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# ARTIFICIAL ORGANISMS WITH ADAPTIVE SENSORS

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## ABSTRACT

**We try here to outline some basic ideas for developing a model of the evolution of interacting inteligent agents in a relatively complex artificial world, in the sense that it includes, along with physical characteristics, purely adaptive organisms (plants). The cognitive agents we deal with are endowed with a genetic algorithm, which permits its evolution, and with a neural network for its ontogenetic learning. But if we consider that the cognitive capacities are the result of the evolution of the sensorimotor loop, then the processes that lead to the modularity of the information processing network should be entangled with similar processes at the level of the sensors and effectors. Therefore, the agents we are trying to model here have also adaptive sensors and effectors, in the sense that the mapping from the inputs to the outputs can vary in somatic time, according to the functional needs of such agents.**

**KEYWORDS:** Artificial Life, Evolution, Cognition, Adaptive Sensors/Effectors

## 1. INTRODUCTION

In this paper we pose the problem of how to model basic cognitive processes in the frame of models of simulation of artificial worlds in the style of Artificial Life (Langton, 1989; Langton et al, 1992; Varela & Bourgine, 1992). The main difficulty of simulating cognitive processes in this context lies in the search of forms of representation of organisms that will allow the establishment of functional relationships of the systems with their environments, so that forms of emergent behavior can be observed. In order to attempt it, we present a model of representation that will be used to raise a discussion on the advantages and limitations of this approach as a research program in biology and cognitive science. The distinction between what we call adaptation (either phylogenetic or ontogenetic) to the environment and learning (ontogenetic) motivates a definition of two different degrees of complexity of that interaction (Merelo, Moreno et al, 1992). While the first one generates a structural variety of organisms on an evolutionary scale, the second one brings about an ontogenetic variety of structures created and developed during the life of each organism.

One of the most peculiar features of the methodological style of AL is an attempt to ground all the processes that concern living systems with the purpose of --sooner or later-- be able to artificially emulate them.[1] After the functionalism which was the main characteristic of AI, now a way is open for a new kind of structurallism that will make possible to study living and cognitive phenomena through relations that are closer to what is materially realizable. The AL approach is developed towards the ideal of being able to display real evolutions of artificial natures in the computer, so that the simpler will generate the more complex through an emergent evolution. Given that an absolute fidelity to that ideal would not make possible to study systems so complex as the cognitive ones we are interested on, the only option left in order to be able to study phenomena that are more complex than the ones that can be in fact grounded on an artificial materiality is to design certain features, thus considerably simplifying the underlying materiality.

Then, in this domain we have developed an artificial world model whose main interest is the study of the entanglement between evolutive and cognitive capacities of the artificial organisms. This approach can uncover various types of problems that are often left aside when cognitive phenomena are taken into account only at a high level (Belew, 1991).

## 2. COGNITION AND THE DEVELOPMENT OF ADAPTIVE SENSORS AND EFFECTORS

From the perspective of their origin, cognition and learning arise as a result of an increase of the complexity of the sensorimotor loop. Functionally speaking this complexity is directed to the control, integration and hierarchical modulation of an increasing number of biological activities. Although cognition does not define the set of biological needs, it accomplishes an optimization of their realization. Therefore, even if it cannot be studied apart from biological functions, cognition has a different specificity: their global integration through mechanisms that imply informational processes.

While in purely adaptive organisms perception is a direct cause of certain metabolic-motor actions, in cognitive organisms the physical patterns impinging on sensors are transformed in trains of discrete sequences (which constitute information) that modify the state and dynamics of the network of connections where sensory information is processed. Unlike in metabolic networks, where there is no distinction

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[1]Artificial emulation is not defended as an useful goal in itself, but as a scientific or epistemological one, as we tried to explain in more detail in previous occasions (Etxeberria, 1992; Fernandez & Moreno, 1992), the properties of living systems cannot be completely grasped through formal models of them.

between units and connections, in neural networks the stress is made on the variability of connections and on the control (by/of the very network, throughout other layers or global patterns) upon such structural variations. Therefore in the former case structural changes take place only in the frame of phylogenetic evolution, while in the later this kind of process can also take place in somatic time (learning) (Bray, 1990). That is why the concept of (epistemic) information processing needs the development of a system of channelling as rich and modulable as possible.

When high level cognitive functions are being considered, most research strategies take essentially into account variations taking place at the level of the connection net between sensors and effectors. Even when, no doubt, this is a fundamental factor, we should not forget that evolution towards more complex forms of sensory information processing is correlative to the complexification of sensors and effectors. Frequently, even more when we face the task of building artificial models of cognitive systems, this is forgotten or undervalued, mainly because cognition is not approached from a radically evolutionary perspective. At higher levels of cognition the increase of the complexity of the cognitive elements makes them appear as nearly autonomous subsystems. But it is an empirically verifiable fact that in natural cognitive systems there is a closed and tangled correlation between development of sensors, of the information processing network and of effectors, and cognitive science should take it into account.

As a consequence, we think that if the models of artificial cognitive systems present a neural networks to allow learning, their sensors and effectors must be also adaptive.

## 3. TOWARDS A MODEL OF A COGNITIVE ARTIFICIAL ORGANISM

If we want to place the problem of modelling a cognitive system in its biological ground, we should move from the domain of Artificial Intelligence (AI) to the one of Artificial Life (AL). There are, however, two different (though non incompatible with each other) approaches and research programs in AL. The most popular one is based on computational simulations; the other one attempts to construct artificial living beings in the physical world: this one (as opposed to pure simulations) belongs to the research program of "realizations" in AL. In spite of some recent attempts to create an "evolving hardware" (Higuchi et al, 1992), the main difficulty to artificially implement physical organisms with evolutive capacities is in fact the problem of reproduction (for in darwinian sense, evolution cannot be conceived without reproduction). Thus, given current technology, when we try to model artificial systems whose cognitive capacities are entangled with the evolutive ones, we should basically work on simulations.

### 3.1. Limitations of current models of artificial cognitive organisms

Right at this moment, research in the field of AL has not developed any truly cognitive system, in the sense that all its structure, effectors, sensors and the intermediate information processing system varies in a phylogenetic as well as an ontogenetic scale. The vast majority of artificial organisms show only a moderate grade of adaptation, usually through the change of the neural net weights, being change at the level of the neural net structure far more difficult.

The tools we have at hand, in order to implement this, are neural networks and genetic algorithms (Ackley & Littman, 1991). A neural net is the most powerful instrument to implement a learning system and, if its structure is genetically coded, it will be able to evolve (Hinton & Nowland, 1987). The procedure is the following: all the information contained in the organism genome is compiled (in the computer language sense) at the time of birth, when also perceptive and active rules are created as well as the neural network structure, to which weights are assigned.

In principle, this process is deterministic, i.e., compiled structures follow necessarily from its encoded form. Nevertheless, new forms of representation should be sought in which development were similar to the real one, so that the phenotypic structures were described in the genome only loosely, while other dynamical properties would follow the genome in a functional way. Anyway even if it is very difficult to think of ways of achieving this, the genome complexity and the generated structures are positive steps towards it.

At present, the neural net structure remains frfrozen like it has been created, and only weights change during the lifetime of the organism. These weights, that reveal the ontogenetic learning of the organism, are not inherited by the next generations.

### 3.2. The entanglement between evolution and cognition

The system we propose here has been implemented with the aim of studying several problems of population evolution taking into account the cognitive capacities of artificial organisms (Merelo, Moreno et al, 1992; Merelo, Paton et al, 1992). Now we intend to improve this model by developing the idea of *adaptive sensors*, previously proposed in Moreno et al (1992).

The artificial world contains a population of artificial organisms and all the elements of their cognitive systems should be phylogenetically and ontogenetically adaptive. The main problem that researchers face in this field is the use of variable-length genes in the genetic algorithm (GA), that would allow for open-ended evolution (usually by an enlargement of the genome, as shown in Harvey, 1992). Nevertheless, this problem can be solved in several ways, as has been proposed by Koza (1990) and other authors (for instance Goldberg et al (1991) proposed their mGA paradigm). A system with open-ended evolution should use one of these algorithms. For an artificial being to be cognitive, it must obviously learn inside the artificial world. But as it was proposed by Cariani (1989), learning does not mean only change of internal rules, it implies also the possibility of assigning new meanings to the detected features of the environment (inputs), as the interaction of the artificial organisms with the environment takes place in different circumstances. It requires the development of adaptive sensors, capable of varying the realized mappings according to learning (and similarly, the possibility of creating new effectors).

## 4. A PROPOSAL: ORGANISMS WITH ADAPTIVE SENSORS

We can distinguish the following generic elements within the artificial environment that constitutes our model:

- World (inanimate objects)
- Plants
- Cognitive Organisms

All living activities will be developed in the scenario of this world. It is three-dimensional and certain limits are pre-established that can be modified depending on the needs of different users. We include in it certain components like water, mountains, stones, etc. which determine the form of the world. It has some climatic characteristics like temperature, humidity, rain, etc.

In this environment we include as well some organisms with evolutive --but not cognitive-- capacities (plants), which will be the food of the cognitive ones.

Cognitive Artificial Organisms (CAO) are the most complex and important part of this environment, where our research will be focused. They can evolve as a species, but they can also learn at an individual level. We can distinguish three parts or subsystems in their cognitive structure: Sensors, Neural Net and Effectors.

The perceptive subsystem of the CAO is formed by a set of sensors, capable of detecting concrete characteristics of the objects within their perceptual domain.

The neural net of the CAO will take decisions on the most adequate action to undertake, depending on the inputs provided by the perceptual subsystem. This neural net changes by phylogenetic evolution.

The effectors determine the actions that the CAO can exert, they can be described as rules for world modification, which include rules of change of the objects and of the situation of the CAO itself.

The CAOs present certain connections between their perceptual and effector subsystems since birth, so that they are able to develop some forms of coordinate behavior even before learning. These behaviors can be considered the species specific instinct. Changes of the neural net modulate the existing connections.

### 4.1. Perceptive System

The perceptive subsystem of the CAOs is characterized, as we previously said, by being formed by adaptive sensors. Sensors cannot be understood if they are not related to a world, their function is to react to certain characteristics of the world that surrounds the artificial organism and convert physical data in high-level sensory information: size of the object in front, odour, distance and so on.

The artificial organism sensors can be adaptive in two senses:

-in a phylogenetic scale, they can develop the capacity of detecting new features of the environment.

-in an ontogenetic scale, they can vary the internal meaning assigned to previously detected inputs, as the functioning of the sensorimotor loop acquires new experience of its surroundings.

Thus, in a phylogenetic scale, there must be a development of new sensory structures, able to perceive different properties of the environment, but this cannot occur at an ontogenetic scale. Our artificial organism system is capable of developing a variety of connections or input-output associations during its lifetime as it learns by experience in its environment.

Adaptive sensors present two limitations: 1) a physical one that determines the physical propagation of the stimuli across it; 2) another one peculiar to the sensors that determines how far can this one perceive.

Each sensor has a *perceptual field* determined by a cube and the position of the CAO with respect to it. Therefore we need six values in order to identify the perceptual field: three for the X, Y, Z dimensions of the cube and three more for the relative position in X, Y, Z of the CAO with respect to the cube. These six values of each sensor are genetic traits of the CAO and therefore are subject to possible mutations.

In the case of visual sensors we take into account the possibility of object hiding, that is to say, it only makes sense that the CAO *sees* objects directly and not those that are behind others, and therefore, hidden.

The size of the objects present in the world can be of a cube (like a CAO) or more than one (stones, water, etc...). Those forming the latter have uniform qualities, that is to say, all the cubes have the same characteristics. This way, the information of the objects present in the perceptual field is sent to the CAO through discrete squares of the world, so that if any object occupies more than a square the information received is the generic information of the object for each one of the squares that form it.

When there is more than one object within the perceptual field of a sensor, the logical OR of all of them will be executed. For example, if a sensor detects green objects, its output will be NO if no object is green, and YES when any of them is green.

Thus, the qualities of the objects of the environment are modeled in the following way:

• ODOUR: each object family has an specific odour; in the case of the CAO (and plants), it is species specific.

• SOUND: We define two characteristics, *volume* and *pitch*. Volume changes according to the distance to the center of the perceptual field; pitch determines the type of sound, depending on whether it is a side effect (noise produced by each CAO species when they move) or a sound emitted by the CAO itself with a special purpose. The size of the auditory field of the CAOs corresponds to the space where a sound emitted with a maximum volume can be heard; sounds produced outside this field will reach the CAO with zero volume.

• VISION: Aspects perceived through vision are:

• *Color*: It takes values between 1 and n, which correspond to the colors of the surroundings of the CAO (other CAOs, plants, inanimate objects).

• *Size*: It can be big and small: anything bigger than a CAO will be *big* and anything of the size of a CAO (a cube) will be *small* (a square of the world = a cube unity).

• TEXTURE: It takes values between 1 and m, they correspond to the different aspects that objects can present (rough, smooth, soft, hairy, etc...).

• MOVEMENT: It indicates if an object has moved in the previous execution step, it can tale values between 1 and 27, being the first 26 the possible movement positions and the last one corresponding to *no movement*.
• Other possible qualities of the inanimate objects are temperature, humidity, etc.

All these characteristics --except sound and movement for plants and movement for CAOs-- can vary genetically when they are attributes of living beings.

The world of this model would be composed of a potentially unlimited number of objects, being all possible programs written in this language. They include also qualities of reaction to actions; for instance, if it is movable, if it can be decomposed in smaller units, and so on. In this way, the artificial organism can interact with the world, and in turn, this one can interact with it.

### 4.2. Neural Net Subsystem

Neural Nets (NN) are usually modeled using adaptive algorithms that are already well known, so we will not refer further to them. The only problem here is to implement a neural network of variable structure and size, and how to code this NN inside a gene; the goal of simulating a complete world restricts the use of the available computational resources.

Once again, we cannot pretend to evolve complicated learning algorithms from simple rules. Besides, each of these algorithms would have such a huge set of inputs (present and previous states and weights of the network) and outputs (variation of all weights), that even a simple set of rules would be computationally cumbersome. Thus, we can only hope to label each weight or directed connection as hebbian or antihebbian (in fact all learning rules can be reduced to this one), and let the structure change genetically. Each neuron is then labelled as input, output, or pass through, and information cascades from inputs to outputs, every discrete step going from one neuron to the next one. Information from several timesteps is then concentrated in the output neurons.

The genetic coding of the neural network will include:

- A connection map that tells how many neurons there are, and their connections.
- A neuron labelling that classifies each neuron as input, output or pass-through.
- A connection or weight labelling, possibly mixed with the first, that tells if the connection is antihebbian or hebbian.
- Initial values of weights.

### 4.3. Adaptive Effectors

In order to simulate effectors, we will take the same approach used for sensors. Effectors manipulate the world, affect some characteristics of the objects of the environment or change the spatio-temporal relation of the CAO with respect to the world. Features of the objects of the world vary as events take place, but this variation will only be appreciated in the following step, for in a simulated artificial world time is discrete.

## 5. DISCUSSION: GROUNDING COGNITION ON BIOLOGICAL FUNCTION

The attempt to pose the problem of the appearance of new cognitive capacities in relation to the biological structure of organisms, so that it is possible to jointly observe phenomena such as evolution or self-reproduction and a cognitive relationship of an artificial organism with its environment in artificial worlds is a great challenge for cognitive science. Traditionally, AI and cognitive science have focused on the study of high level phenomena and have considered that the underlying biological structure played a small if not insignificant role in the realization of the different cognitive tasks: perception, learning and memory.

This way, our model could overcome some epistemological limitations of current connectionist approaches of cognition. In such approaches, cognitive systems are not able to autonomously find solutions for certain tasks, nor to determine their goals by themselves or change the ones specified from the outside (Van der Vijver, 1991). As a consequence the (relative) self-organization occurring in the cognitive process is external and not linked to the constructive self-organization of the organism. In our opinion, the root of this unsatisfactory situation lies in the fact that the cognitive process is not grounded on the biological functions of an organism, so that it is possible to relate evolution with cognition (Moreno and Etxeberria, 1992), and this has important consequences in the debate on the problem of representation in cognitive science.

Critics to classical AI maintain that the knowledge an organism has of its environment does not rely on a symbolic representation that can be specified from the outside, but it is not easy to explain how can representations arise in the organism that are functional be originated and accomplish an epistemic function in relation to the environment. Very often this problem has been taken so far as to the adoption of anti-representationalist positions of different sorts, for example when it is defended that most of behavior is based on sensorimotor automatisms that do not require internal representational models. This case is usually argued either defending that knowledge depends of the real or detailed structure of the environment whose perception guides action without the need of forming internal structures (Brooks, 1991), or that representation is the result of the structure of the cognitive organism itself and information can be considered embodied in the internal constraints of the organization of the subject, which can make sense out of certain perturbations coming from the outside (Varela et al 1991).

The first position reduces the problem of cognition to a mere reactivity towards the environment and, even if it can lead to an interesting engineering strategy that is biologically more realist than the one of previous AI, epistemologically it erases the problem of cognition for there is no more cognitive subject left. The second one underestimates the problem of cognition in a similar way, because the transformations undertaken by the subject in relation to the environment cannot be considered as knowledge of anything, as there is no environment to be known.

A study of cognitive process grounded in the biological structures of organisms like the one we have proposed here makes it possible to re-settle the problem of cognition as a phenomenon of construction of a cognitive system in the interaction with its relevant environment, a process through which hierarchical representational structures are created with a functional value associated to the biological survival of the artificial organism.

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