Embedded Mobile Systems: From Brain Theory To Neural-based Robots

Alfredo Weitzenfeld*

Abstract—In order to understand the underlying structural and behavioral mechanisms of living organisms, scientist follow cycles of experimentation and simulation. Experimentation, in the form of data gathering (ethological, physiological and anatomical), feed theoretical models that, through simulation, generate predictions to be validated by further experimentation in both robots as well as living organisms. Due to the inherent complexity of these biological neural models and the resulting architectures, most biologically inspired robotic systems are behavior based but not neural based, i.e. behavior is described by processes other than neural networks. Yet, biological neural mechanisms are crucial in modeling and giving new insights into adaptation and learning. In order to overcome the expensive computational requirements of biological neural based robotic systems, it is necessary either to incorporate very powerful robotic hardware or, particularly in the case of mobile robots, embed the robot via wireless communication into remote distributed computational systems. While the first approach simplifies the overall robotic architecture it results in bulky and expensive robots. The second approach results in smaller and less expensive robots, although involving more complex architectures. The work presented in this paper discusses neuroethological prey acquisition and predator avoidance models as basis for embedded distributed robotic systems. The robotic architecture integrates the MIRO (Mobile Internet Robotics) system and the NSL/ASL neural simulation system.
Index Terms-- robot, schema, neural, embedded, distributed

I. INTRODUCTION

The study of biological systems comprises a cycle of biological experimentation, computational modeling and robotics experimentation as depicted in Figure 1. This cycle serves as framework for the study of the underlying neural mechanisms responsible for animal behavior. At the moment most brain modeling is done through simulations. By providing an experimentation platform, many issues that are over simplified in simulation can be further analyzed while serving as inspiration in the design of more advanced neuroethological robotics architectures.

While many robotic architectures have been inspired in biological studies [6] the most currently used approach involves behavioral based robotics [5], intended to imitate animal behavior or "ethology" as opposed to "neuroethology" intended to imitate both neural structure as well as behavior. And while many robot architectures do incorporate some kind of neural processing, most of them are of the artificial neural kind involving non-biological training algorithms, such as back-propagation or reinforcement learning [24].

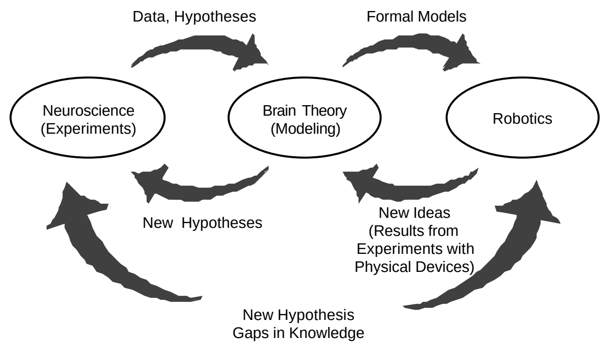

Figure 1. Framework for the study of living organisms through cycles of biological experimentation, computational modeling, and robotics experimentation.

An important concern with biologically inspired neural based robotics is how to achieve real-time performance considering the expensive nature of neuroscientific computation. One approach to overcoming this challenge is to have "super-robots" in analogy to supercomputers, something that usually results in prohibitively expensive and bulky robotic systems, or very specialized and hard to program hardware systems. A second approach is to incorporate simpler and less expensive robotic hardware although embedding it to an inexpensive network of computers. Under such a computing architecture time-consuming processing is done remotely outside the robotic hardware, with the robot sending sensory input and receiving motor output commands via wireless communication. Such an approach reduces the robot's physical size, power requirements as well as cost.

In general, a number of embedded robotic architectures have been proposed together with many different kinds of robotic applications, mostly teleoperated [21]. These efforts have highlighted the potential of the Internet when linking in a distributed fashion remote robotic devices to humans or other computational resources. Yet, to take advantage of such embedded architectures it is necessary to overcome restrictions in wireless transmission bandwidth, unreliable communication or even complete failures.

In the next sections we discuss our current work on biologically inspired robots and embedded mobile systems in pursuing adaptable and inexpensive robotic architectures.

* Associate Professor, Computer Eng Dept, ITAM, Mexico, DF, MEXICO

II. BIOLOGICALLY INSPIRED ROBOTS

Many living organisms have been studied, both at the behavioral and structural level, in trying to develop neural-based mobile robots. Some examples of animals that have been studied include: frogs and toads [1], praying mantis [11], cockroaches [9], and hoverflies [13]. To address the underlying comp lexity in simulating and building such robotics systems we usually distinguish between two different levels of modeling, behavior (*schemas* [3]) and structure (*neural networks* [2]).

A. Schemas and Neural Networks

At the behavioral level, neuroethological data from living animals is gathered to study the relationship between living organisms and their environment, giving emphasis to aspects such as cooperation and competition between them. Examples of behavioral models include the praying mantis *Chantlitaxia* ("search for a proper habitat") as models for *ecological* robotics designed and implemented at the behavior level using finite state automata [7], and the frog and toad (*rana computatrix*) prey acquisition and predator avoidance models [14]. We describe behavio r in terms of perceptual and motor *schemas* decomposed and refined in a recursive fashion. Behaviors, and their corresponding schemas, are processed via the Abstract Simulation Language ASL [26].

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. These models try to explain the underlying mechanisms for sensorimotor integration in visually guided animals [30]. Examples of neural network models are tectum and pretectum-thalamus responsible for discrimination among preys and predators [10], the toad´s prey acquisition and predator avoidance neural models [12], the toad´s prey acquisition with detour behavior model involving adaptation and learning [15] and higher-level models such as the monkey oculomotor system controlling eye saccades [18]. Neural networks are processed via the Neural Simulation Language NSL [28].

In general, models that involve neural networks are usually limited in behavioral scope, while more comprehensive behavioral models are usually simplified in terms of their inherent neural complexity [4].

In order to model comprehensive biological systems involving both behavior and structure, we have developed a schema computational model defined in terms of schema hierarchies representing a distributed model for action-perception control [29]. The schema computational model follows a tree or graph-like structure as shown in Figure 2. At the schema level, b locks correspond to *schemas* or *behavior agents* representing animal or robot behavior. At the neural level, blocks represent neural networks, some having a direct correspondence to brain regions. High-level schemas may be decomposed into more detailed lower level schemas. At the same level, schemas are interconnected (solid arrows), or when at different levels, schemas are relabeled having their task delegated (dashed arrows) to neural network implementations or other processes.

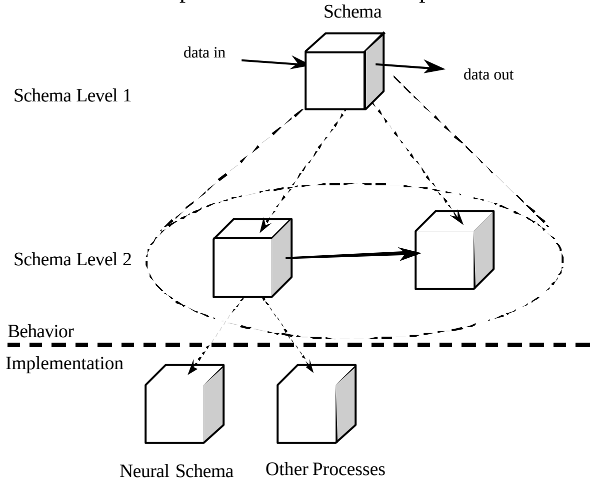

Figure 2. The ASL/NSL computational model is based on hierarchical interconnected schemas. A schema at a higher level (level 1) is decomposed (dashed lines) into additional interconnected (solid arrow) subschemas (level 2). At the lowest level schemas are implemented by neural networks or other processes.

At the schema level, schemas are interconnected by matching schema interfaces consisting of multiple unidirectional control/data, input and output ports, as shown in Figure 3. When doing *connections*, *output ports* from one schema are connected to *input ports* from other schemas, and when doing *relabelings*, ports of similar type (input or output) belonging to schemas at different levels in the hierarchy are linked to each other. The hierarchical port management methodology enables the development of distributed architectures where schemas may be designed in a top-down and bottom-up fashion implemented independently and without prior knowledge of the complete model or their final execution environment, encouraging component reusability.

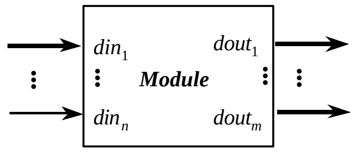

Figure 3. Each schema may contain multiple input, $din_1,...,din_n$, and output, $dout_1,...,dout_m$, ports for unidirectional communication.

In the top-down approach a complete system is first described at the schema level with schemas implemented by neural modules when available. In the bottom-up approach neural models are developed and then integrated in creating more complete schema systems. In order to build models involving both schemas and neural networks we integrated our two modeling languages ASL and NSL under a single simulation system.

B. *A Toad's Schema Model*

In order to represent, for example, a toad schema model we first describe a particular set of behaviors, such as prey acquisition (with detour) and predator avoidance. The corresponding schema model is described in terms of schema and neural modeling levels as depicted in Figure 4 [16]. We include a single schema layer (level 1) 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*. When possible, tasks at this level are delegated next layer down, where schemas perform more refined tasks. At the neural level, blocks represent neural networks. In this model, a number of neural networks are incorporated: *Retina* [25], *Stereo* [22], *Maximum Selector* [17], *Tectum* and *PreTectum-Thalamus* [10], together with neural *motor heading maps*.

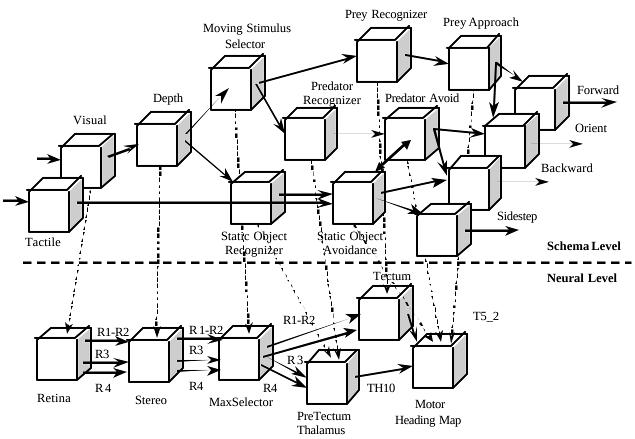

Figure 4. Toad's prey-predator visuomotor coordination model architecture with schema and neural level modules.

III. EMBEDDED MOBILE SYSTEMS

In the past years a number of research efforts have been carried out to embed mobile system into computer networks via wireless communication [19]. These efforts have highlighted the benefits of embedded systems in general and robotics in particular, including control and monitoring of sometimes expensive and/or remotely located robotic devices such as in the case of teleoperated robots in search and rescue applications [23]. Furthermore, embedding autonomous robots to computer networks has the additional benefit of not only monitoring internal behavior but also enhancing its capabilities by linking the robot to remote computational resources, such as image processing or neural processing.

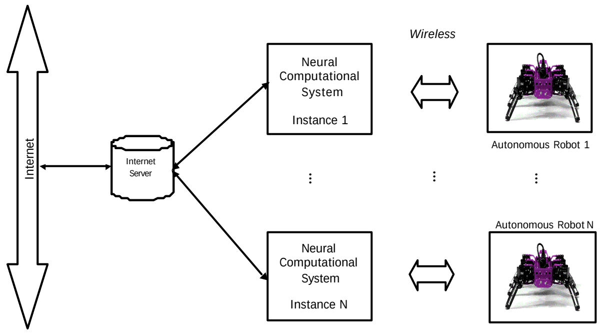

Figure 5. MIRO embedded robotic architecture consisting of multiple autonomous robots linked to their own instance of the distributed neural computational system. All such instances are connected to Internet for remote monitoring.

A. *Embedded Robotics*

As part of our current work in the design of embedded robotic systems we have developed the MIRO (Mobile Internet Robotics) architecture shown in Figure 5. The architecture consists of multiple robots each one connected to its own particular instance of the neural computational system. Processing is distributed among the robotic hardware and the remote computational system. Although it is possible to share robot "intelligence" among multiple robots where application could easily take advantage of information sharing (see [8] for a discussion on distributed versus centralized robotic systems), we are particularly interested in keeping a truly autonomous robot architecture where neuroethological experimentation can be conducted. Under the MIRO architecture: (i) time-consuming processes are carried out in the (neural) computational system, implemented using the NSL/ASL system while (ii) sensory input, motor output and other limited tasks are carried out in the robot hardware. In such a way, the computational system provides the robot's "intelligence", while the robot does limited processing. The most important challenge is how to achieve real-time processing under such an architecture.

B. *Distributed Neural Processing*

Neural network models produce and consume large amounts of data and take a very large number of processing cycles to obtain meaningful results. A typical computation cycle starts by obtaining sensory input (visual and tactile) and ends by producing motor output. In between, the different recognizers process input data in order to instantiate the corresponding behaviors, prey acquisition, predator avoidance, static object avoidance or a combination. Cycles continue indefinitely or until some specific task is completed, such as eating the prey. For example, a "typical" retina model [25] may consist of more than 100,000 neurons and half a million interconnections requiring many hours of simulation to complete these cycles.

The expensive nature of neural computation is further exacerbated by the fact that a comprehensive schema-neural model includes multiple neural modules. This becomes even worse in the case of higher-level animals involving more behaviors and other brain regions [4]. By taking advantage of the parallel and distributed nature of neural network computation [27], we extended the original NSL/ASL simulation system into a distributed architecture [31].

IV. EXPERIMENTS AND RESULTS

We have prototyped the embedded robotic system with a number of biologically inspired experiments involving prey acquisition and predator avoidance. In Figure 6 we show three different experiments involving a toad and a barrier in front of a prey, where fencepost gaps have the same width [16].

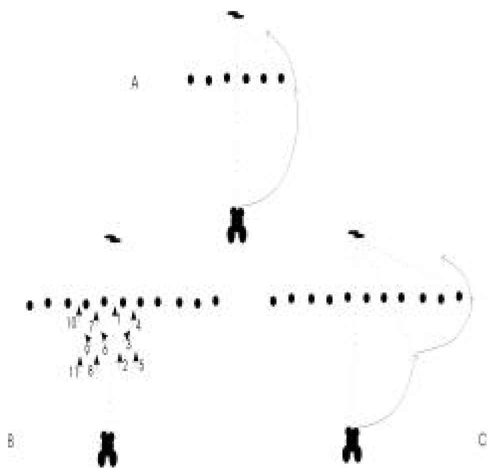

Figure 6. **A.** Approach to prey with single 10cm barrier with immediate detour. **B.** Approach to prey with single 20 cm barrier: first trial with frog in front of 20cm barrier (numbers indicate the succession of the movements). The toad directly approaches de center of the barrier requiring successive trials to manage the detour around it. **C.** Approach to prey with single 20cm barrier. After 3 trials the frog detours directly around the 20cm barrier. Arrowheads indicate the position and orientation of the frog following a single continuous movement after which the frog pauses.

A. **Experiment I**: A 10cm wide barrier with the toad starting from a long enough distance (15 -25cm) in front of the barrier and the worm 10cm behind the barrier. The experiment shows (in 95% of the trials) reliable detour behaviors from the first interaction with the 10cm barrier producing an immediate approach towards one of the edges of the barrier.

B. **Experiment II**: A 20cm wide barrier where the "naïve" toad (a toad that has not been yet exposed to the barrier) tends to go towards a fencepost gap in the direction of the prey (this was the case for 88% of the trials). The toad initially approaches the fence trying to make its way through the gaps. During the first trials the toad goes straight towards the prey thus bumping into the barrier. Since the toad is not able to go through a gap it backs-up about 2cm and then reorients towards one of the neighboring gaps.

C. **Experiment III:** A 20cm wide barrier where the "trained" toad, after 2 (43%) or 3 (57%) trials, is already detouring around the barrier without bumping into the barrier. The behavior involves a synergy of both forward and lateral body (sidestep) movements in a very smooth and continuous single movement.

The model and corresponding experiments were developed and simulated with the NSL system. In Figures 7 we show simulated output for the three experiments.

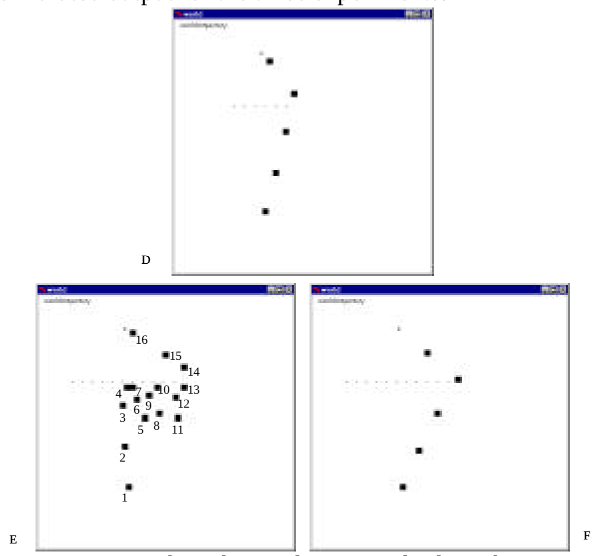

Figure 7. The above diagrams display the *Rana Computatrix* basic experiments for the prey acquisition and detour model. The different dots correspond to the frog's trajectory from its initial location as it finally reaches the prey. The left-hand side shows the resulting motion path for the 10cm barrier. Note how the frog heads directly towards the side of the barrier. The middle diagram displays the resulting motion path for the 20cm barrier experiment before learning. We have added numbers corresponding to the frog's position in time. In this particular experiment the frog hits the barrier three times before perceiving the side of the barrier and moving towards the prey. The right-hand side diagram shows the resulting motion path for the 20cm wide barrier after learning.

In Figures 8 we show experimental results for the prey acquisition model with a 10cm barrier showing direct detour. The experiment was carried out using a Lego-based robot remotely controlled by the MIRO system. A wireless camera was added on top of the robot transmitting video to remote video capture devices. This robotic framework is currently being expanded to OOPIC and PC/104 based robots with Internet based wireless cameras.

In Figure 9, we show how scenes are visualized directly from Internet, in this case consisting of an aerial and robot camera. User interaction includes additional graphic displays showing neural network states for the different neural schemas as the experiment progresses.

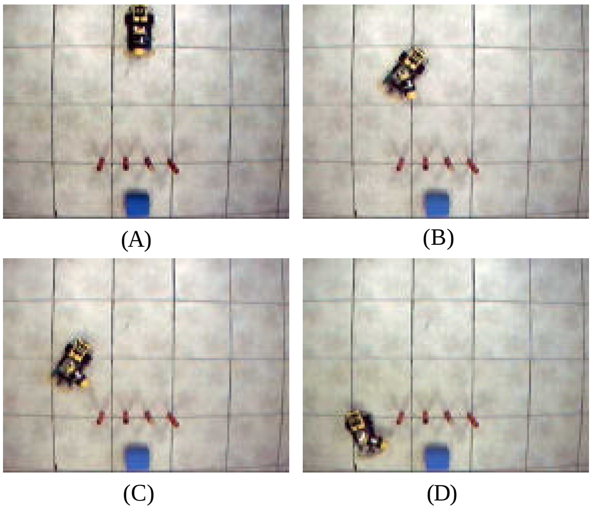

Figure 8. Results from prey acquisition experiment for 10cm barrier with direct detour around barrier.

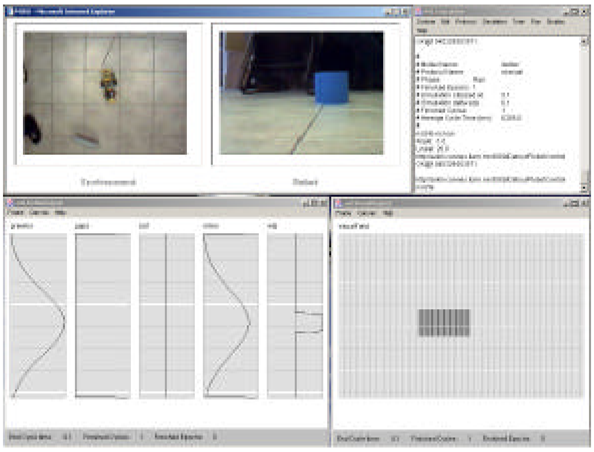

Figure 9. Internet aerial view of autonomous robot and robot's camera view of "blue" prey-like stimulus with NSL/ASL frames showing results from different visual and neural modules in a basic prey acquisition robot experiment.

V. CONCLUSIONS AND DISCUSSION

The work presented in the paper overviews the challenges and complexity in modeling robotic systems inspired by neuroethological brain models. The motivation behind this work is: (1) to provide neuroscientists a testbed for robotic experimentation, and (2) to provide scientists with biologically inspired architectures in designing more advanced robotic systems.

In terms of neuroethological modeling complexity is managed by taking a multi-level approach emphasizing both top-town and bottom-up designs through different levels of granularity. At the top-level behaviors are described in terms of schema models such as in the frog's prey acquisitions and predator avoidance. Schemas may be refined in a hierarchical structure until reaching lower-level neural networks representing schema implementations. The main challenge with these implementations is the need to link independently developed neural models, such as those shown in Figure 4, where input and output specifications do not necessarily match. For example, the original neural models for *Stereo*, *MaxSelector*, *Tectum* and *Pretectum* incorporated their own visual input instead of more faithful *R2*, *R3*, and *R4 Retina* class cells. This was done in order to obtain quicker results and make them independent from other models. It should be that the original neural models were developed mostly as part of PhD theses, taking quite some time to develop. At this time it is necessary to reexamine the different neural models in order to: (1) separate what relates to actual visual input from specialized module processing and (2) modify these models to accept R2, R3, and R4 output coming from the *Retina* model. To complicate matters further, the logic of one module may be based on different assumptions to those of other modules, e.g. different experiments, parameters or time frequencies. Yet, if we do not manage this integration, it will not be possible to "reuse" neural modules in more comprehensive neuroethological models while serving as basis for more advanced robotic architectures.

Historically, most brain modeling has been accomplished through simulation, but simulation is not quite the same as real-world robotic experimentation. In particular, many shortcuts are taken in simulation. For example, simulated cameras and world objects are usually made quite ideal; cameras have large visual fields while objects have "perfect" sizes. Once models are experimented under real world conditions with physical cameras, where visual fields vary in size and objects become harder to recognize. As part of our initial model experimentation with real robots, an interesting problem appeared in our prey acquisition with detour experiment, the problem of "losing" the prey once the robot orients towards one of the edges of the barrier. In the simulated version the robot always perceived the prey as well as predators. While toads do take care of this problem the actual model did not. This is an example where simulated models may do fine under simulated environments but do not address specific issues originating from actual embodied robot experimentation. A simple solution to this problem is to add a new motor to control the camera independently from the robot movement while providing separate control. In dealing with this issue, we can get inspiration from other neurobiological models, for example the oculomotor system in monkeys [18] responsible for controlling eye saccades among other functions. An interesting function of the oculomotor system is the control of "memory" saccades where the eye's fovea redirects itself to a stimulus from information previously recorded, something of particular interest to the prey acquisition and predator avoidance models. Yet, it is not simply a matter of integrating across the two models. The prey acquisition and predator avoidance models are based on toad and frog studies, while the oculomotor system previously mentioned is based on monkey studies, varying quite a bit in terms of neurobiological systems involved. To neurobiologist this is quite significant. On the other hand, to robotic designers this is not necessarily important.

Additionally, most of our experiments until now have involved single robots. The reason for this has been mostly due to the underlying complexity of the actual models. Our next goal is to experiment with multiple robots, where each robot represents a prey, toad or predator. The idea is not only to test the interaction among multiple neurothological robots but also to test behaviors that require such dynamics.

In terms of actual robotic systems, one particular concern is the expensive nature of neural processing. To improve on performance and reduce the size and cost of neural based robots, we have developed an embedded distributed robotic architecture where neural networks are remotely processed. For this purpose we have extended the NSL/ASL neural simulation system into a distributed environment. While we are in the process of assessing the efficiency of the MIRO embedded architecture there are many interesting questions that have to be dealt with, for example, what happens when communication between the robot and computational system actually fails or becomes extremely slow or unreliable. When such situation arises, the robot could respond in many ways, simply waiting without doing anything until communication is restored, ending its mission, or performing other more limited tasks that may put it back in action such as actively searching for a location where communication can be reestablished.

VI. ACKNOWLEDGMENTS

We thank the UC MEXUS CONACYT Advanced Network Services Collaborative Grant: “MIRO: Adaptive Middleware for a Mobile Internet-based Robot Laboratory” as well as the "Asociación Mexicana de Cultura, A.C." and the different students at the CANNES Laboratory at ITAM who participate in this project.

VII. REFERENCES

[1] Arbib, M.A., Levels of Modelling of Mechanisms of Visually Guided Behavior, *Behavior Brain Science* 10:407-465, 1987.

[2] Arbib, M.A., *The Metaphorical Brain 2*, Wiley, 1989.

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

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

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

[6] Arkin, R.C., Ali, K., Weitzenfeld, A., and Cervantes-Perez, F., Behavior Models of the Praying Matis as a Basis for Robotic Behavior, *in Journal of Robotics and Autonomous Systems*, 32(1), pp 39-60, Elsevier, 2001.

[7] Arkin, R.C., Cervantes-Perez, F., and Weitzenfeld, A., 1997, "Ecological Robotics: A Schema-Theoretic Approach", "Intelligent Robots: Sensing, Modelling and Planning", eds. R.C.Bolles, H.Bunke, and H.Noltemeier, pp 377-393, World Scientific.

[8] Balch, T. and Arkin, R.C., Communication in Reactive Multiagent Robotic Systems, Autonomous Robots, 1, pp 1-25, 1994.

[9] Beer, R. D., *Intelligence as Adaptive Behavior: An Experiment in Computational Neuroethology*, San Diego, Academic Press, 1990.

[10] Cervantes-Perez, F., Lara, R., and Arbib, M.A., A neural model of interactions subserving prey-predator discrimination and size preference in anuran amphibia, Journal of Theoretical Biology, 113, 117-152, 1985.

[11] 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.

[12] Cervantes-Perez, F., Herrera, A., and García, M., Modulatory effects on prey-recognition in amphibia: a theoretical 'experimental study', in *Neuroscience: from neural networks to artificial intelligence*, Editors P. Rudomin, M.A. Arbib, F. Cervantes-Perez, and R. Romo, Springer Verlag Research Notes in Neural Computing vol 4, pp. 426-449, 1993.

[13] Cliff, D., Neural Networks for Visual Tracking in an Artificial Fly, in *Towards a Practice of Autonomous Systems: Proc. of the First European Conference on Artificial Life (ECAL 91)*, Editors, F.J., Varela and P. Bourgine, MIT Press, pp 78-87, 1992.

[14] Cobas, A., and Arbib, M.A., Prey-catching and Predator-avoidance in Frog and Toad: Defining the Schemas, *J. Theor. Biol* 157, 271-304, 1992.

[15] Corbacho, F., and Arbib M. Learning to Detour, *Adaptive Behavior*, Volume 3, Number 4, pp 419-468, 1995.

[16] Corbacho, F., and Weitzenfeld, Learning to Detour, in *The Neural Simulation Language NSL, A System for Brain Modeling*, MIT Press, July 2002.

[17] Didday, R.L., A model of visuomotor mechanisms in the frog optic tectum, *Math. Biosci.* 30:169-180, 1976.

[18] Dominey, P., and Arbib, M.A., A cortico-subcortical model for generation of spatially accurate sequential saccades, Cerebral Cortex, 2, pp 153-175, 1992,

[19] Estrin, D., Govidian, R., and Heidemann, J. (Eds.) Special issue on Embedding the Internet, Communication of the ACM, 43(5), May 2000

[20] Fagg, A., King, I., Lewis, A., Liaw, J., Weitzenfeld, A., A Testbed for Sensorimotor Integration, Proceedings of IJCNN '92, Baltimore, MD, 1:86-91, 1992.

[21] Goldberg, K., and Siegwert, R., (eds), Beyond Webcams: An Introduction to Online Robots, MIT Press, 2002.

[22] House, D., Depth Perception in Frogs and Toads: A study in Neural Computing, Lecture Notes in Biomathematics 80, Springer-Verlag, 1985.

[23] Sukhatme, G.S., and Mataric, M.J., Embedding Robots Into the Internet, Communication of the ACM, 43(5) pp 67-73, Special issue on Embedding the Internet, D. Estrin, R. Govidian, and J. Heidemann, eds., May 2000.

[24] Sutton, R., and Barto, A., Reinforcement Learning: An Introduction, MIT Press, 1998.

[25] Teeters, J.L., and Arbib, M.A., A model of the anuran retina relating interneurons to ganglion cell responses, *Biological Cybernetics*, 64, 197-207, 1991.

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

[27] Weitzenfeld, A., Arbib, M., A Concurrent Object-Oriented Framework for the Simulation of Neural Networks, *Proceedings of ECOOP/OOPSLA '90 Workshop on Object-Based Concurrent Programming, OOPS Messenger*, 2(2):120-124, April 1991.

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

[29] Weitzenfeld A., "A Multi-level Approach to Biologically Inspired Robotic Systems", *Proc of NNW 2000 10th International Conference on Artificial Neural Networks and Intelligent Systems*, Prague, Czech Republic, Juy 9-12, 2000.

[30] Weitzenfeld, A., Cervantes, F., Sigala, R., NSL/ASL: Simulation of Neural based Visuomotor Systems, in *Proc. of IJCNN 2001 International Joint Conference on Neural Networks*, Washington DC, July 14-19, 2001.

[31] Weitzenfeld A., Gutierrez-Nolasco, S., "ASL/NSL: A Multi-level Computational Model for Distributed Neural Simulation", in *Proc of SCSC 2000 Summer Computer Simulation Conference*, Vancouver, Canada, July 16-20, 2000.