

BIOMIMETIC MECHANISMS OF SELF-ORGANISATION AND ADAPTATION IN ANIMATS

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ABSTRACT

This article describes two ways of including biomimetic mechanisms of self-organization and adaptation in the control architecture of animats. The first one relies on a human designer and the second one on artificial selection. It is shown that such mechanisms contribute to the survival capacities of animats. In particular, they make it possible to walk, to avoid obstacles, to reach goals, to build cognitive maps, and to plan detours. Conditions for future developments are also discussed.

1 INTRODUCTION

In various application areas there is a growing need for autonomous artifacts that should be able to adapt their behavior to changing circumstances. Given some overall mission in an unpredictable environment - such as seeking some specific information within the Internet or performing a specific task on the surface of Mars - one wishes such artifacts to be able to cope with unforeseen and possibly hostile circumstances in the absence of any human intervention, and to take any initiative that makes it possible to fulfill their objective.

Although animals are living examples of such fully autonomous, self-organizing and adaptive agents, it turns out that artifacts with equivalent properties yet remain to be synthesized. However, some progress has been recently made in this respect by people who attempt to devise so-called *animats*, i.e., artificial animals or real robots whose structure and functionalities are as much inspired from current biological knowledge as possible, in the hope that these animats will exhibit at least some of the survival capacities of real animals (Cliff et al., 1994; Maes et al., 1996; Meyer et al., 1993; Meyer and Wilson, 1991).

An animat is usually equipped with sensors, with actuators, and with a behavioral control architecture that relates its perceptions to its actions and allows it to survive in its

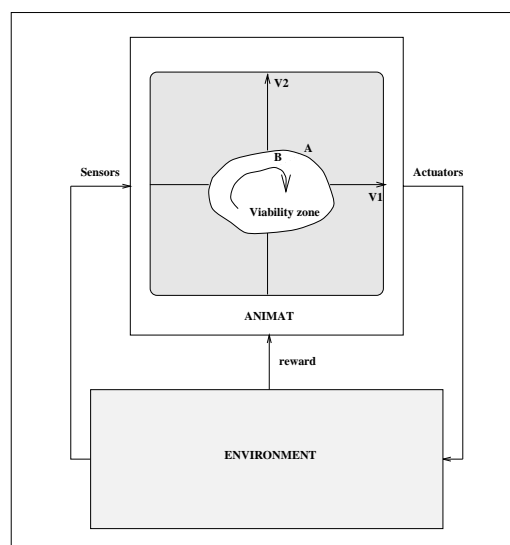


Figure 1: The interactions between an animat and its environment. The behavior of this animat is said to be adaptive because a corrective action has been taken at point B so as to avoid crossing at point A the viability zone associated with the two essential variables V1 and V2.

environment. In this context, survival depends upon some essential variables that must be monitored and maintained within a given viability zone, an ability that can be enhanced, should the animat be capable of learning which actions elicit a positive or negative reward from the environment (Figure 1).

This paper will describe two ways of including biomimetic mechanisms in the control architectures of animats with the perspective of providing these animats with useful self-organization and adaptation properties. The first one relies upon a human designer who purposively translates biological structures or processes into programming instructions or hardware implementations. It will be exemplified herein through the description of a navigation system that calls upon a model of the hippocampus as a cognitive map in

rats. The second one relies on evolutionary design and on the likelihood that, under similar constraints, artificial and natural selection will invent similar mechanisms. It will be exemplified herein through the automatic design of the control architecture of a walking insect.

2 HUMAN DESIGN

The ability to navigate - i.e., to reach as directly as possible any goal place from any start place, while avoiding passing through unnecessary or dangerous places - is probably the most basic requisite for an animat's survival. Indeed, without such an ability, the animat wouldn't be able to reach energy sources, to avoid bumping into damaging obstacles, or to escape from dangerous hazards.

A navigation strategy that seems to be currently used by animals like rodents is the so-called *topological navigation* (Trullier et al., 1997; Trullier and Meyer, 1997a) that allows trajectory planning, i.e., the running of internal simulations that, being decoupled from overt behavior, makes it possible to avoid the hazards of dangerous encounters. In particular, such a strategy allows an animal to plan a detour in the presence of a new obstacle (Figure 2).

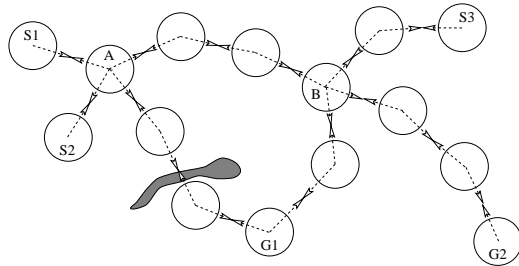


Figure 2: Within the framework of topological navigation, an animal is able to merge its representations of routes into a topological graph. According to such a representation, it knows that a specific move will lead from place S1 to place A, for example. Thus, starting from place S1, it can plan to reach goal-place G1 according to the shortest route. However, if it encounters an unforeseen obstacle (in grey) along its path, it can go back to place A, take the sub-route between places A and B, and take the sub-route from place B to the goal G1. The resulting path will be the concatenation of three sub-sequences, derived from three different routes.

In Trullier and Meyer (1997b), a model based upon the morphology and physiology of the *hippocampus* of the rat - a structure that is known to be involved in navigation tasks in this animal - is used to implement a topological navigation strategy. This model calls upon *place cells* of the CA3 and CA1 regions of the hippocampus (O'Keefe and Dostrovsky, 1971) - that selectively fire when the rat is in specific and restricted regions of its environment (their *place fields*) -, upon *head-direction cells* - that have been observed in other regions of the brain (Taube et al., 1990) and whose firing rate depends upon the rat's orientation -, and upon *goal cells* - of which we postulate the existence downstream of the hippocampus (as in Burgess et al., 1994) and whose activity would code the direction of

the rat's current goal.

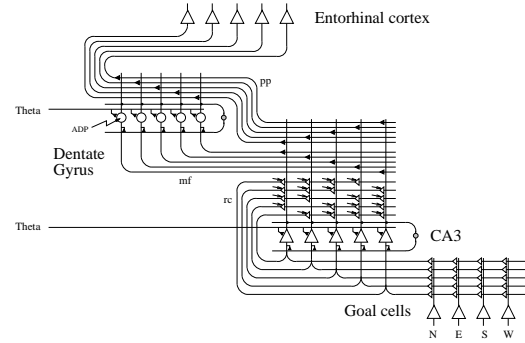


Figure 3: Architecture of the model of Trullier and Meyer. Large triangles stand for pyramidal cells, unfilled circles for granule cells, and small shaded circles for inhibitory interneurons. An activity-dependent afterdepolarizing current (ADP) is intrinsic to each granule cell. Synapses are represented as small triangles with weights that are either fixed (black) or plastic (white). Arrows indicate synapses that are gated by head-direction cells. mf: mossy fibers; pp: perforant path; rc: recurrent collaterals; 8 goal cells (4 shown) represent North, North-East, East and so on.

The model also takes into account the physiological mechanisms detailed in Jensen et al. (1996) and, notably, the modulation of place cell firing by the overall *theta rhythm* - a sinusoidal EEG oscillation, ranging between 4Hz and 10Hz, which occurs during locomotion. Thus, as the rat travels through a place field, the firing of the corresponding place cell precesses from late to progressively earlier phases of the theta cycle.

Finally, each neuron in this model is described as a single compartment model where the membrane potential V obeys the following differential equation:

$$C \frac{dV}{dt}(t) = \sum g_k(t) \cdot (V(t) - V_k)$$

where C represents the cell capacitance and k stands for different currents - i.e., the leak current, the fast afterhyperpolarization, the theta modulation, the feedback inhibition, the AMPA and NMDA synaptic inputs, and the afterdepolarization. Likewise, g_k and V_k stand for the corresponding conductances and reversal potentials.

According to this model (Figure 3), when the rat moves around in its environment, it experiences a sequence of places that is encoded in the hippocampus as a topological graph recording that places are neighbors or that their corresponding place fields overlap. This is made possible through a biophysically plausible Hebbian learning, which changes the synaptic weights between place cells during a first exploratory phase, and builds up the topological graph. According to such learning, each enhanced synapse represents the fact that the post-synaptic place cell is situated next to the pre-synaptic place cell, in the direction coded by a gating head-direction cell. In other words, thanks to such a *cognitive map* (O'Keefe and Nadel, 1978), the rat knows through which sequence of places it will travel if it moves in a given direction from a specific place.

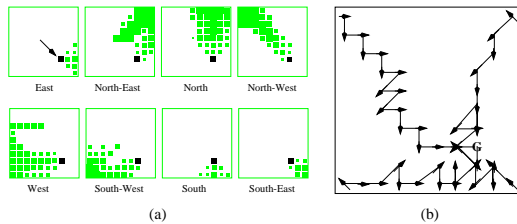


Figure 4: (a) Weight distributions for synapses from place cells to goal cells. Each labeled large square represents the 10 by 10 environment shown in (b) and each filled square represents the synaptic weight (proportional to size) from the corresponding place cell to the labeled goal cell. For instance, the arrow on the top left points to a square that represents the synaptic weight from place cell (8,8) to the East goal cell. (b) Trajectories to the memorized goal (G) from different starting positions. The animat uses the goal representation shown in (a). The fact that trajectories tend to oscillate a little bit near the goal is probably due to the low level of discretization of the environment.

During a second exploratory phase, the rat occasionally learns reward sites. Such a learning involves 8 goal cells that are recruited at each reward site in the environment. The activity of each goal cell can be tuned to a direction - arbitrarily labeled North, North-East, East, and so on - given by a head-direction cell. Consequently, when the rat encounters a reward, it looks into each of the 8 directions. The simultaneous activation of the place cell representing the goal location and of the head-direction cell that specifies a given direction drive all the place cells that represent locations in the corresponding direction with respect to the goal. Place cells that fire during such episodes are associated through a simple Hebbian learning rule to the goal cell dedicated to each direction. The result of this learning process is that the goal cells partition the environment in 8 directional sectors around the goal location. According to such a partitioning, the rat knows that it is globally “West” of the goal, for instance (Figure 4a). This, in turn, triggers an internal signal to move to the “East” to reach the goal. Once the topological representation is acquired and the goal direction learned, the rat can return to the goal from any starting position, as shown in Figure 4b.

3 EVOLUTIONARY DESIGN

Because the nervous system of animals has been shaped by natural selection, not by a human designer, several researchers advocate the use of automatic design procedures that would bypass human intervention insofar as possible, and that would adapt the control architecture of an animat to the specific environment it lives in, and to the specific survival problem it has to solve. Thus, several research efforts have addressed the simulation of processes that improve the behavior of individuals in a population from generation to generation. These efforts involve the implementation of artificial selection processes that eliminate individuals with ill-adapted behaviors and favor the reproduction of individuals displaying well-adapted be-

haviors. Most often, they involve a classical *genetic algorithm* or some variant, which operates on chromosomes that directly encode the control architectures of the various individuals in the population.

In Kodjabachian and Meyer (1997a,b) an indirect approach is undertaken, which encodes in a tree-like chromosome the developmental program of a neural network that controls the locomotion of a six-legged animat. Within such a framework, each cell in a developing network has a copy of the chromosome that codes the developmental process, and each cell reads the chromosome at a different position. According to standard *genetic programming* practice (Koza, 1992, 1994), the chromosome is represented as a grammar tree, with ordered branches whose nodes are labeled with character symbols. These character symbols represent instructions for cell development that act on the cell or on its connections to other cells. During a given step of the developmental process, a cell executes the instruction referenced by the symbol it reads and moves its reading head down in the tree. Depending on what it reads, a cell can divide and generate a daughter cell in a given direction and at a given distance, draw connections in a given direction and at a given distance, or stop developing and become a mature neuron. Figure 5 illustrates the corresponding process.

The developing architectures are afforded the possibility to draw connections with sensory and motor neurons whose spatial organization are imposed by the body plan of the animat. Each neuron is modeled as a *leaky-integrator*, characterized by a time constant and a bias that can be set by specific developmental instructions. According to this model, the mean membrane potential m_i of a neuron N_i is governed by the equation:

$$\tau \cdot \frac{dm_i}{dt}(t) = -m_i(t) + \sum w_{i,j} x_j(t) + I_i(t)$$

where $x_j = (1 + e^{-(m_j + B_j)})^{-1}$ is the neuron’s short-term average firing frequency, B_j is a uniform random variable whose mean b_j is the neuron’s firing bias, and τ is a time constant associated with the passive properties of the neuron’s membrane. I_i is the input that neuron N_i may receive from a given sensor, and $w_{i,j}$ is the synaptic weight of a connection from neuron N_j to neuron N_i .

The development starts with six neurons placed as shown on Figure 6. They all execute the instructions of the same program that turns them into sub-networks that may be connected to each other. Figure 7 provides an example of a developmental program obtained after 700 generations, when the initial population was made of 200 randomly-generated programs, and when the *fitness* of any animat was given by the distance it covered during a given evaluation time.

Figure 8 illustrates the walking behavior of the corresponding animat.

The same methodology made it possible to evolve the control architecture of an insect capable, not only of using its

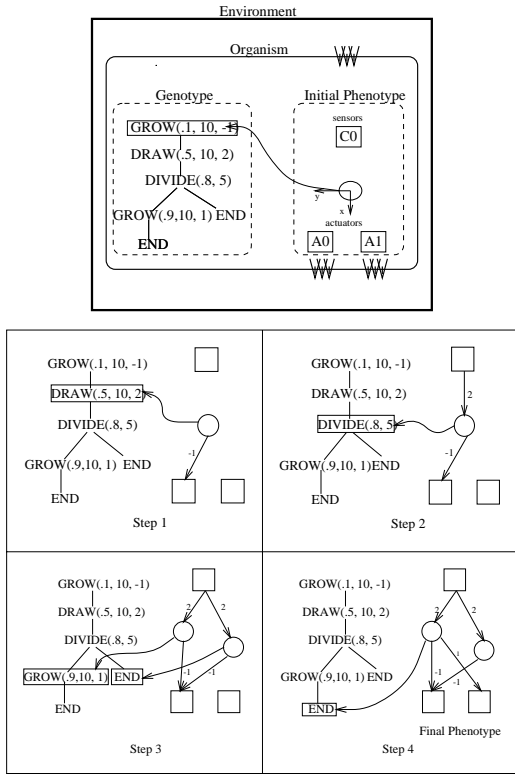


Figure 5: Developmental encoding scheme used by Kodjabachian and Meyer. The genotype that specifies an organism's nervous system is encoded as a grammar tree whose nodes are specific developmental instructions. Within such chromosomes, mutations change an instruction into another, and crossovers swap branches. Each cell in the developing network reads the chromosome at a different position. The DIVIDE instruction causes a cell to divide and generate a daughter cell in a given direction and at a given distance - according to the arguments of the instruction. Likewise, GROW and DRAW instructions cause a cell to draw respectively efferent and afferent connections with other cells, in a given direction, at a given distance, and with a given synaptic weight. END instructions cause a cell stop developing and become a mature neuron. Each neuron is modeled as a leaky-integrator, characterized by a time constant and a bias that can be set by specific instructions named SETTAU and SETBIAS. More or less developmental steps are required to generate a phenotype, depending upon the length of the corresponding genotype.

legs to quickly walk according to a *tripod rhythm*, but also of using its antennas to skirt around obstacles and to reach an odorous goal somewhere in the environment (Figure 9).

Such results demonstrate that quite complex control architectures can be generated by much simpler developmental programs, thus tremendously reducing the size of the solution space that the evolutionary process explores. Moreover, it turns out (Kodjabachian and Meyer, 1997a,b) that, inside the controllers that have been thus evolved, it is possible to identify numerous mechanisms that are known to be implemented in real insects, such as reflexes, feedback circuits, oscillators, central pattern generators, chronometers and rudimentary memories.

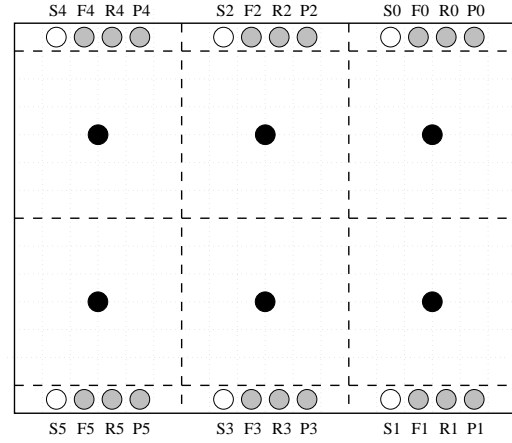


Figure 6: The arrangement of sensors, actuators and initial neurons used by the developmental program of a six-legged animat. S: angle-sensor neuron, which detects the angle a given leg makes with the vertical; F: foot-motor neuron, which lifts a given foot when active; R: return-strike motor neuron, which propels a given leg forward; P: power-strike motor neuron, which propels a given leg backwards.

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Figure 7: An evolved developmental program (instruction arguments excluded) of a six-legged animat. This program is expressed as a parenthesized expression, i.e., in a formalism that is equivalent to the grammar trees used in Figure 5. I: DIVIDE; G: GROW; D: DRAW; S: SETBIAS; E: END. SETTAU was not used in this run. Besides the 24 sensory and motor neurons that have been provided by the experimenter, the neural network generated by this program contains 168 inter-neurons and 2222 connections after development.

4 DISCUSSION

For a human designer, including biomimetic mechanisms into the control architecture of an animat is seldom an easy task. We have argued elsewhere (Meyer, 1997) that this is due to the shortcomings of current biological knowledge and to the traditional research strategy of biologists, who usually favor a *reductionist, analytical, and top-down* approach, whereas the design of *situated* animats (Steels and Brooks, 1995) that characterizes so-called *artificial life* preferentially calls upon the *synthetic and bottom-up* study of *emergent properties* (Meyer, 1996). It is to be expected that such a situation will last until the tenants of traditional biology and those of artificial life will complement each

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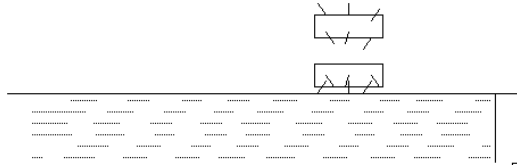


Figure 8: The upper part of the figure shows a top view and a side view of the six legged animat, at a given time and a given distance from start. The lower part illustrates the walking rhythm of the animat. Dotted lines indicate periods of protraction (leg off ground and moving forward relative to the body and ground) for each leg. By convention, these lines refer to legs in the following vertical order, from top to bottom: Rear Right, Middle Right, Front Right, Rear Left, Middle Left and Front Left. The walking rhythm exhibited by this animat is a variety of so-called *Wilson's rhythms* that are known to be exhibited by real insects.

other to the best avail.

As for the evolutionary design of behavioral controllers, if such an approach is clearly capable of rediscovering some of the mechanisms that nature has invented to secure adaptive behaviors in animals, it remains to be assessed how far it leads when more *cognitive processes* than mere stimulus-response pathways are requested for survival. The inclusion of a developmental process between the genotype and the phenotype of an animat has obviously improved the potentialities that are afforded by a direct encoding of the phenotype into the genotype (Kodjabachian and Meyer, 1996). Likewise, it is to be expected that future developments that will enhance the biological realism of artificial evolution - such as taking *co-evolutionary processes* into account or calling upon *implicit fitnesses* - will also increase the chances of automatically generating some of the yet unknown mechanisms of natural self-organization and adaptation in animats.

5 CONCLUSION

It has been demonstrated here that the inclusion of biomimetic mechanisms within the control architecture of animats affords non-trivial self-organization and adaptation capacities. In particular, such mechanisms make it possible to walk, to avoid obstacles, to reach goals, to build cognitive maps, and to plan detours. Further progress will be made as new natural mechanisms will be discovered by biologists, an endeavor that advances in the simulation of evolutionary processes are likely to facilitate.

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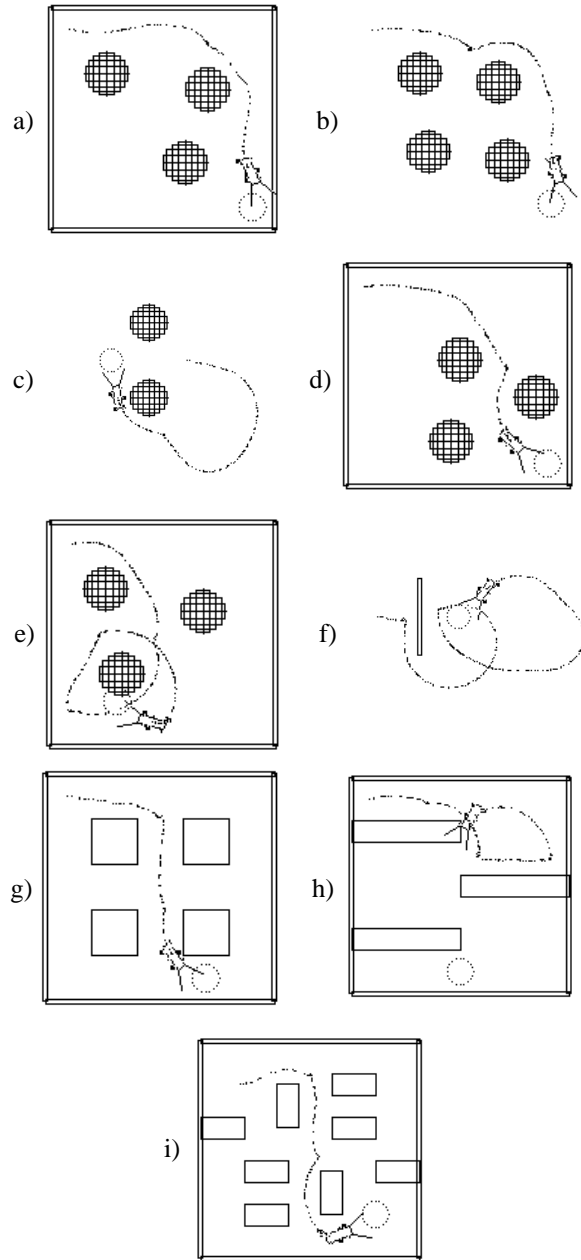


Figure 9: Experimental results obtained with a simulated insect when walking, odour-following and obstacle-avoidance behaviors are evolved. Dotted circles represent goals that emit an odour whose intensity decreases with the distance to the source. Cases (a-c) show the animat's trajectory within 3 out of 5 environments that have been used during the evolutionary process to evaluate the fitness of every individual. Cases (d-i) show results of generalization experiments, in 6 new environments. The animat can deal with obstacle shapes never met during evolution (f-i). However, because of the dead angle between its antennas, it cannot always avoid hitting sharp corners (h).

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