In J. Koza & al., editors, *Genetic*

Programming 1997, Proceedings of the Second Annual Conference, pp. 510-511. Morgan Kaufmann, San Francisco, 1997.
[2] G. Tempesti, D. Roggen, E. Sanchez, Y. Thoma, R, Canham, A. Tyrrell, J.-M. Moreno. A POEtic Architecture for Bio-Inspired Systems. *Proc. 8th Int. Conf. on the Simulation and Synthesis of Living Systems (Artificial Life VIII)*, Sydney, Australia, December 2002, pp.111-115.
[3] A.M. Tyrrell, E. Sanchez, D. Floreano, G. Tempesti, D. Mange, J.-M. Moreno, J. Rosenberg, A. Villa. POEtic Tissue: An Integrated Architecture for Bio-Inspired Hardware. *From Biology to Hardware: Proc. 5th Int. Conf. on Evolvable Hardware (ICES '03)*, Trondheim, Norway, March 2003 (to appear).
[4] www.poetictissue.org

2) Developmental approaches in hardware

State of the art

Aside from some theoretical models for implementing developmental approaches to computer science, this axis of bio-inspired research has been exploited mostly for the growth and on-line structural adaptation of neural networks (see, for example, [1]) or, to a lesser extent, for the morphogenesis of robots (e.g., [2]). With some rare exceptions [3], the overhead implicit in the realization of developmental approaches have limited their application to simulations.

[1] B. Fritzke. Growing Cell Structures: A Self-Organizing Network for Unsupervised and Supervised Learning. Neural Networks 7(9):1441-1460, 1994.
[2] F. Dellaert and R.D. Beer. Toward an Evolvable Model of Development for Autonomous Agent Synthesis. Artificial Life IV: Proc. 4th Intl. Workshop
on the Synthesis and Simulation of Living Systems. MIT Press, Cambridge, MA.
[3] D. Mange, M. Sipper, A. Stauffer, G. Tempesti. Towards Robust Integrated Circuits: the Embryonics Approach. Proceedings of the IEEE 88(4):516-541.

Vision for the future

While in the past the implementation of ontogenetic approaches in hardware has been essentially limited to simulations, the projected complexity of the future generations of computing circuits (e.g., nanotechnologies) introduces a need for hardware-friendly developmental mechanisms to provide the twin properties of self-organization (to give structure to circuits too complex to be designed by conventional means) and fault-tolerance (to generate circuits able to operate in the presence of unavoidable faults). Some recent research efforts have been going in this direction [1][2][3], but much remains to be done, particularly where development is coupled with other bio-inspired mechanisms such as evolution (evolving development) and learning (growth of adaptive systems).

[1] D. Mange, M. Sipper, A. Stauffer, G. Tempesti. Towards Robust Integrated Circuits: the Embryonics Approach. Proceedings of the IEEE 88(4):516-541.
[2] T.G.W. Gordon, P.J. Bentley. Towards Development in Evolvable Hardware. Proc. 2002 NASA/DoD Conference on Evolvable Hardware (EH'02), IEEE Computer Society Press, Los Alamitos, CA.
[3] R. Timothy Edwards. Circuit Morphologies and Ontogenies. Proc. 2002 NASA/DoD Conference on Evolvable Hardware (EH'02), IEEE Computer Society Press, Los Alamitos, CA.

3) Neural networks for locomotion and motor control in animals and robots

State of the art

Animal-like locomotion, i.e. the use of multiple degrees-of-freedom in a rhythmic way such as to obtain forward motion, is a fascinating phenomenon which requires complex control mechanisms. In animals, the locomotor neural networks are often based on Central Pattern Generators (CPGs), networks capable of producing multiple stable rhythmic signals which are modulated by simple tonic (i.e. non-rhythmic) inputs. Numerical simulations of neural networks are extensively used to get a better understanding of these circuits (cf [1, 2]). Since the 1990's, biomimetic robots are increasingly used to test the validity of these neural network models [3]. This creates interesting interactions between neuroscience and robotics, with on one hand robots being used as tools for testing hypotheses of animal motor control, and on the other hand the development of new biologically-inspired adaptive control algorithms for robots.

[1] Grillner, S., Degliana, T., Ekeberg, O., El Marina, A., Lansner, A., Orlovsky, G., &Wall_en, P. (1995). Neural networks that co-ordinate locomotion and body orientation in lamprey. Trends in Neuroscience, 18 (6), 270-279.
[2] Ijspeert, A.J.: Vertebrate locomotion, in *The Handbook of Brain Theory and Neural Networks, Second Edition*, M.A. Arbib (Ed.), Cambridge, MA: The MIT Press, 2002, pp 649-654
[3] Neurotechnology for biomimetic robots, Ayers, J., Davis, J.L, Rudolph A. (Eds), Bradford Books, 2002.

Vision for the future

We expect that artificial neural network technologies will play an increasing role in robotics, in particular, in situations where the environment in which the robot has to move is unknown or only partially known. In these situations, trajectories of limbs can not be planned in advance and the most promising approach is the use of adaptive control algorithms which rely on perturbation-resistant rhythm generation and fast reflex pathways for robust locomotion. The use of genetic algorithms to optimize robust pattern generators in simulation appears to be one of the most promising approaches, since genetic algorithms do not require computing a gradient of the cost function (which would be a very difficult task since locomotion is the result of a complex nonlinear interaction between the controller, the body, and the environment) and can directly optimize criteria based on actual movements performed by the robot [1, 2]. In some cases, if demonstrations of useful movements can be obtained, another approach is to use statistical learning algorithms, such as locally weighted learning, to do learning of movements by imitation [3]. Finally, reinforcement learning algorithms have an important role to play for problems of online learning with low dimensional search spaces.

[1] Beer, R. and Gallagher, J. Evolving dynamical neural networks for adaptive behavior. Adaptive Behavior 1, 1992, pp 91-122.
[2] Ijspeert A.J.: A connectionist central pattern generator for the aquatic and terrestrial gaits of a simulated salamander, Biological Cybernetics, Vol. 84:5, 2001, pp 331-348.
[3] Ijspeert A.J., Nakanishi J., Schaal S.: Learning attractor landscapes for learning motor primitives, *Advances in Neural Information Processing Systems 15* (NIPS2002), Becker S., Thrun S., Obermayer K. (Eds), to appear.

4) Neural networks for modular robotics

State of the art

Modular robotics aims at developing robots with multiple degrees of freedom constructed from multiple simple units each possessing their own actuation, energy sources, and control mechanisms. The goal is to obtain robots which can either be quickly constructed by an engineer for a specific task, or which can autonomously self-configure according to the task and the environment. The motivation of using multiple simple units is two-fold: to obtain robustness through redundancy, and to be able to continuously adapt the configuration of the robot to the task at hand (in terms of number of degrees of freedom and energy requirements, for instance), rather than constructing a single but non modifiable sophisticated robot. This second point is especially important for applications in unknown environments where the best configuration of the robot might not be known in advance, and for applications requiring important changes in the robot shape (e.g. a task which requires sliding through a small opening, and then a manipulation of an object with several limbs). Examples of exciting projects working in this field include the CONRO project at the University of Southern California [1], the modular robotics project at the Palo Alto Research Center [2], and the European Swarm-bot project [3] to which EPFL's Autonomous Systems Laboratory participates.

[1] http://www.isi.edu/conro
[2] http://www2.parc.com/spl/projects/modrobots
[3] http://www.swarm-bots.org

Vision for the future

Developing controllers for a modular robot is a difficult task since the controllers must be adapted to the configurations of the robot and to tasks which are not necessarily known in advance. A particularly challenging design problem is the development of controllers which can optimize global behavior of the robot while being implemented locally in each unit. Local learning rules therefore need to be designed such as to optimize global behavior (e.g. the speed of locomotion of the robot) through a process of self-organization. This directly relates to the type of problems addressed by the POEtic project described above, and we therefore intend to extend the notions of self-configurable electronics to control modular robots.

5) Implementing hybrid intelligent methodologies on hardware

State of the art

Living organisms are capable of adapting to changing environments to a far greater degree than man-made devices. To reduce this gap, adaptive methodologies such as evolutionary computation (EC), neural networks (NN), and fuzzy logic (FL) have been conceived. Moreover, recent research tries to combine NN, EC, and FL so as to take advantage of their complementarities: **Neural-fuzzy hybrid approaches** [1, 7] combine plasticity (NN) and knowledge representation (FL) to design adaptive, human-friendly systems; **(2) Evolutionary fuzzy modeling (EFM)** [3, 4, 6] applies evolutionary algorithms to solve the fuzzy modeling problem with knowledge-tuning or structure-learning techniques. **(3) Evolutionary artificial neural networks** [10] are artificial neural networks in which evolution is applied as another form of adaptation for tasks such as connection-weight training, architecture design, and learning-rule adaptation.
In hardware systems, learning and evolution are two forms of adaptation implying, at different time-scales, modifications in the functionality and structure of a circuit. **Evolvable hardware** combines evolutionary algorithms and hardware devices for on- or off-chip evolutionary circuit design, hardware design with embedded evolution, and open-ended hardware evolution [2, 8, 9]. **Configurable Neural Hardware** uses on- or off-chip learning, either adapting the connection weights or modifying the network's topology [2, 5]. **Configurable fuzzy hardware implements** adaptive evolutionary-fuzzy or neural-fuzzy systems.

Vision for the future

The development of adaptive systems is rapidly coming to an impasse, calling for novel solutions to be embedded into electronic devices. A promising approach proposes to replace current software-oriented architectures with novel hardware-oriented computing platforms, whose design will be guided by criteria like evolvability, learning, autonomy, or real-time behavior, instead of classic criteria based on programmability. Adaptive devices built on such platforms will rely on learning strategies for life-time adaptation, and on evolutionary approaches for part of the design process, calling for novel hardware-oriented methodologies to replace the extant programming-oriented adaptive algorithms. Also, these devices shall employ human-friendly knowledge representations, such as those used in fuzzy logic, to simplify human/machine interaction. A major research effort will be required to: (1) analyze the mechanisms that govern adaptation so as to elucidate the potential roles of learning and evolution in the performance of adaptive devices; (2) develop general strategies to design on-chip adaptive algorithms; (3) integrate human-interpretable knowledge representation into adaptive devices either by adding hardware-oriented adaptive techniques to existent fuzzy architectures or by conceiving entirely novel adaptive fuzzy approaches.

[1] O. Cordón and F. Herrera. A proposal for improving the accuracy of linguistic modeling. *IEEE Transactions on Fuzzy Systems*, 8(3):335–344, 06/2000.
[2] S.-W. Moon and S.-G. Kong. Block-based neural networks. *IEEE Transactions on Neural Networks*, 12(2):307–317, 03/2001.
[3] C. A. Peña-Reyes. *Coevolutionary Fuzzy Modeling*. PhD thesis, ´Ecole Polytechnique Fédérale de Lausanne - EPFL, 2002.
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[6] M. Russo. Genetic fuzzy learning. *IEEE Transactions on Evolutionary Computation*, 4(3):259–273, 09/2000.
[7] M. Setnes. Supervised fuzzy clustering for rule extraction. *IEEE Transactions on Fuzzy Systems*, 8(4):416–424, 08/2000.
[8] M. Goeke, M. Sipper, D. Mange, A. Stauffer, E. Sanchez, and M. Tomassini. Online autonomous evolware. *Proc. 1st Int. Conf. on Evolvable Systems: from Biology to Hardware (ICES96)*, Springer-Verlag, Heidelberg, 1997.
[9] A. Stoica, R. Zebulum, D. Keymeulen, R. Tawel, T. Daud, and A. Thakoor. Reconfigurable VLSI architectures for evolvable hardware: From experimental field programmable transistor arrays to evolution-oriented chips. *IEEE Transactions on Very Large Scale Integration (VLSI) Systems*, 9(1):227–232, 02/2001.
[10] X. Yao. Evolving artificial neural networks. *Proceedings of the IEEE*, 87(9):1423–1447, 09/1999.