31st Annual International Conference of the IEEE EMBS
Minneapolis, Minnesota, USA, September 2-6, 2009

A Multi-Level Robotic Architecture for Biologically-inspired Modeling

Alfredo Weitzenfeld and Alejandra Barrera

***Abstract*— Traditionally, modeling of neurobiological systems has involved development of computer-based simulations. As opposed to physical experimentation, simulations tend to over-simplify environmental conditions. Yet, in many cases such environmental conditions are critical to experiment outcome. In the case of animal behavior, simulation-only arenas can serve as a preliminary platform for model experimentation. Realistic physical environments are required for final evaluation of model correctness. In this paper we present our work with physical robots as testbed for animal behavior experimentation under realistic environmental conditions.**

I. Introduction

An important question in the behavioral and brain sciences community is "how should biological behavior be modeled". Webb [9] discusses a methodology using neuroethological models as basis for biological behavior modeling by building physical robots. Neuroethological robotics is different from the more traditional behavior-based robotics [3] in that neural models are incorporated as basis for behavior. The reason for doing robot experimentation as opposed to simulation-only is that models tend to be oversimplified during simulation while embodiment provides a much richer and realistic interaction environment. Yet, simulations play an important role in model development as preliminary assumptions are evaluated although final evaluation needs to take place under the embodied environment. Both, during initial model development and later during robot testing it is necessary to perform modifications to the model architecture. This can be easily achieved with an *embedded* robotic architecture connected to a remote computer in a wireless fashion. The remote computer can perform time-consuming tasks, e.g. neural and image processing. Thus, the robot can effectively be used as a sensory-motor device sending input to the remote computer while receiving motor commands as feedback. Depending on the robotic hardware configuration there may be additional local robot processing, such as image pre-processing or simpler local robot tasks.

In section II we describe the general environment for multi-level model development. Section III presents the embedded robotic architecture for studying biologically-inspired modeling, whereas section IV describes experiments developed using this architecture. Section V presents our conclusions.

II. Biologically-inspired Robots

The study of biologically-inspired robotics comprises a cycle of biological experimentation, computational modeling and robotics experimentation as depicted in Fig. 1. This cycle serves as framework for the study of the underlying neural mechanisms responsible for animal behavior.

Examples of biologically inspired robot models include frogs and toads [10], praying mantis [8], and rats [5, 7] among others. To address the underlying complexity in building neuroethological robotic systems we distinguish between behavior and neural structure modeling [11]. At the behavioral level, neuroethological data from living animals is gathered to generate single and multi-animal systems to study the relationship between a living organism and its environment, giving emphasis to aspects such as cooperation and competition between them. Examples of behavioral models include the frog and toad prey acquisition and predator avoidance models [10], and the praying mantis prey-predator model [4]. Behaviors are described in terms of perceptual and motor *schemas* representing a distributed model for action-perception control [1]. Behaviors, and their corresponding schemas, are processed via the Abstract Simulation Language ASL [12]. At the structural level, neuroanatomical and neurophysiological data are used to generate perceptual and motor neural network models corresponding to schemas developed at the behavioral level. Examples of neural network models are spatial cognition [6], and the prey acquisition and predator avoidance [10]. Neural networks are processed via the Neural Simulation Language NSL [13]. When available, behavior schemas are refined into neural schemas by finding direct mappings to brain regions [11].

This research was supported by NSF-CONACYT Grant "Visually-guided NeuroEthological Autonomous Robots: An Adaptive Middleware Approach to Distributed Embedded Mobile Systems" (CONACYT-2003-C03-42440 in Mexico), and "Asociación Mexicana de Cultura, S. A."
Alfredo Weitzenfeld (alfredo@itam.mx) and Alejandra Barrera (abarrera@itam.mx) are with the Computer Engineering Department at Instituto Tecnológico Autónomo de México. Río Hondo #1, Progreso Tizapán, CP 01080, México D. F., México. Alfredo Weitzenfeld is also with the Department of Information Technology, USF Polytechnic, USA.

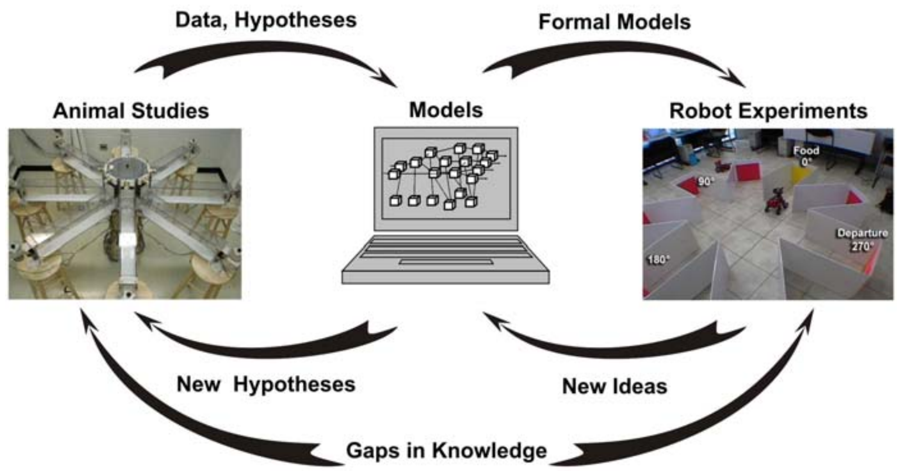

Fig. 1. Framework for the study of living organisms through cycles of biological experimentation, computational modeling, and robotics experimentation.

III. Embedded Distributed Architecture

One of the main concerns with neuroethological robot experimentation is the expensive nature of neural processing, which is exacerbated by the fact that a comprehensive neuroethological model may include multiple neural modules involving multiple brain regions [2]. In trying to achieve real-time performance while experimenting with neuroethological robotic systems, we have designed the MIRO embedded distributed system [14]. Under the MIRO architecture: (i) time-consuming processing is done in the remote computational system, while (ii) sensory input and motor output are carried out in the sensory-motor robot system.

IV. Experimental Application of MIRO

The MIRO robot architecture has been applied to a number of neuroethological models such as prey acquisition and predator avoidance in toads, and spatial cognition in rats. In Fig. 2 we show a two-level schema diagram for the toad's prey acquisition and predator avoidance model [10]. We include a single schema layer describing the different behaviors being modeled, primarily prey approach, predator avoidance and static object avoidance. Additional schemas include visual and tactile input, depth and moving stimulus selector (when more than one prey exists), prey, predator and static object recognizers together with the four types of motor actions: forward , orient, sidestep and backward. At the neural level, a number of neural networks are incorporated: Retina, Stereo, Maximum Selector, Tectum and PreTectum-Thalamus, together with neural motor heading maps.

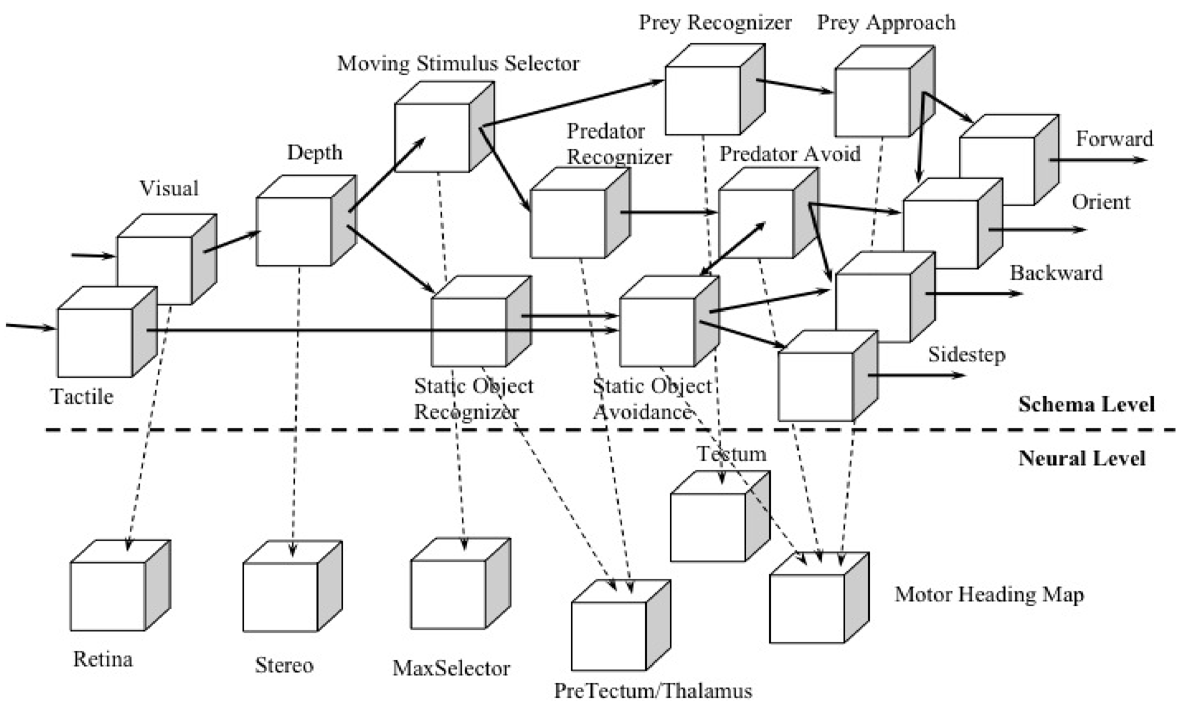

Fig. 2. Toad's prey-predator visuomotor coordination model architecture with schema and neural level modules.

In Fig. 3 we show a two-level schema diagram for the rat's spatial cognition model [6]. At the schema level, behaviors being modeled include motivation, kinesthetic, landmarks and affordances processing, place representation, learning, and action selection. Additional schemas include visual and kinesthetic input, as well as internal drives such as hunger and thirst, and motor actions such as moving forward, direction and body rotation. At the neural level, three neural networks are incorporated: Lateral Hypothalamus, Striatum and Hippocampus.

In Fig. 4 we show a typical computation cycle during spatial cognition in a maze [14]. Computation initiates with image capture from the robot camera sent to the remote computational system where image processing is performed by computing the number of pixels of every relevant color, and determine the possible presence of the goal and landmarks. The amounts of colored pixels are used to estimate the distance and relative orientation of each visible landmark from the robot, and determine possible rotations (affordances) the robot can execute from its current location. The remote computational system processes then the neuroethological model (neural processing) carrying out mapping creation/adaptation, place recognition, and learning processes. As a result, the model produces motor outputs (next robot direction (*d*), required rotation to point to that direction (θ), and moving displacement (*m*)) that are sent back to the robot as navigation control executing rotation and translation operations within the maze [6].

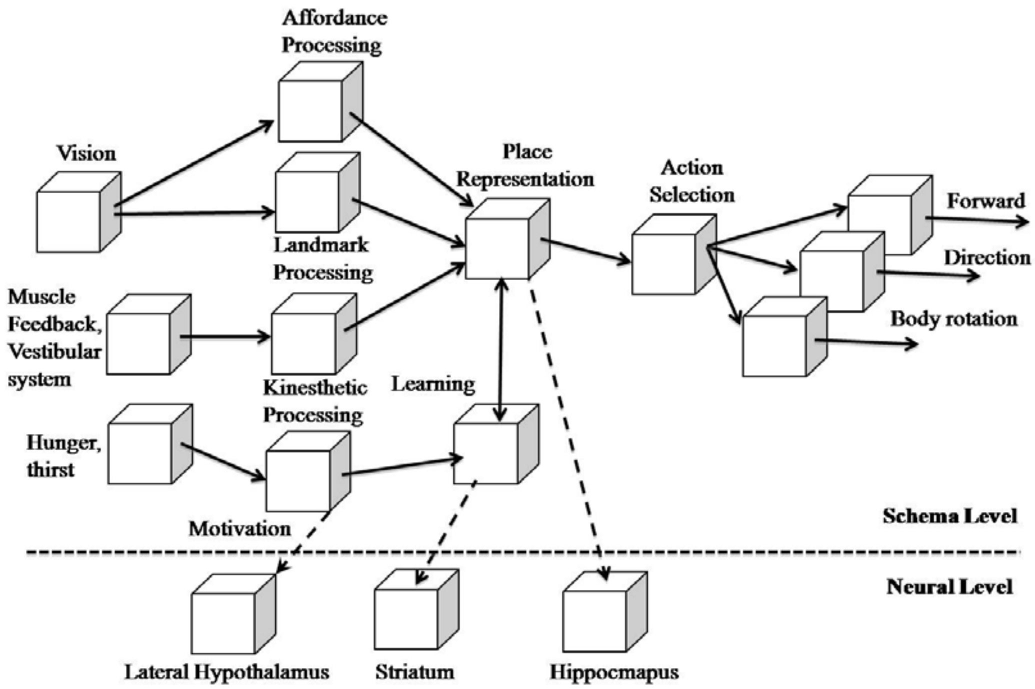

Fig. 3. Schema and neural network architecture for the rat spatial cognition model.

V. Conclusion

The work described in the paper discusses the challenges in experimenting with neuroethological models embedded into robotic systems. Simulation-only environments are desirable for model development, but final model testing requires realistic physical environments that are best tested with robots.

An additional concern with these architectures is the expensive nature of neural processing. In order to overcome these difficulties, we have developed an embedded distributed robotic architecture called MIRO where neural networks are remotely processed using the NSL/ASL neural simulation system. This architecture has proven quite beneficial in terms of processing efficiency, model development where a single version is developed for both simulated and robotic environment, as well as providing real-time robot monitoring and visualization capabilities.

The MIRO architecture has been used in a number of neuroethological experiments involving toad behaviors such as prey acquisition and predator avoidance with detouring, and rat behaviors such as spatial cognition in several mazes.

References

[1] Arbib, M.A., Schema Theory, in the *Encyclopedia of Artificial Intelligence*, 2nd Ed., Editor Stuart Shapiro, 2:1427-1443, Wiley, 1992.

[2] Arbib, M.A., Erdi, P. and Szentagothai, J., *Neural Organization: Structure, Function and Dynamics*, MIT Press, 1998.

[3] Arkin, R.C., Behavioral *based Robotics*, MIT Press, 1998.

[4] Arkin, R.C., Ali, K., Weitzenfeld, A., and Cervantes-Perez, F., Behavior Models of the Praying Mantis as a Basis for Robotic Behavior, *in Journal of Robotics and Autonomous Systems*, 32 (1) pp. 39-60, Elsevier, 2000.

[5] Barrera, A., and Weitzenfeld, A., Computational Modeling of Spatial Cognition in Rats and Robotic Experimentation: Goal-Oriented Navigation and Place Recognition in Multiple Directions, BioRob 2008, Oct 19-22, Scottsdale, AZ, USA, 2008.

[6] Barrera, A., and Weitzenfeld, A., "Biologically-inspired Robot Spatial Cognition based on Rat Neurophysiological Studies," *Autonomous Robots* 25 (1/2): pp. 147-169, Springer, 2008.

[7] Barrera, A., and Weitzenfeld A., Biologically Inspired Neural Controller for Robot Learning and Mapping, IJCNN – International Joint Conference on Neural Networks, Vancouver, Canada, July 16-21, 2006.

[8] Cervantes-Perez, F., Franco, A., Velazquez, S., Lara, N., 1993, A Schema Theoretic Approach to Study the 'Chantitlaxia' Behavior in the Praying Mantis, *Proceeding of the First Workshop on Neural Architectures and Distributed AI: From Schema Assemblages to Neural Networks*, USC, October 19-20, 1993.

[9] Webb, B., Can robots make good models of biological behaviour?, *Behavioral and Brain Sciences*, 24: 1033-50, Cambridge Press, 2001.

[10] Weitzenfeld, A., A Prey Catching and Predator Avoidance Neural-Schema Architecture for Single and Multiple Robots, Journal of Intelligent and Robotics Systems, Springer 51(2): 203-233, Feb, 2008.

[11] Weitzenfeld, A., From Schemas to Neural Networks: A Multi-level Modeling Approach to Biologically-Inspired Autonomous Robotic Systems, Journal of Robotics and Autonomous Systems, Elsevier, Vol. 56, No. 2, pp. 177-197, Feb, 2008.

[12] Weitzenfeld, A., ASL: Hierarchy, Composition, Heterogeneity, and Multi-Granularity in Concurrent Object-Oriented Programming, *Proc. Workshop on Neural Architectures and Distributed AI: From Schema Assemblages to Neural Networks*, USC, October 19-20, 1993.

[13] Weitzenfeld, A., Arbib, M., Alexander, A., *The Neural Simulation Language: A System for Brain Modeling*, MIT Press, July 2002.

[14] Weitzenfeld A., Gutierrez-Nolasco S., and Venkatasubramanian N., MIRO: An Embedded Distributed Architecture for Biologically inspired Mobile Robots, Proc ICAR-03, *11th International Conference on Advanced Robotics*, June 30 – July 3, Coimbra, Portugal, 2003.

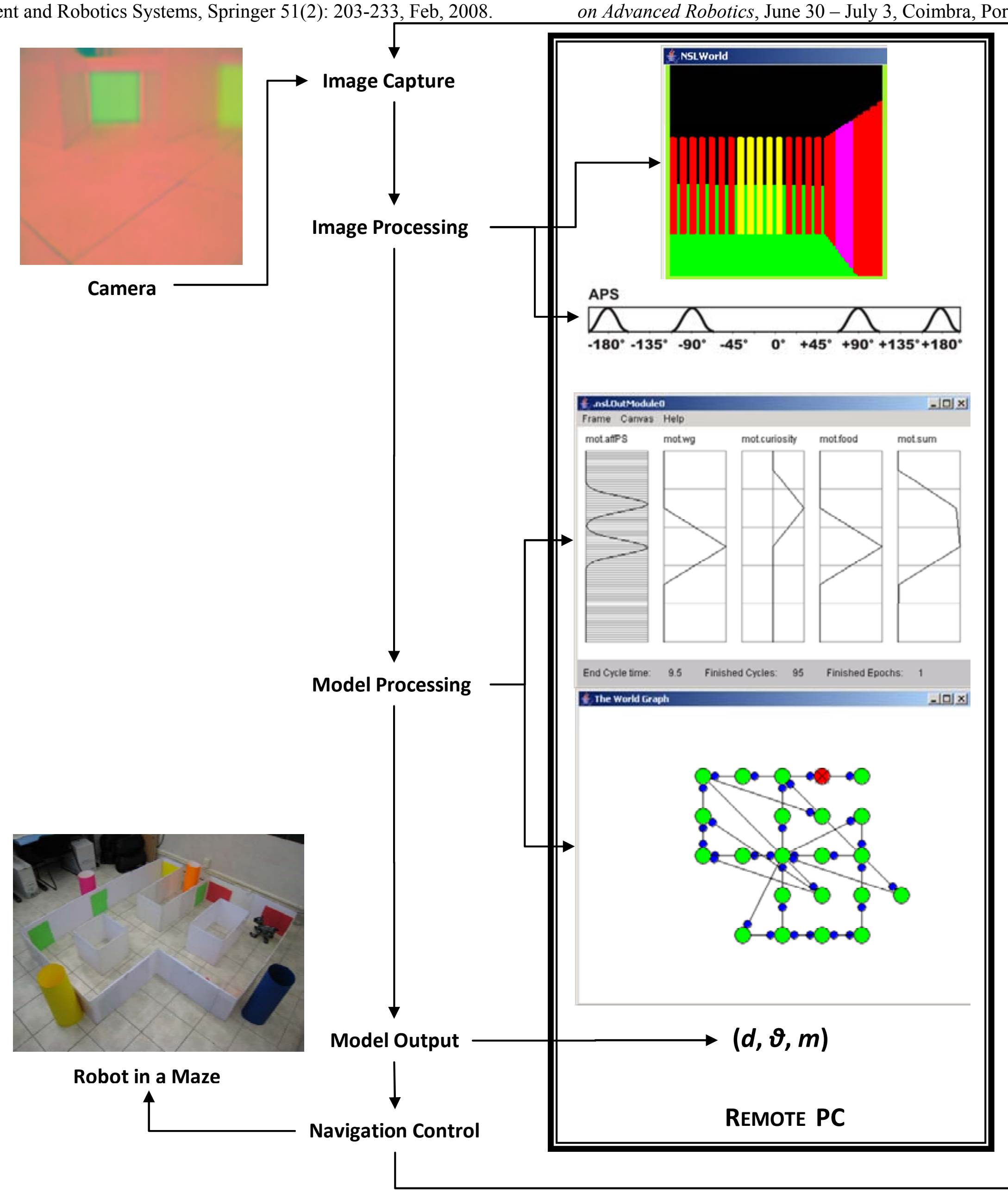

Fig. 4. Robotic architecture computing cycle during spatial cognition in a maze. An image is captured by the robot camera and sent to the remote computational system for image processing. Once the image is processed, mainly color filtering, distances and relative orientations of the goal and each visible landmark from the robot, as well as possible rotations (*APS*) the robot can execute from its current location are sent to the neural processing unit where the neuroethological model is computed. The model performs place representation and learning processes. At the end of each cycle, motor output is produced (next robot direction (d), required rotation to point to that direction (θ), and moving displacement (m)) and sent back to the robot for navigation control. These cycles continue until the robot reaches a specific learning criterion.