A Neural Schema Architecture for Autonomous Robots

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Areas: Robotics, Agent-oriented programming, Neural Nets

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Abstract

As autonomous robots become more complex in their behavior, more sophisticated software architectures are required to support the ever more sophisticated robotics software. These software architectures must support complex behaviors involving adaptation and learning, implemented, in particular, by neural networks. We present in this paper a neural based *schema* [2] software architecture for the development and execution of autonomous robots in both simulated and real worlds. This architecture has been developed in the context of adaptive robotic agents, *ecological robots* [6], cooperating and competing with each other in adapting to their environment. The architecture is the result of integrating a number of development and execution systems: NSL, a neural simulation language; ASL, an abstract schema language; and *MissionLab*, a schema-based mission-oriented simulation and robot system. This work contributes to modeling in Brain Theory (BT) and Cognitive Psychology, with applications in Distributed Artificial Intelligence (DAI), Autonomous Agents and Robotics.

Areas: Robotics, Agent-oriented programming, Neural Nets

Keywords: Autonomous Robots, Autonomous Agents, Schemas, Neural Networks, Architecture

1 Introduction

To enable the development and execution of complex behaviors in autonomous robots involving adaptation and learning, sophisticated software architectures are required. The neural schema architecture provides such a system, supporting the development and execution of complex behaviors, or *schemas* [3][2], in a hierarchical and layered fashion [9] integrating with neural network processing.

In general, *schema theory* helps define brain functionality in terms of concurrent activity of interacting behavioral units called *schemas*. Schema-based modeling may be specified purely on behavioral data (*ethology*), while becoming part of a neural based approach to adaptive behavior when constrained by data provided by, e.g., the effects of brain lesions upon animal behavior (*neuroethology*). Schema modeling provides a framework for modeling at the purely behavioral level, at the neural network level or even below [28]. In terms of neural networks, *neural schema theory* provides a functional/structural decomposition, in strong contrast with models which employ learning rules to train a single, otherwise undifferentiated, neural network to respond as specified by some training set. Neural schema-based modeling proceeds at two levels: (1) model behavior in terms of schemas, interacting functional units; (2) implementation of schemas as neural networks based on neuroanatomical and neurophysiological studies. What makes the linking of structure and function so challenging is that, in general, a functional analysis proceeding "top-down" from some overall behavior need not map directly into a "bottom up" analysis proceeding upwards from the neural circuitry.

The work described in this paper is the product of a collaborative research depicted in Figure 1.

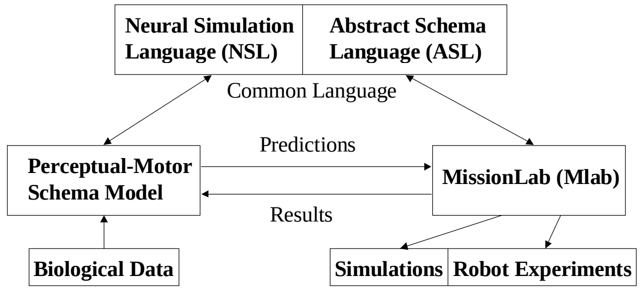

Figure 1. Collaboration Map

Biological data from behavioral studies in the praying mantis "Chantitlaxia" [11] and the frog and toad prey acquisition and predator avoidance behaviors [12][14], are used to generate neural schema models: *perceptual* schemas, dealing with sensory input or perceptions; *motor* schemas, dealing with motor action; and *sensorimotor* schemas, integrating between sensory input and motor action. These studies are modeled in terms of computational schemas in the Abstract Schema Language (ASL) [25], implemented as neural networks in the Neural Simulation Language (NSL) [27], and simulated in a virtual world or executed in the real world with the *MissionLab* (Mlab) robotic system [23].

2 Schemas, Neural Networks and Autonomous Robots

The neural schema architecture for autonomous robots comprises the integration of three separately developed architectures, each built to support a different aspect of schema modeling.

2.1 Schemas

As a computational model, schemas define a hierarchical and distributed architecture for the development of complex adaptive systems. A number of schema-based architectures have been developed for different application domains, e.g. VISIONS [18], in vision; RS (Robot Schemas) [22] and MissionLab [3], in robotics. Based on these domain specific architectures, a unified schema computational model, ASL (Abstract Schema Language) [25], was designed with the ability to integrate with neural networks processing across different domains as well. Schemas in ASL are hierarchical and distributed autonomous agents, where ASL integrates concurrent object-oriented programming methodologies [29] with agent modeling [8]. As a language ASL corresponds more to a specification language rather than to an explicit programming language. The detailed implementation is left unspecified, only specifying what is to be achieved. Different implementations may correspond to a single schema, where implementation are in terms of neural networks or other schema process. The ASL computational model is shown in Figure 2.

At the top of Figure 2, a schema is shown decomposed into other schemas. This decomposition gives rise to schema aggregation, or schema *assemblages*. Schemas are specified and implemented either through *wrapping*, which enables static integration of external programs, or through *task delegation*, which enables dynamic integration of schemas as separate specification and implementation tasks. (Solid arrows between boxes represent connections between objects, while dashed arrows represent task delegation.)

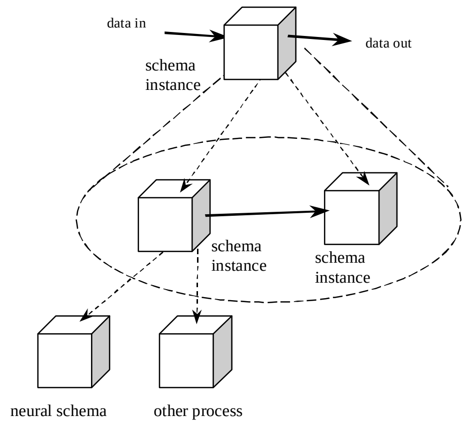

Figure 2. Schema Hierarchy

Schema interfaces consists of multiple unidirectional control or data, input and output *ports*, and a method section where schema behavior is specified. Communication is in the form of *asynchronous* message passing, hierarchically managed, internally, through anonymous port reading and writing, and externally, through dynamic port *connections* and *relabelings*. When doing connections, output ports from one schema are connected to input ports from other schemas, and ports from schemas at different hierarchies are linked to each other when doing relabelings. The hierarchical port management methodology enables the development of distributed systems where objects may be designed and implemented independently and without prior knowledge of their final execution environment, encouraging model reusability. This supports both top-down and bottom-up system designs as required by neural schema modeling.

In order to support complex schema modeling, ASL is design as a distributed multithreaded system architecture, executing on different platforms [10], as shown in Figure 3.

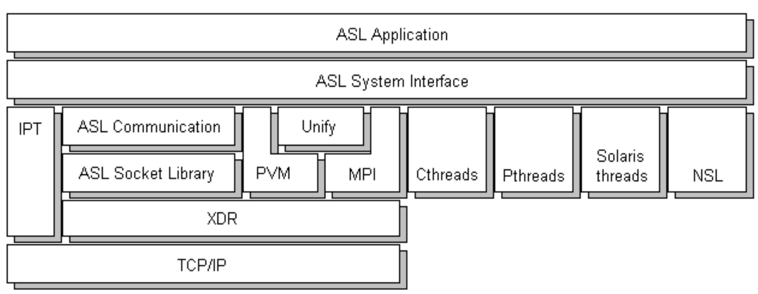

Figure 3. Abstract Schema Language (ASL) System Architecture

2.2 Neural Networks

Neural networks serve as the underlying implementation for neural schemas. Lower level neural network components integrate with higher level schemas, as shown in

Figure 4:

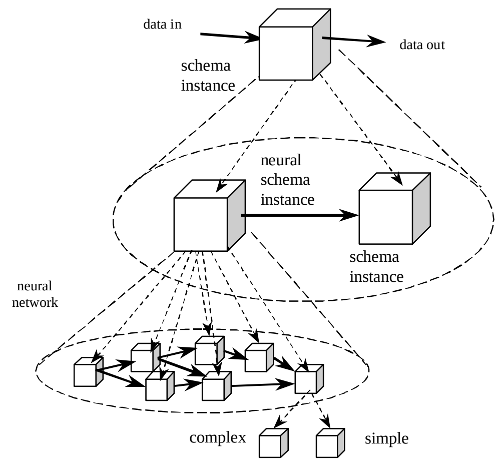

Figure 4. Neural Schema Hierarchy

The Neural Schema Language (NSL) [27] provides the linkage to ASL, enabling the integration of neural networks as schema implementations. The ability to implement schemas through different neural networks results in the added benefit of enabling the construction of distributed neural networks. Mapping between schemas and neural networks may not only be 1 to 1, but also many to many. The neural schema model not only enables the encapsulation of neural networks into schemas, but also provides an extended model where neurons themselves may have their task delegated by neural implementations of different levels of detail, from the very simple neuron models to the very complex ones [26].

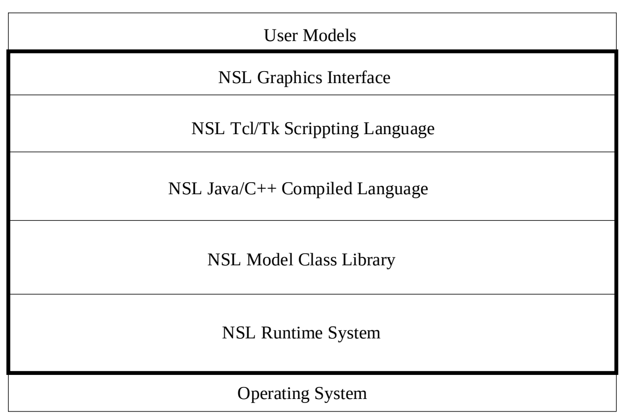

Figure 5. NSL System Architecture

The NSL system architecture is shown in Figure 5. Models are described via a compiled language, where graphics displays and a scripting language provide the interfacing mechanisms between the model and the user. Two implementations of the system currently exist: NSLC in C++ and NSLJ in Java.

2.3 Schema-based control for autonomous robots

In robotics, schemas have been used to provide the underlying software control mechanisms for a number of systems, e.g. MissionLab [3] and RS [22]. In particular, in the control of autonomous robots, such as with MissionLab, motor schemas have been encoded as a variant of the potential field methodology [21]. In this context, schemas have the following characteristics:

1. Each is an independent asynchronous computational agent executing in parallel with other schemas.
2. Sensing is directly tied to motor control following the action-oriented perception paradigm, where information is obtained via sensing on a need-to-know basis [4].
3. Each active schema produces a vector that encodes the behavioral response for a given stimulus.
4. Coordination of schemas is typically conducted via behavioral fusion: vector summation and normalization of the individual schemas outputs.
5. Schemas can be aggregated into assemblages, which provide a higher level of abstraction.
6. Their use is rooted in neuroscientific and psychological theory.

This particular form of behavioral control has been tested on a wide range of robotic systems: from teams of small robots used for competitions to military sized vehicles [5], as shown in the Figure 6.

Figure 6. Collection of schema-based robots

MissionLab [23] is a tool that has been recently developed for the testing and deployment of schema-based reactive controllers for autonomous robots. It incorporates a graphical user interface, reusable software libraries, a simulation facility, and the capability to download executable robot code for a range of real mobile platforms. MissionLab serves as the testbed for the results in this project. The architecture of MissionLab is shown in Figure 7.

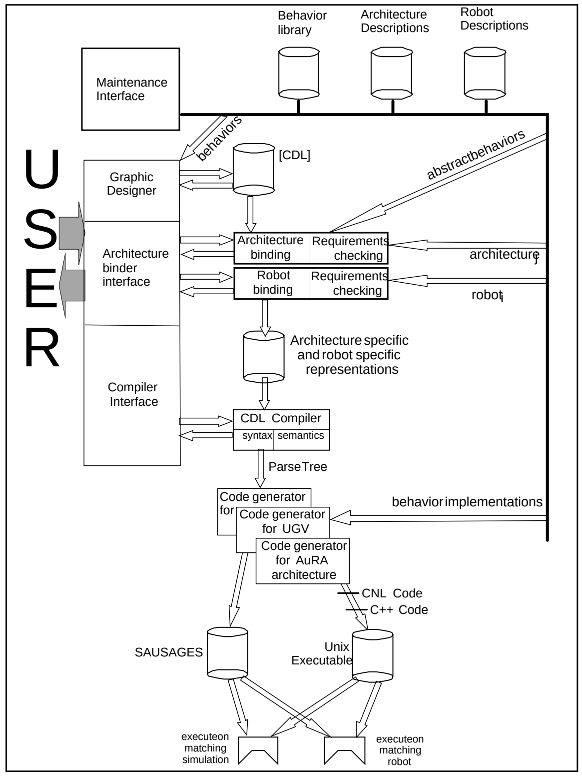

Figure 7. MissionLab System Architecture

2.4 Integrated Architecture

In order to enable the described schema modeling, the three architectures: ASL, NSL and Missionlab, were integrated under a single system environment. ASL was first integrated to NSL [10], and then the ASL/NSL system to MissionLab [24]. The integrated architecture is shown in Figure 8.

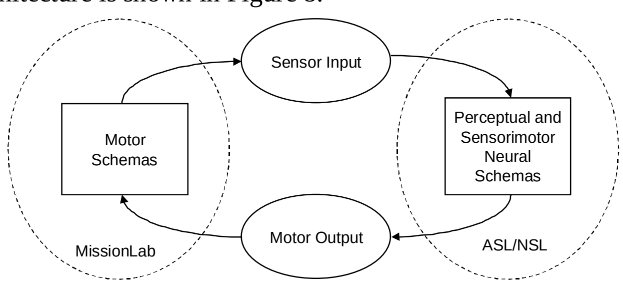

Figure 8. ASL/NSL/MissionLab Integrated Architecture

Integration is carried out through binding points between ASL/NSL and MisionLab. Sensor input from MissionLab, simulated data or real world data from actual robots, is read by the perceptual neural schemas in the ASL/NSL system. Sensorimotor neural schemas in ASL/NSL generate output to the motor schemas executing in MissionLab, either in the simulated or real world.

3 Computational Neuroethology

Neuroethology, the study of the nervous system and animal behavior, has inspired a number of computational models, such as *Rana Computatrix*, the computational frog [1], the computational cockroach [7], and the computational hoverfly [13]. Such computational models involve a rich number of neural based behaviors, such as the *Chantlitaxia*, searching from a proper habitat, taken from the Praying Mantis behavior [11], as described in the ethogram in Figure 9.

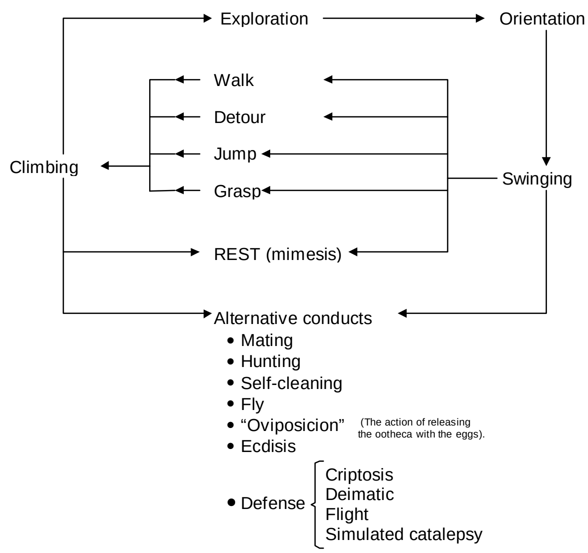

Figure 9. Praying Mantis' *Chantlitlaxia* Ethogram

Different models are currently being developed under the ASL/NSL/MissionLab neural schema architecture. Besides the Chantlitlaxia behavior [6], we have prototyped the adaptive toad's prey acquisition behavior due to a static barrier [14], and developing a prey acquisition and predator avoidance behavior modulated by learning processes in neural networks [20].

3.1 Prey Acquisition with Detour Behavior

As an example of a model developed under the neural based schema architecture we describe the toad's detour behavior due to stationary objects on its way to a prey [14]. The experiment being modeled consists of a barrier placed between a prey and a toad, as shown in Figure 10.

Two different barrier sizes were tried, 10 and 20 cm. Both barriers are made of fenceposts, where each fencepost has a very small width, but tall enough not to have the toad jump over it. The fence posts are distanced 2 cm from each other. The toad is 20 cm away from the barrier, and the prey is 10 cm away opposite the barrier.

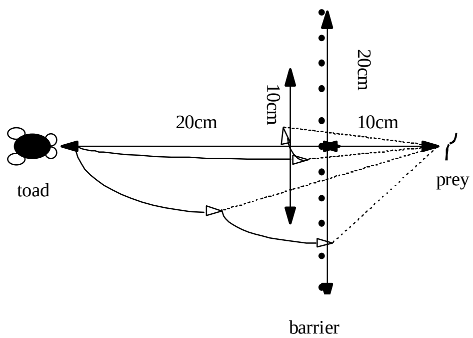

Figure 10. Toad's prey acquisition with detour behavior experiment

When the barrier is 10 cm wide the toad approaches directly to the barrier edges and from there continues to the prey, as shown in Figure 10. When the barrier is 20 cm wide, the toad advances to the middle of the barrier, more precisely to the closest gap between the fenceposts. Not being able to go through the gap, the robot backs up, reorients and tries again. This adaptive process continues until the edge of the barrier is in sight. Figure 11 shows the toad's behavior with a 20 cm barrier without and with learning. These experiments are further described in [17][15].

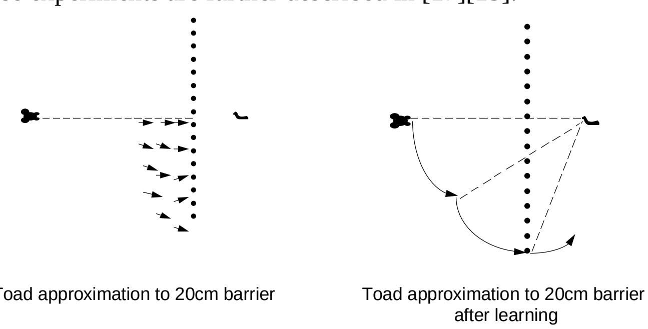

Figure 11. Toad's prey acquisition model for a 20 cm barrier, without and with learning.

Schemas

In order to reproduce these experiments we developed a schema based model with a robotic agent taking the place of the toad. At the highest level, model behavior is described by means of schema specifications. The complete model at this level is described by a network of interconnected schemas as shown in Figure 12:

The model consists of visual and tactile sensory input, perceptual schemas for recognizing stationary objects and prey moving objects, sensorimotor schemas for prey approach and static object avoidance, and motor schemas for performing forward, backward, sidestep and orient motions. Visual input is used to recognize both the static barrier and the moving prey, while tactile input is triggered when the robotic agent bumps into the barrier (not being able to go through the gap).

Rather than processing input symbols to yield output symbols, the individual schemas have *activation levels* which measure their degree of confidence. In response to the perceptual schemas input, the *more active* of the two sensorimotor schemas will *trigger* the appropriate motor schema to yield the appropriate response.

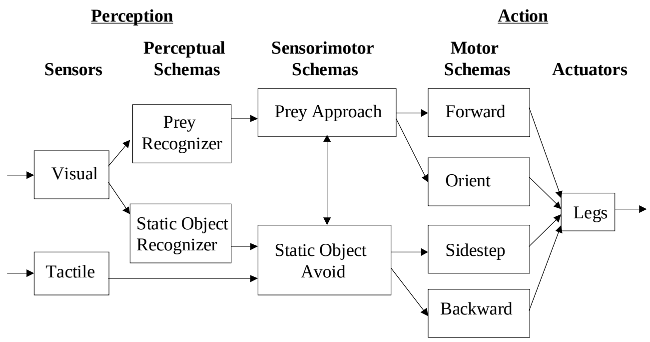

Figure 12. Schemas for toad's prey acquisition with detour behavior.

In other words, the sensorimotor schemas *compete* to control the behavior of the animal. This is a very simple example of the type of mechanisms of *competition and cooperation* that can be exhibited by a network of schemas. In particular multiple motor schemas may be coactivated to control subtle behaviors. The perceptual schemas are not simply *yes-no* recognizes, being equipped with a confidence level to provide a *parametric description* which can be used in tuning motor behavior appropriately. When the toad recognizes the prey, the animal does not respond by moving in a standard or random direction, bur rather it snaps at the position in space where the prey is located as indicated by the "prey-recognizer" schema.

Neural Networks

Some of the schemas in the toad's prey acquisition model are implemented all the way down to neural networks. Other schemas, for which the detailed neural circuitry is not known or involves unnecessary computation for the range of phenomena under study, are modeled in a simpler manner. For example, motor schemas in this model were not implemented through neural circuitry for simplification reasons. The neural network level implementing higher level schemas is shown in Figure 13.

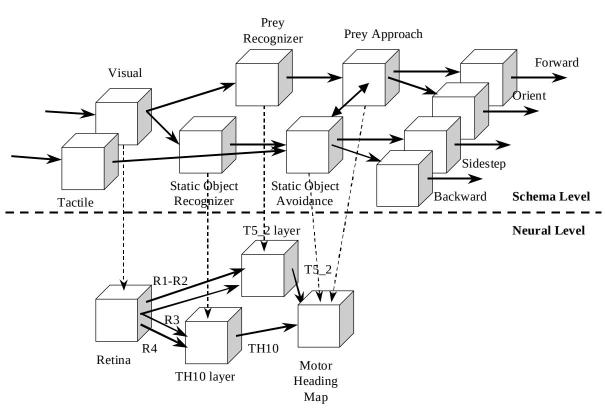

Figure 13. Neural schemas for toad's prey acquisition with detour behavior.

The neural level consists of a Retina corresponding to the Visual input, T5_2 and TH10 neural layers corresponding the moving prey and static object recognizer, and a motor heading map where the static object and prey maps integrate. The motor heading map produces a target heading angle corresponding to the strongest map activity; providing inhibition between the prey approach and static object avoidance. This inhibition is important to avoid activating antagonist motor schemas simultaneously. A tactile modulation component provides adaptation to the model by increasing the inhibition repetitively, every time the robot hits the barrier. (The detailed model description can be found in [14].)

Autonomous Robots

The complete autonomous robotic agent is built by integrating the perceptual and sensorimotor schemas in ASL/NSL with the motor schemas in MissionLab, as shown in Figure 14.

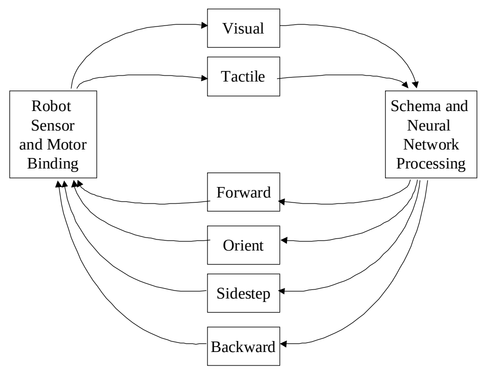

Figure 14. Perceptual and Motor Schema Linkage for toad's prey acquisition model.

The robot provides visual and tactile input to the neural schema process. These respond by producing appropriate forward, orient, sidestep and backward activations, generating robot movement. The cycle continues indefinitely, terminating only when reaching the prey. When executed in a real robot, only sensory and actuator binding is modified in MissionLab without the need to change any of the actual model details.

4 Results

4.1 Prey Acquisition with Detour Behavior

As seen from the Missionlab simulation console, the robot (SP Frog) is initially positioned in front of a barrier, with a prey away from it, as shown in the left of Figure 15. The right hand side shows the resulting trajectory generated by the agent.

Figure 16, left, shows the agent's view of the barrier. Figure 16, right, the resulting attraction field integrating the prey attraction and the barrier repulsion. The highest value activity in the figure corresponds to the robot's preferred orientation (which initially corresponds to the prey's direction).

As the robot bumps into the barrier, the barrier's gap inhibition gets incremented resulting in a new attraction field in the motor heading map, Figure 17, left, producing reorientation. Every time the frog hits the barrier, it backs down and sidesteps. Following, the frog gets attracted by the prey again, hitting the barrier, this time on a different gap. This process continues until the edge of the barrier is perceived, generating a direct path to the prey, as shown in Figure 17, right.

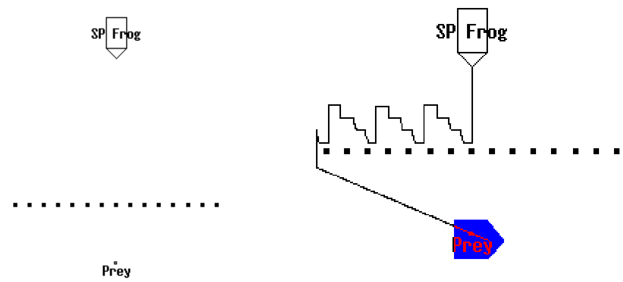

Figure 15. MissionLab Console view of agent response to the 20cm wide barrier.

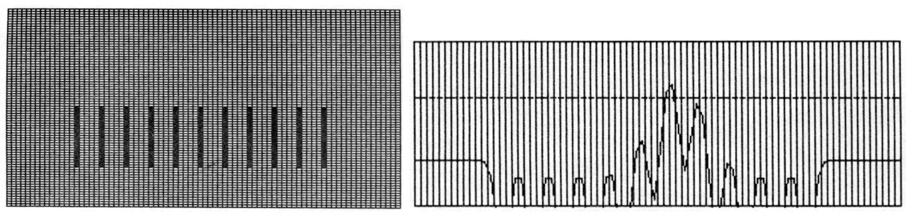

Figure 16. Attractant field integrating prey attraction and barrier repulsion.

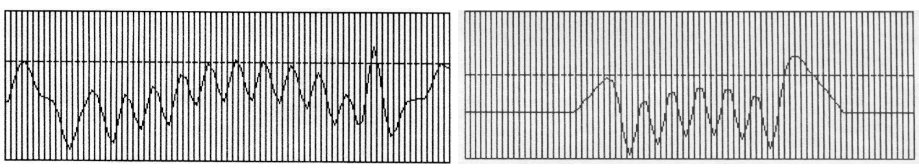

Figure 17. Attractant field when barrier gap is in sight.

This specific trajectory was generated due to the model reorientation specifics. Other simulated results, and more detailed results, can be found in [14].

5 Conclusions and Future Work

This paper has shown the fundamentals of the ASL/NSL/MissionLab neural schema architecture for autonomous robots. A previous architecture is described in [19].

An important aspect of this architecture is the ability to incorporate adaptation and learning through neural network processes in developing new behavioral architectures for autonomous agents [16] as well as robots. This goes beyond architectures where behaviors are described in terms of global states or architectures limited in terms of adaptation and learning mechanisms. Furthermore, as models become more complex in their nature, the distributed and concurrent nature of the ASL/NSL/MissonLab architecture becomes of even greater importance. The prey acquisition model presented in this paper reproduces one of a number of behavioral experiments with toads. Other experiments are currently being tested under this architecture, in particular, extensions to the toad's and praying mantis prey acquisition and predator avoidance models as they are modulated by learning processes [17]. Furthermore, we are also in the process of experimenting with these models with actual robots in the real world [6].

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