Fundación Arturo Rosenblueth

Artificial Societies of Intelligent Agents

Thesis

for majoring in Computing Engineering

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"The best way to understand man is by creating him"
—José Negrete Martínez

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Надя,
ты не только даёшь мне Надежду,
но ещё мне даёшь любовь и веру.

Contents

Abstract

In this thesis we present our work, where we developed artificial societies of intelligent agents, in order to understand and simulate adaptive behaviour and social processes. We obtain this in three parallel ways: First, we present a behaviours production system capable of reproducing a high number of properties of adaptive behaviour and of exhibiting emergent lower cognition. Second, we introduce a simple model for social action, obtaining emergent complex social processes from simple interactions of imitation and induction of behaviours in agents. And third, we present our approximation to a behaviours virtual laboratory, integrating our behaviours production system and our social action model in animats. In our behaviours virtual laboratory, the user can perform a wide variety of experiments, allowing him or her to test the properties of our behaviours production system and our social action model, and also to understand adaptive and social behaviour. It can be accessed and downloaded through the Internet. Before presenting our proposals, we make an introduction to artificial intelligence and behaviour-based systems, and also we give notions of complex systems and artificial societies. In the last chapter of the thesis, we present experiments carried out in our behaviours virtual laboratory showing the main properties of our behaviours production system, of our social action model, and of our behaviours virtual laboratory itself. Finally, we discuss about the understanding of adaptive behaviour as a path for understanding cognition and its evolution.

Introduction

"As much as you go, and even if step by step you proceed through all the ways, you will not find the limits of the soul, so deep the λογος has penetrated in her"
—Heraclitus

"La Incomprensión del Hombre". Carlos Gershenson, Mexico City, 1998. Oil on canvas, 100 x 70 cm.

Why engineer systems simulating living creatures and their societies? Well, it helps us understand better those living creatures and their societies. But in the process, we obtain artificial creatures with the same capabilities as the ones *simulated* from the living creatures. So we have a benefit, both for engineering and biology (Maes, 1991).

Also, understanding adaptive behaviour paves the road for understanding higher cognition.

0.1. Behaviour and the Evolution of Cognition

"The more we can find out about how our brains evolved from those of simpler animals, the easier the task will be"
—Marvin Minsky

We can classify adaptive (animal) behaviour in the following types of behaviours: vegetative, reflex, reactive, and motivated behaviours. **Vegetative behaviours** would be the ones that are in the organism by "default", such as breathing, heart beating, metabolizing, etc. They can be seen as implicit, internal behaviours, that are not noticed by an observer because they are always there. They do not require to be modelled, because they are "obvious[1]". **Reflex behaviours** would be action-response-based behaviours, such as the response to a burn, that is to move the injured part from the heating source. We would argue that bacteria's behaviours are controlled only by reflex behaviours. We could say that in vertebrate animals, reflex behaviours are controlled at a medular level. We can see that there is no problem of action selection in the previous behaviour types, as it is in the following. **Reactive behaviours** would be the ones that depend strongly of an external stimulus, or a set or sequence of external stimuli (McFarland, 1981). For example, if I perceive a tasty chocolate cake, even if I am not hungry (no internal motivation), I might reactively eat it; but also I might decide not to eat it, because I have other internal needs to be satisfied (such as vanity). Most simple social behaviours could be classified as reactive, such as flock and school formations, stampedes, and crowd behaviours. This is because each individual in the society imitates the neighbours, but without the "need" of doing so (it is not that they do not need it, but that they can live without it). We can see that reflex and reactive behaviours are similar, but the difference is that the reactive behaviours go through an action selection process, which may cause that they will not be executed, and the reflex behaviours will always be executed. **Motivated behaviours** would be the ones that need an internal motivation and an external stimulus (which might be also the absence of a stimulus) in order to be executed. For example, the searching for water by an animal may be caused by his thirst. We understand by internal motivations those that are needed to be satisfied so that the entity will be in a "comfort zone". Not only those motivations needed for survival are internal motivations. Emotions can also be seen as internal motivations, or as expressions of

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[1] They are obvious at the level of the individual, for example, hunger decreasing because of feeding is obvious at an individual level, but quite complex at a protein or cellular level.

internal motivations. We should note that in reactive behaviours, there might be motivations that we do not perceive. That is why the borders between the different types of behaviours are not sharply defined and are fuzzy, but this is not important for our purposes.

We hold that in terms of evolution, first were vegetative behaviours, then reflex, then reactive, then motivated, then reasoned, and then conscious ones. **Reasoned behaviours** require concepts (symbolic representations), and manipulation of those concepts in order to select the behaviour. Some might not have any differences, for an outside observer, from the previous ones. But reasoned behaviours require concepts and a logic in the action selection process. So, in individuals with reasoned behaviours, motivated and reactive behaviours might or might not be reasoned. But there are plenty of complex reasoned behaviours that require of concepts and logic in order to be achieved. Extreme examples would be designing a spaceship and the planning of a perfect murder. We can see that reasoned behaviours require of a language and a culture, in order to evolve from previous behaviours. Also here the border is fuzzy, because there can be many different degrees (complexities) of reasoned behaviours. We can say that **conscious behaviours** are the ones that are executed while being *aware* of them, without falling in the debate of what and where consciousness is. This might be also seen as reasoning about what we are reasoning (similar to what Dennet calls a second order intentional system (Dennet, 1987)). Reasoned and conscious behaviours imply higher cognition. We can see that the more evolved types of behaviours are more complex. We also argue that plasticity is increased through the different levels of behaviours as well. This is, more evolved behaviours adapt (learn) faster to changes in the environment. More basic behaviours should not be too plastic, because they are in charge of more vital functions (*e.g.* if we would need to be conscious of our breathing, we could forget about it). Figure 1 shows graphically the previous classification.

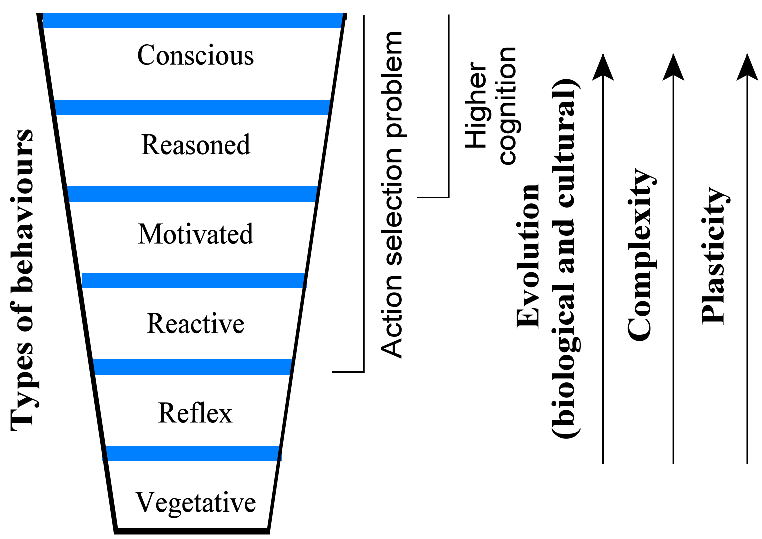

Figure 1. Organization of different types of behaviours.

We believe that, in order to model plausibly reasoned behaviour in an open, unpredicted, non deterministic environment, we should model first convincingly reflex, reactive, and motivated behaviours. Reasoned behaviours need the other behaviours, not only because reason (and higher cognition) evolved from adaptive behaviour, but because we can distinguish a hierarchy among the types of behaviours described above. For example, if I am in a night club, hierarchically, first, I will breathe to stay alive (vegetative); then, I will move my foot if someone steps on it (reflex); then, I will probably clap if everyone begins to clap (reactive); then, I will ask a girl for a dance if I feel attracted to her (motivated); then, I will begin to think about what to speak with her (reasoned); and finally, I will ask myself what am I doing in such a place (conscious). We can see that the less complex types of behaviours will dominate the more complex, not only because the execution of the more complex behaviours (in most cases) does not prevent the execution of the less complex (I can keep breathing while moving my foot, I can reflexively move my foot while clapping and dancing, etc.), but also because the more complex types of behaviours need of the execution of the less complex in order to be executed (I need to breathe to live, I need to move my foot to dance, I need to like a girl to think how to seduce her, and I need to have all the previous experiences in order to be aware of them and rethink what I am doing). Also, the low plasticity in the less evolved behaviours makes them hard to control by the more evolved. For example, we can control hunger (motivated) with reason more or less successfully, but it is harder to control our dance steps (reactive) in a different way than we are used to, and it is very hard indeed not to scream if some part of us is burning (reflex). Behaviours that took generations to be learned by evolution are harder to forget than behaviours learned in one day.

Each type of behaviour solves a problem. The next behaviour was evolved over the previous without losing the capability of solving previous problems. We believe we should engineer our artificial systems in the same manner: build a subsystem to solve a problem. Then build over the previous subsystem another one to solve a new problem, but without losing the capabilities of solving the first problem(s), in a *bottom-up* fashion. By following the steps of natural evolution, we can **simulate** more completely creatures created by it.

Before being humans, we are animals. *If we want to simulate human reasoning, we need to simulate properly animal behaviour*. Also, we would need *a culture, a language, and a society* to obtain reasoned behaviour from adaptive behaviour.

In the present work, we join the effort of the community to model adaptive behaviour, in order to set a *behavioural basis of cognition*. We do this by engineering artificial societies of intelligent agents, to understand intelligence emerging from adaptive behaviour, building artificial societies on the way.

0.2. Objects vs. Concepts

"Objects do not depend on the concepts we have of them"

A "problem" in scientific research is that different people are working in similar concepts in parallel, so they can name the same thing with different names, or different things with the same names. We should just do not care so much about terms[2]. We should care about the research itself. Since objects do not depend on the concepts we have of them, we can study objects without putting much attention in the definitions of the concepts (not that it is not important). Other people can discuss "how should we call things". John Locke said it well: "Words should not be taken as adequate portraits of things, because they are no more than arbitrary signs of certain ideas".

It is because of this that in this work we will not give sharp definitions of our concepts, only notions.

Objects can have many different, and even contradictory concepts representing them (*e.g.* information (Wiener, 1948; Shannon, 1948), complexity (Bar-Yam, 1997), etc.). No matter how similar or diverse are these concepts, the objects referred by them will not be affected. This is because they are independent of them.

How can we make science then? We need to have **agreements**. We do not have absolute truths or falseness. Our universe appears to be relative. We can say that our agreements are our beliefs, and that our beliefs are the axioms of our thought. As Kurt Gödel proved (Gödel, 1931), all systems based in axioms are incomplete. Also, Alan Turing proved that "there can be no general process for determining wether a given formula of the functional calculus K is provable" (Turing, 1936). This can be generalized saying that there is no method to say if a theorem in an axiomatic systems is provable, or not provable in a finite time. These issues imply that theorems derived from axioms cannot prove the axioms. These axioms are agreements. But we cannot be sure of them. One example can be seen with multidimensional logic (Gershenson, 1998a; Gershenson, 1999), a paraconsistent logic (Priest and Tanaka, 1996) that is able to handle contradictions. This is because we disposed the axiom of non contradiction of consistent logics. After this we built our logic on our own axioms (allowing contradictions), and the result is there. We can understand contradictions and map them to consistent logics.

This is not a thesis in philosophy of science, so we will just conclude saying that in order to obtain the agreements needed in science, we need to doubt of everything. We cannot trust blindly our beliefs because we cannot prove them, neither anything based on them.

[2] As Pattie Maes suggested me.

0.3. Motivations

The objective of this thesis is to contribute to the understanding of the *behavioural basis of cognition*. We do this in three ways:

We expose a behaviours production system (González, 2000) that is able to simulate many properties of adaptive animal behaviour. This gives the community a tool for engineering adaptive artificial creatures, and also contributes to the understanding of animal adaptive behaviour itself.

We present a simple social model for imitation and induction of behaviours. This helps us understand better social systems, and also gives us a tool for engineering artificial social systems.

Finally, we build a Behaviours Virtual Laboratory (Gershenson, González, and Negrete, 2000b) incorporating the mentioned behaviours production system and social model in artificial animals (animats (Wilson, 1985)). This allows us to experiment and simulate conditions from real and artificial systems.

0.4. Structure

This thesis has been structured in the following way:

Chapter 1 makes an introduction to Behaviour-based Systems, their background in artificial intelligence, their properties, and areas where they have been applied.

In Chapter 2 we make an introduction to complex systems, to then fall into the theme of Artificial Societies, their characteristics, and previous work related with them.

Chapter 3 deals with Behaviour-based Intelligence. We first make a short review of behaviour-based systems for the control of artificial creatures. Then we present the Behavioural Columns Architecture (BeCA) (González, 2000), a context-free behaviours production system, and its properties.

In Chapter 4 we introduce our simple social model of imitation and induction (I&I), which allows social processes to emerge using a behaviour-based approach.

In Chapter 5 we present our Behaviours Virtual Laboratory (BVL) (Gershenson, *et. al.*, 2000b), its components and functionality.

Chapter 6 consists of two series of experiments elaborated in our BVL: one to test intelligence emerging from BeCA, and another to test social phenomena emerging from the interactions of the animats socializing through I&I.

At the end of the thesis we include a brief glossary, giving a notion of important terms used through the thesis.

This thesis is available in PDF format at http://132.248.11.4/~carlos/asia, with images in colour.

Figure 2 shows a graphical structure of the thesis.

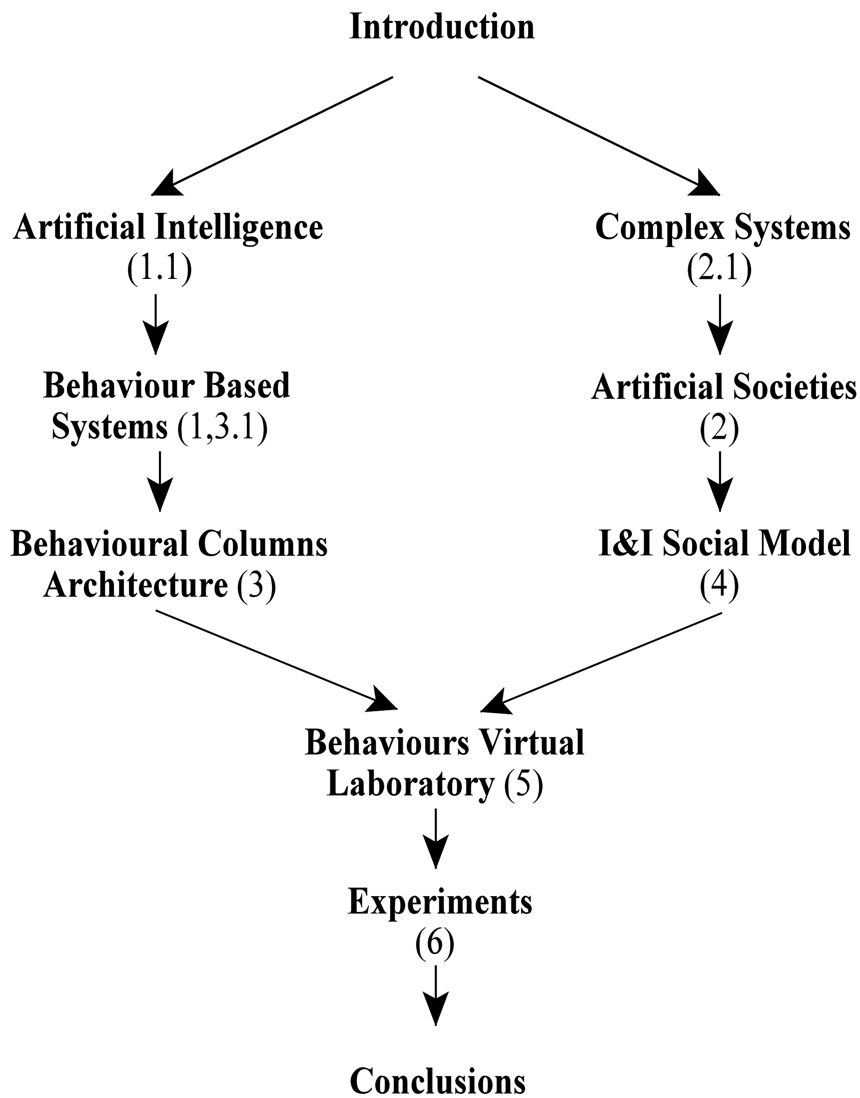

Figure 2. Structure of the thesis.

1. Behaviour-Based Systems

"... they have been created for life,
not for thinking!"
—Hermann Hesse

"Polar bears". Carlos Gershenson, Mexico City, 2000. Ink on paper.

Before we start with the description of behaviour-based systems, we will set a background in artificial intelligence, of how, why, and from where is that behaviour-based systems come from. We also address some problems present in artificial intelligence, such as the concept of intelligence, and the capabilities of intelligent machines. Then we describe behaviour-based systems. Finally, we mention some of the applications of behaviour-based systems.

1.1. Background

"The hardest thing to understand is why we can understand anything at all"
—Albert Einstein

From the beginnings of Artificial Intelligence (AI), in the late 1950's, researchers in the area have tried to **simulate** human intelligence by representing **knowledge**. Knowledge representation is among the most abstract ways of exhibiting intelligence. It is also among the most evolved ways of exhibiting intelligence. This is, animals less evolved than humans might exhibit intelligence, but not at a knowledge level[3]. This has lead researchers **simulating** intelligence to create the so called **knowledge-based systems** (KBS). Thus, KBS are tailored for the simulation of the most abstract elements of thought (reasoning, for example). This has lead KBS to be very effective in simulating abstract ways of exhibiting intelligence, by successfully demonstrating theorems, solving problems, playing chess, etc. Essentially, simulating things which were "very difficult", from an intellectual point of view. KBS were good at where the people who gave the knowledge to build the KBS were good at. But it came that it was very difficult for KBS to simulate successfully "very simple" things, also from an intellectual point of view; activities such as walking in crowded corridors, cleaning, parking a car, etc. Basically, things we do subconsciously, without any intellectual effort, but require a lot of coordination, and complex interaction with an open environment. It was clear that modelling "simple" intelligence from "abstract" intelligence was neither easy, nor computationally efficient.

So, by the middle 1980's, researchers in AI realized that the "simple" intelligence they were trying to model was present in animals, in their **adaptive behaviour** (McFarland,1981; Beer, 1990; Pfeifer and Scheier, 1999), which is studied by ethology (Manning,1979; Tinbergen, 1951; Lorenz, 1981). Animals perhaps cannot play chess successfully (Brooks, 1990), but it seems that it is very easy for them to search for food if they are hungry, organize in societies if they need it, run away if they perceive a predator, etc. In general, animals can **react**, and **adapt**, to the changes in their dynamic environment. This behaviour, for an observer, appears to be

[3]Recent studies show that animals are capable of exhibiting simple forms of knowledge (*e.g.* congo parrots (Pepperberg, 1991)), but these issues were not considered by AI researchers in the middle of the twentieth century.

intelligent[4]. From this perspective, researchers began to model intelligence based on behaviour, instead of on knowledge, creating the so called **behaviour-based systems** (BBS) (Brooks, 1986; Brooks, 1991).

Figure 3 shows a diagram of the issues discussed above. We perceive natural exhibitions of intelligence (*i.e.* what we judge to be intelligent), and then we model it in a synthetic way (Steels, 1995; Verschure, 1998; Castelfranchi, 1998). Our synthetic theory will help to explain our perceptions if it is capable of reproducing what we perceive. For example, we will know more about how language works if we build an artificial language module, or we will understand more about perception if we engineer a robotic vision system, instead of "just" making theories of them. We will understand more about intelligence as we build artificial intelligence. This "synthetic method", as described by Steels (1995), is different from the "inductive method". The inductive method observes facts, then makes a generalization or abstraction, to develop a theory. The theory is used to predict facts, which are verified against observed facts, which falsify or justify the theory. A diagram of this method can be seen in Figure 4. The synthetic method, also generalizes or abstracts observed phenomena to produce a theory. Only that this theory is used to engineer an artificial system, as a substitute of the natural system. This artificial system is operated, and its performance is observed, which falsifies or justifies the theory in dependance of how similar the observed performance is to the observed facts. A diagram of this method can be seen in Figure 5. The idea of this method, is to build a "parallel", or artificial system, which should behave in a similar way than the natural system in which it was inspired. If it does, it helps to comprehend the real system.

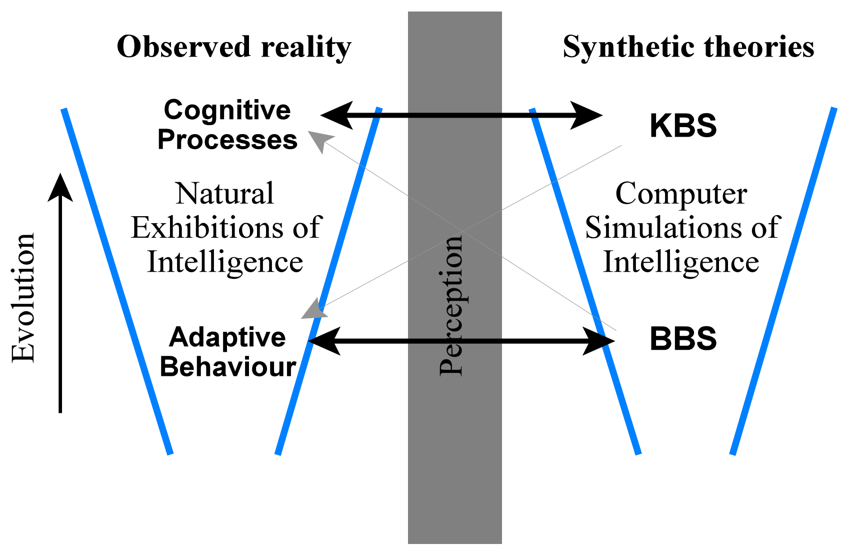

Figure 3. Observed exhibitions of intelligence, and how we synthetically represent them in simulations of intelligence.

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[4]Section 1.1.1. addresses our concept of intelligence

In Figure 3, we can see that KBS are mainly synthetic theories of cognitive processes. KBS have not been able to model successfully adaptive behaviour (Maes, 1993; Clark, 1997). BBS are mainly synthetic theories of adaptive behaviour. At this moment, it has not been possible to model cognitive processes from BBS, but it seems that this, once achieved, would allow to simulate all ranges of human intelligence: from adaptive behaviour to cognitive processes (Castelfranchi, 1998). This is because such a system would evolve in a similar way to the way our capability for thought has. One way to achieve this would be by learning patterns from behaviour. After learning patterns, concepts would have to be learned, in order to learn a language. This can only be made in a society, because an individual can perceive himself only in his similars. After the language, a logic should be learned (abstracted) from the language. All this processes should be **emergent**. Once at a logic level, cognitive processes should be successfully reproduced. We would have a **behaviour-based cognitive emergence.**

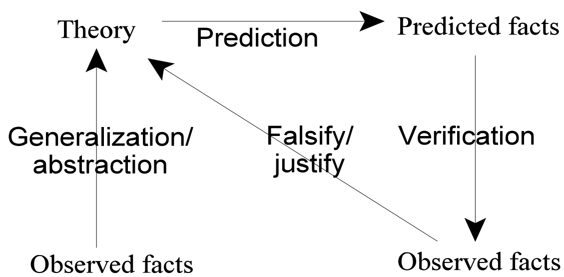

Figure 4. The inductive method tests a theory of a system by matching predicted facts against observed facts (Steels, 1995).

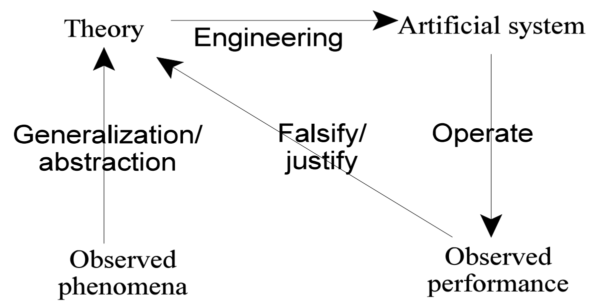

Figure 5. The synthetic method builds up theories of a system attempting to construct an artificial system that exhibits the same capabilities of the natural system (Steels, 1995).

KBS are also known as "top-down" systems (Maes, 1993), because they are (in most cases) designed and constructed from the whole to the parts. This means that from the beginning of the development, we should have a complete idea of what the system should do. The problem domain should be defined and limited. The control is (usually) centralized. BBS are also known as "bottom-up" systems (Maes, 1993), because they are designed and constructed from interacting parts (usually autonomous agents[5]) that together make the system functional (also in most cases). This approach allows an incremental development of the system, and also a "graceful" and **robust** degradation when some parts of the system fail, or are removed. This also allows BBS to respond to open, incomplete, or unknown problem domains, allowing flexibility in the case of unexpected events. In BBS the control is (usually) distributed. A useful comparison between the advantages and disadvantages of KBS and BBS was made by Maes (1993).

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[5]We give a notion of the concept of "agent" in Section 1.2.

1.1.1. What do we understand for intelligence?

"Intelligence is given when in the mind there are two contradictory thoughts. One proof of it is that mankind knows that it is lost, and although, it does everything it can to save itself."
—Scott Fitzgerald

We could do as Sir Isaac Newton, when he was questioned about the definition of time, movement, and space: *"I do not need to define them, for they are well known of everyone"*. We could say: "We all know what intelligence is, we use the word every day, so why should we spend a whole section on trying to define it?". We will **not** give a **formal** definition of intelligence. We will give a notion of what we understand when we say "something is intelligent", so at least we know in what context we are talking about intelligence.

This is Dr. Mario Lagunez's definition of intelligence: *"In order for us to say that something is intelligent (a person, a robot, a system), first, he/she/it must perform an action. Then, a third person (an observer) should* ***judge*** *if the action was performed intelligently or not"*. We agree with this definition, which is similar to Turing's (Turing, 1950). Not only it describes what we can understand for intelligence, but also what the problem is when we try to define intelligence. The problem is that, the judgement of intelligence depends entirely on the observer's criteria. For example, we believe than a creature, natural or artificial, able to *survive* in his or her environment, is intelligent (of course there are different degrees of intelligence). This obviously changes from observer to observer, so about the same action, one observer might say that the action was intelligent, and another that it was not. So, the first definitions of intelligence sticked to the criteria of the definer of what he judged to be intelligent. And people with different criteria would disagree with this definition of intelligence.

Abstract concepts, as intelligence, cannot have a concise, unequivocal definition. This is because abstract concepts are applied in many different situations. So, we take a similar stance as Metrodorus of Chius had with his phrase *"all things are what one thinks of them"*. We say: *"Intelligent actions are the ones people judge to be intelligent"*.

Intelligent is an adjective useful for a *post hoc* clarification of a behaviour. In describing an intelligent system, it is more important the action (the *what*) than the functioning of the system (the *how*)[6]. Of course, the more we understand about intelligence, the clearer the notion we will have of it (Steels, 1996).

[6]Some people (Marvin Minsky and Lynn Stein, for example) do not care about the *how* at all.

1.1.2. Will machines be able to have the same, or more intelligence than humans?

"...even if these artifacts (machines) perform certain acts better than us, they would do it without the conscience of them... ...it is ***morally*** *impossible that a machine will work in all the circumstances of life in the same way as our reason makes us work".*
—Descartes.

One of the main objectives of classical AI was to develop machines with the same, and superior intellectual capabilities as the ones we have. After more than forty years, this still seems not near, and some people believe it will never be.

One of the strongest arguments against this was the so called "Chinese room problem" (Searle, 1980): We set an Englishman which does not know Chinese, in a closed room, with many symbols of the Chinese language, and a book of instructions in English of how to manipulate the symbols when a set of symbols (instructions) is given. So, Chinese scientists will give him instructions in Chinese, and the Englishman will manipulate symbols in Chinese, and he will give a correct answer in Chinese. But he **is not conscious** of what he did. We suppose that a machine behaves in a similar way: it might give correct answers, but it is not conscious of what it is doing.

Well, according to what we stated about intelligence in the previous section, we could judge that the consciousless answer was an intelligent one. But let us discuss about consciousness. We can drive a car without being conscious of how the engine works. We can use a computer without knowing anything about electronics or microprocessors. We can live, without knowing what life is. We can love, without knowing what love is. And, we can think without knowing how our minds work. So let us apply the Chinese room problem to ourselves. How can we think if we do not know how we think? We think **without the conscious** of how we do it. **We are conscious of what we understand and we are able to explain and predict**. A machine has no reason for not being able to do the same thing. We, and machines, cannot be **completely** conscious because we would have to know **everything**. So, we can say that men and machines have certain degrees of consciousness. At this point, men have higher degrees of consciousness than the ones of machines (even to play chess?).

Many people think that a machine cannot be more intelligent than the one who created it. How can a student be better than his teacher, then? Well, many people thought that it was impossible for men to fly, or to go to the moon, or that a machine will ever play chess better than men. It is possible, indeed, to create machines more intellectually capable than a single man. And, there are several ways to achieve this. For example, a multi expert system can contain knowledge of many experts of different areas (*e.g.* González, 1995). Perhaps it will not know more about a speciality than each expert which knowledge was used to create the system, but it will have a much more general vision of a problem because of the knowledge of the other experts. So, by *aggregation* of knowledge, a machine might be more intelligent (and more conscious) than a single human.

If we "teach" (program) a machine to learn, it could learn its way to be more intelligent than the ones who "taught" it to learn, the same way as a child learns his way to (perhaps) be more intelligent than his teachers (of course "one could not send the machine to school without the other children making excessive fun of it" (Turing, 1950)). This would be *learning* of knowledge.

We could also attempt that machines might reach the capability of learning by themselves, in a similar way as we did. This is, by *evolution* of knowledge. Machines might evolve themselves into beings more intelligent and more conscious than men, improving from generation to generation (always depending in what we understand for intelligence and consciousness). Evolution, natural or artificial, is a slow (but sure) process, because it requires of experimentation of how suited are individuals in their environment, and how they might change, in order to improve without losing their useful capabilities. In any case, artificial evolution would be not as slow as natural evolution, because it can learn from its mistakes (in natural evolution the information of dead animals (some of which might have been mistakes) is lost), and it can be directed (natural evolution seems to have no goal). But nevertheless, this would take a lot of time[7].

Should we panic? Not yet. The information contained in one cell cannot be contained in a normal computer. Other issue is that we should not throw away millions of years of evolution, and start from zero. Genetic engineering and genetic computing might allow that we will produce "machines" "better" than humans, basing ourselves in humans.

Will machines make us prescindable, and will they do with us what we did with god?[8] Perhaps, but, as Nietzsche stated, our goal is to create *superior* beings than us. He meant about our children, but our machines are also our creation. In other words, it is our **nature** to create superior beings. If this also includes our extinction, it does not matter. We are finite anyway.

1.2. What is a Behaviour-Based System?

As we said in Section 1.1, behaviour-based systems (BBS) are inspired in the field of ethology, which is the part of biology which studies animal behaviour (Manning, 1979; Tinbergen, 1951; Lorenz, 1981; McFarland, 1981). This is because many properties desirable in autonomous intelligent systems are present in animal behaviour: autonomy (self-control), adaptation to changes in the environment, learning, situatedness, goal-directedness, and persistence, among others.

We can say that the goal of a BBS, is to offer the **control** (cybernetics (Wiener, 1948)) of an **autonomous agent**. The term agent[9] has been used in a wide variety of contexts. For us,

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[7]This issue came from discussing with Marvin Minsky and Push Singh.

[8]This issue was introduced by Fernando Contreras.

[9]In English, people used the pronoun "it" for animals when they considered that they had no intelligence. Since the paradigm of behaviour-based systems consists precisely in assuming that animals are intelligent and in building intelligent systems inspired in animal intelligence, researchers often call animals, agents, robots, and animats with the pronouns "he" or "she". We will refer to agents and animats as "he", because we consider that, although they exhibit intelligence, it is low enough to be considered as masculine.

an **agent** is a system that has **goals** to fulfill. An agent is within an environment, which may be dynamic and complex. An agent is said to be **situated** in his environment if he can perceive it and act upon it. Examples of agents would be robots in a physical environment, software or interface agents in "cyberspace", and agents that inhabit simulated environments. An agent is said to be **autonomous** if he can determine by himself his own goals. If the autonomous agent is able to adjust his goals in terms of what he perceives in his changing environment (his **beliefs**) it is also said to be **adaptive**. If this adaptation is **opportunistic**, we can say that the autonomy and the adaptation themselves are of a higher order: **intelligent**.

We can find three basic types of adaptation in an **adaptive autonomous agent** (AAA) (Meyer and Guillot, 1990):

- *Preprogrammed adaptation* is present when a BBS exhibits adaptive behaviour because it was programmed that way.
- *Learned adaptation* is given when a BBS has learning processes by means of which the AAA can improve the adaptiveness of his behaviours in time.
- *Evolved adaptation* is given when the behaviour of an AAA is partially determined by his genome, and the behaviour is capable of evolving through natural selection. A population of AAAs is needed in this adaptation, but not necessarily these AAAs should be social.

The main problem to be solved for building a BBS is: *"to come up with an architecture for an autonomous agent that will result in the agent demonstrating adaptive, robust, and effective behaviour"* (Maes, 1993). We can find that there are many subproblems to be solved in order to solve the main problem:

- How the agent perceives his environment and himself (how he obtains his beliefs and his goals)?
- How the agent acts upon his environment?
- How the agent selects which action to perform depending of his actual goals and beliefs? This is also known as the **action selection problem**.
- If the agent exhibits adaptation by learning, how can he improve his performance over time based on its experience?

If the BBS consists of a **society of agents,** we may have more subproblems:

- How the agents might **cooperate** to achieve individual or social goals?
- How the agents should **compete** to decide which goal should be achieved next?
- How the agents should avoid to interfere the achievement of other agents goals?
- If a population of agents exhibits adaptation by (social) learning, how can they improve their performance over time based on the experience of other agents?
- If a population of agents exhibits adaptation by evolution, how can they improve their performance from generation to generation based on their experience?

BBS often present **emergent** properties. Emergence in BBS will be discussed in Section 2.1, after we state some notions about complex systems and emergence.

1.3. Some Areas of Application of BBS

BBS may be applied in a wide range of fields. Wherever a control system is needed to take quick adaptive decisions, a BBS may be used. In the following sections, we will describe its applications to robotics, software agents, artificial life, and philosophy.

1.3.1. Robotics

"If we consider the (human) body as a machine, we shall conclude that it is much more ordered that any other; and its movements are more admirable than those of machines invented by man, because the body has been made by God."
—Descartes

Robots which have specific functions, like the ones which work in manufacturing plants, are more or less fully developed. We mean that people have a clear idea of how to build them. This is because they are rather simple. They are rather "dumb". But what about mobile autonomous robots, which develop in a real and dynamic environment, that have many goals and must take decisions[10]? Researchers in AI have been building them for a long time, but they still do not fulfill all the requirements that are desired in them. But indeed there has been a great improvement in the design and building of these robots. We can say that the evolution of robotics is at an insect level. We can successfully imitate an insect's behaviour (Beer and Chiel, 1993; Brooks, 1993).

Most researchers began to build robots using knowledge representations (*e.g.* rules). But they easily malfunctioned and hardly achieved their goals. Since the properties desired in these robots were present in animal behaviour, researchers began to model and imitate this behaviour. This was one of the main reasons of the development of BBS.

Examples of these robots are: Herbert (Connell, 1989), a robot which goal was to collect empty cans around the MIT Mobot Lab; Periplaneta Computarix (Beer *et. al.*, 1992; Beer and Chiel, 1993), a robotic cockroach, inspired in the neural circuits of the American cockroach; Kismet (Breazeal, 1999), a robot for social interactions with humans; and COG (Brooks, 1993), a humanoid robot capable of restricted communication with humans.

Other applications of these robots include extraterrestrial exploration, where the robots must have some autonomy, due to the time that a signal from Earth takes to reach the robot. Also a great deal of research has been put into robots which play soccer, and the organization of the Robocup has stimulated this research. Robots have been also developed for submarine exploration, bomb deactivation, and entertainment (*i.e.* toys).

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[10]From now on, we will refer to this type of robots just as "robots".

While building robots, several problems must be solved, such as perception, action, and decision. The decision part is solved using BBS when the robot will have to take quick decisions, be situated in a dynamic environment, and perhaps learn from its experience. But also the motion and perception tend to be biologically inspired.

1.3.1.1. Why do we build intelligent robots?

Or what for, do we build intelligent robots? Some people might answer:

- Because they are nice expensive toys.
- Because researchers have nothing better to do.
- Because they are useful in industry.
- Because a university with a robot prowling its hallways is *in*.
- Because researchers like to play god.
- All of the above.

Perhaps all of them might be applied in some cases, but none is the main reason to develop robots.

We would agree that robots are built in order to develop synthetic theories of animals and humans (Steels, 1995). By building robots, we understand how do the processes of perception, action, decision, integration of information, and interaction take place in natural systems. If the robot has no usefulness *per se*, it does not matter. Robots in AI are not built mainly to be useful. How useful is a twenty-thousand-dollars robot that knows how to go for coffee? The point is to understand **how** are we capable of doing so. Of course, *once you know the rules of the game, you can change them.*

1.3.2. Software agents

"Agents are objects with soul."
—A. Guzmán Arenas

Software agents have been inspired in AI and in the computer sciences' theory of objects. We can say that they are programmes with agent properties. There are many definitions of software agents, and some authors may have weaker or stronger notions of an agency (Genesereth and Ketchpel, 1994; Wooldridge and Jennings, 1995; Russell and Norvig, 1994; Gershenson, 1998b). Since there are a wide variety of definitions of software agents, we will give a loose definition.

A software agent is a programme that has some autonomy. He is in an environment, which he might perceive and act upon. He has a specific goal or function, which he will try to complete. He might interact with other agents, which will make him social. Examples of agents may go from a UNIX daemon, to a spider (an agent who crawls in the web); from a computer game character, to a personal digital assistant (PDA). Agents might be embedded in other agents.

From the computer science perspective, a software agent is a component: an object (Booch, 1994) which might communicate with other components.

Since the tendency in software systems is to develop them in a distributed way, agent theories are having a great influence on computer science. For example, with agent-oriented programming (Shoham, 1993) and agent-based software engineering (Wooldridge, 1997; Jennings, 2000). Because of the properties of agents, and also because of the needs of the market, the software industry is already moving from the object paradigm to the agent paradigm.

The SWARM Simulation Environment, developed at the Santa Fe Institute, is a wonderful agent-oriented approach for building simulations, which extends software agent theory itself. It would be not surprising that the SWARM ideology would be used in the near future for every kind of software development, although it was designed with simulation purposes, including artificial intelligence and artificial life.

It is clear that, since autonomous agents have to take decisions, BBS are linked to systems using software agents. Advances in BBS will influence software agents, and vice versa.

1.3.3. Artificial life

"Ninety percent of life is just being there"
—Woody Allen

Artificial life (Alife) simulates life, in a similar way that AI simulates intelligence. Alife is a synthetic representation of life. Since we perceive intelligence in many living organisms, AI and Alife are closely linked, and sometimes overlapped.

Since BBS are inspired in animal behaviour, we could say that all BBS are included in Alife.

Perhaps we could roughly distinguish the research done in Alife and in BBS. Alife has studied more social behaviour (*e.g.* Reynolds, 1987) and evolution (*e.g.* Sims, 1994), while BBS have studied more adaptive behaviour. Of course they have overlapped.

1.3.4. Philosophy

"How can we ask ourselves how can we ask ourselves?"

BBS have lead researchers and philosophers to propose theories of "how the mind works".

One example of this is Marvin Minsky's Society of Mind. He sees the mind as a society of non intelligent agents, from which intelligence emerges (Minsky, 1985).

Another example is the theory proposed by Andy Clark. By studying BBS (which have studied ethology), he has seen that the mind is not isolated from the body nor from the world. That **our mind is distributed in our brains, bodies, and worlds** (Clark, 1997).

As we explained in the beginning of this chapter, with the synthetic method, by building artificial systems, we can understand the natural ones. As AI develops, it affects more advanced philosophical concepts and their relations, such as self, reason, beliefs, truth, and being.

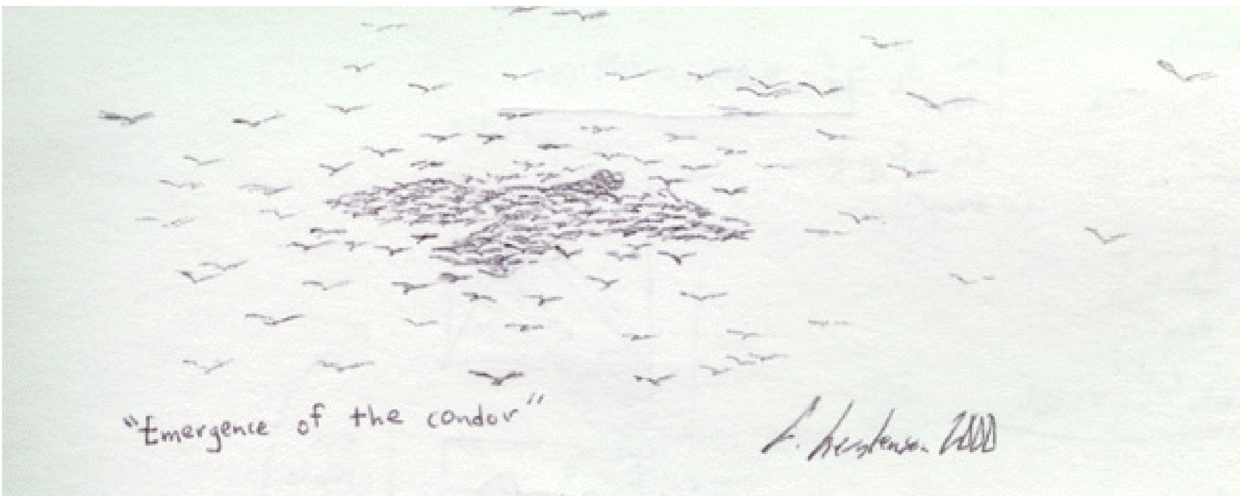
1.4. About BBS

"If something has an explanation, you can explain it.
If it has no explanation, you should explain why you cannot explain it"

Behaviour-based systems are a promising paradigm for understanding intelligence, in animals and humans, and for developing systems simulating such intelligences. If we want to understand the evolution of cognition, this is, how animal intelligence evolved into human intelligence, we also need to address other issues, such as culture, language, and society. In the next chapter, we will make a brief introduction to artificial societies, which, in a similar way than BBS, are assisting in the understanding of social processes.

2. Artificial Societies

"There are souls that will never be discovered, unless we start by inventing them"
—Nietzsche



"Emergence of the Condor". Carlos Gershenson, Mexico City, 2000. Ink on paper.

"Dolphins out of unbounded chaos". Carlos Gershenson, Mexico City, 2000. Gel on paper.

In this chapter we will expose Artificial Societies (AS) and previous work that has been made using them. But first, we will give some notions of what is a complex system, since societies are complex systems, and we will use the terminology through this work.

2.1. Introduction to Complex Systems

"A complex object is an object which has more than one non-overlapping description"
—Jack Cohen

Indeed defining complex systems is a complex task. There are more than seventy definitions of complexity, used in diverse areas. We can say that there are many non-overlapping descriptions of complex systems, perhaps because it is inspired in practically all branches of knowledge, and also because it is a very new field of study (Bar-Yam, 1997).

With this panorama, we will not attempt to define complex systems. We will only try to describe them.

A complex system is usually constituted of many elements which interact. The complexity of the system is proportional to the number of elements, the number of interactions in the system, and the complexities of the elements and of their interactions. In natural complex systems, every element is also a complex system, therefore we can only obtain a **relative complexity** depending on a reference point. Since we can use various reference points, there cannot be an **absolute complexity**, and each relative complexity will be different.

The global behaviour of the system arises from the interactions of the elements of the system. In this sense, we can say that a complex system is more than the sum of its parts.

A complex system has properties not present in its parts. These properties are called **emergent**. They emerge from the interactions of the components of the system.

There is not a crisp boundary between complex and simple systems. Also the complexity of a system is strongly dependent from the context in which it is being studied. But generally speaking, simple systems are easily predictable, have a single or few parts, and few or none interactions. There is little or no emergence in a simple system. Examples of simple systems might be:

- A pendulum.
- A bouncing ball.
- An elevator.

We can see that the behaviour of the system might be easily predicted or described with few rules or formulae. Also, they are not too abundant in nature. If we look around, most things surrounding us are complex systems. Some examples might be:

- A cell. Its function is determined by interactions of proteins. The proteins are not alive. Life emerges from their interactions.
- The human's central nervous system. It is composed of millions of neurons. One neuron is not intelligent. One brain is capable of exhibiting emergent intelligence.

- An ant society. There is no "leader" ant. There is no ant with a central plan. But every ant knows its duty, and this allows their society to act as a whole.
- A flock of birds. Each bird sets its direction in dependence of the direction of its neighbours. This leads to complex behaviour of the flock. This can also be seen in schools of fishes, insect swarms, buffalo stampedes, raging crowds, and furious mobs. Each individual, to decide its action, takes into account the actions of the neighbours.

Other examples of complex systems might be the weather, traffic jams, Mother Web, the stock market, and an ecosystem.

We suggest the reader to think about natural systems, and think if they're complex or simple. Most of them are complex (otherwise the reader is simple minded???).

A usual mistake is to confuse complexity with complication. A complex system might be complicated or not, and vice versa. Other usual mistake is to confuse complexity with chaos. A complex system might also be chaotic or not, and vice versa.

The approach of complex systems allows to understand the behaviour of the system by understanding the behaviours and interactions of its parts. Studying the system as a whole is too complicated. And studying only the parts of the system does not allow to understand the behaviour of the whole system and its emergent properties.

In the last few years, several companies have solved problems in different businesses using complex systems techniques with very good results (Wakefield, 2001).

2.1.1. Behaviour-based systems as complex systems

BBS might not be complex systems, but adaptive behaviour is indeed a complex system. Adaptive behaviour in animals (and even in bacteria), requires the interaction of many components to provide robust perceptions, action selections, and actuations. If adaptive behaviour would be made out only of simple rules (IF food AND hunger THEN eat), it would not be capable of adaptation in an unpredictable environment (IF Boeing 757 AND unknown noise THEN... !). So, a good BBS will be also a complex system. Some properties of a BBS, like those of an animal, will emerge from the interaction of its components.

2.1.2. Social systems as complex systems

An individual belonging to a society, natural or artificial, might be complex or not. But in a society, its individuals have to interact (otherwise they would not be social, we would have just a population). Thus, a society is a complex system (Goldspink, 2000). And social phenomena emerge from the interactions of the members of a society.

Perhaps the most simple example of this might be given by cellular automata, such as The Game of Life[11] (Conway, 1970; Gershenson, 1997). Each cell is represented by a "life"

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[11]Programs of the Game of Life, in two dimensions (using boolean, fuzzy, and multidimensional (Gershenson, 1998a; Gershenson, 1999) logics) and in three dimensions with source code can be found at

value in a matrix, which is regulated by simple rules that take into account the "life" values of the neighbouring cells. With these simple rules, complex behaviours emerge, present in natural cell colonies, such as pattern formations and oscillations in structures, translations, generations, and even predations.

With such examples it has been seen that complex social phenomena might emerge from the interaction of simple individuals. But, if the individuals are complex systems themselves, with emergent properties, the potential of emergence is increased.

2.2. Artificial Societies?

"One day the creator searched for the companions and the sons of his *hope, and it came that he could not find them if he did not start by creating them himself."*
—Nietzsche

Yes. An artificial society (AS) is a synthetic representation of a society. It simulates social phenomena. Artificial societies are used to understand how societies work by synthetically creating them[12].

Societies were considered to be groups only of humans. But again, since we consider that animals and artificial creatures are also capable of exhibiting intelligence, we consider a **society** as a group of individuals (humans, animals, animats, etc.) exhibiting intelligence and interacting socially among them.

Sociality presupposes two or more agents in a common shared world. If we do not want them to be a mere population, they need to **interact**. If this interaction is made as an agent with a goal-oriented behaviour[13] dealing with another entity as an agent, then we can say that the interaction is **social** (Castelfranchi, 1998). This is because an agent could see another agent, for example, as a moving obstacle, **without goals**. The behaviour would not be social. A social behaviour needs not only two or more interacting agents, but these agents need to perceive each other as their *similar*.

Some theories about joint or group action (Tuomela, 1993) are built on the basis of individual action. But we agree with Cristiano Castelfranchi, who also notes the importance of the individual social action (Castelfranchi, 1997). In a society not only the individual action should have a social perspective, but also the individual action is influenced by the society.

There can be social action among non cognitive agents, but most social phenomena involve the interaction of **cognitive** agents (agents that are able to **know**). We believe that a

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http://132.248.11.4/~carlos

[12]See Section 1.1.

[13]A goal oriented behaviour is based on the operational notion of goal and **purposive behaviour** (Rosenblueth and Wiener, 1968).

cognitive agent does not need to have an explicit mental (knowledge) representation of goals and beliefs, because these can emerge[14].

We can distinguish two types of social action (Castelfranchi, 1998): **weak social action**, which is based on beliefs about the mind of other agents; and **strong social action**, which is based on goals about others' minds and actions. A weak social action considers what another agent is doing, and might affect the considering agent. A strong social action involves social goals. A social goal is directed towards another agent. This is, the social goal of one agent is to influence the mind or actions of another agent.

Social structures and organizations emerge from social actions of the agents, and also the individual actions of the agents in a society are influenced by social structures and organizations.

2.3. Previous Work on Artificial Societies

Given our notion of sociality in agents, we can see that many multi agent systems (Russel and Norvig, 1994) have some kind of sociality (Hogg and Jennings, 1997; Jennings and Campos, 1997). Here we will just review some of the work in AS that are related with the study of societies. This is, AS that were created with the purpose of studying social processes. AS that are a synthetic representation of a society, and not only works involving social agents with other purposes.

Perhaps the most classical work in AS is the one of Epstein and Axtell (1996). They used a cellular automaton with "simple" rules, which caused the emergence of complex processes in the global system, such as population migration, cultural evolution, and warfare (Epstein and Axtell, 1996). This work was severely criticized by some, and admired by others. This was because some people did not believe on how such complex and obscure things could be explained with such simple rules, while others were amazed by it.

Mitchel Resnick (1994) in his book "Turtles, Termites and Traffic Jams" showed clearly how very complex social phenomena, as ant foraging, termite nest building, and traffic jams, are caused by very simple local rules. But when thousands of individuals follow simple rules, the behaviour of the systems turns out to be very complex, with social properties emerging.

The fascinating work of Gode and Sunder (1992) of "zero intelligence" traders shows that simple agents, without the capability to theorize, recall events, or maximize returns, but only bidding in ways that would not yield to immediate losses, were 75% efficient. When they replaced the agents with humans, the efficiency was 76%. This showed that the institutional settings and constrains of a system may determine the role of the individuals of the system, instead of the individuals determining it by themselves. This means that in such systems a human will not perform much better than even a random selection generator.

Artificial societies have also been useful in the social sciences. For example, Jim Doran has made a simulation where the agents might have collective misbelief (Doran, 1998). He uses this simulation for studying ideologies in human societies. Dwight Read has studied the

[14]We will discuss the emergence of cognition from non-cognitive processes in the next chapter.

relationship between culture and behaviour also with artificial societies (Read, 1998). There can be found many other examples, and we can see that AS, although very recent, is a rapidly growing area of study.

AS are headed towards the understanding of social processes, where theories were very hard to prove because the long duration of real social processes, but thanks to computer simulations, theories can be not only proven, but also proposed by studying artificial societies.

2.4. About Artificial Societies

"It is not that you cannot understand it,
it is that you cannot compute it."

Synthetic representations of societies are useful for understanding the complex processes that take place in societies. The shaping of the society by the individuals and their environment, and the shaping of the individuals by their society, is crucial in the understanding of intelligence and cognition.

Before presenting our model for social action in Chapter 4, we will present in the next chapter the Behavioural Columns Architecture, a behaviours production system which is able to simulate animal intelligence in individuals. Intelligence desired in order to simulate complex social phenomena.

3. Behaviour-Based Intelligence

"Before being humans, we are animals"

"Ah, qué tiempos aquellos". Carlos Gershenson, Mexico City, 1999. Oil on canvas, 60 x 100 cm. Mata García collection.

In Chapter 1 we exposed the idea that intelligence might be perceived from the adaptiveness of the behaviour in an individual. For example, if an animal avoids successfully its predators, we will say that he behaved intelligently (at least, more intelligently than the eaten ones...). If a robot is capable of successfully navigating through crowded corridors, we will say that he also behaved intelligently.

In this chapter we expose first a brief review of action selection mechanisms and what are they. Then, we present the Behavioural Columns Architecture[15] (BeCA) (González, 2000), a behaviours production system (BPS) for AAAs inspired in ethology and implemented in a double blackboard architecture. We do this by first defining and describing Behaviours Production Systems and giving a brief description of the Blackboard Node Architecture. Next we introduce the elements of BeCA, in order to model in an evolutionary bottom-up fashion reflex, reactive, and motivated behaviours. Then we refine our BPS by implementing two learning schemes: associative learning, and a simple reinforcement learning of the motivation degree. Finally we describe the properties of BeCA.

BeCA was used to provide the control of the animats of our Behaviours Virtual Laboratory, presented in Chapter 5.

3.1. Action Selection Mechanisms

"Look to nature, and let simulated nature take its course"
—Andy Clark

An **action selection mechanism** (ASM) computes which action should be executed by a BBS in dependence of the internal state and the external perceptions of the agent controlled by the BBS.

The building of ASMs has two benefits, which feedback each other: the better understanding of adaptive behaviour (how animals are able to adapt to their environment), and the development of adaptive artificial creatures.

Reviews of ASMs can be found in (González, 2000) and (Tyrrell, 1993).

Here we present a brief review of works related to ASMs, taken from González *et. al.* (2000):

- Tinbergen's mechanism (Tinbergen, 1950; 1951), a hierarchic network of nodes or centres, which approaches the complete action selection problem with a noticeable emphasis in the reproductive stage.
- Lorenz's psycho-hydraulic mechanism (Lorenz, 1950; 1981), a model that tries to explain some ethological phenomena, without completely approaching the action selection problem.
- Baerends' model (Baerends, 1976), a hierarchic network of nodes, a model inspired by ethologist studies made in particular species of insects and birds.

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[15]BeCA has been developed by Pedro Pablo González, José Negrete, Ariel Barreiro, and the author.

- Brooks' subsumption architecture (Brooks, 1986; 1989), which can be used as a mean to implement robot control systems, which include tasks of perception and action, in addition to the emergency of behaviours.
- Rosenblatt and Payton's hierarchical network (Rosenblatt and Payton, 1989), a mechanism similar in many aspects to the hierarchical models proposed by Tinbergen and Baerends, but with nodes like formal neurons inspired in Brooks' subsumption architecture.
- Maes' bottom-up mechanism (Maes, 1990a; 1990b), a distributed non-hierarchical network of nodes, where each node represents an appetitive or consummatory behaviour that the entity can execute.
- Beer's neural model (Beer, 1990; Beer, Chiel, and Sterling, 1990), a semi-hierarchical network of nodes, where each node represents a neuronal circuit. It is inspired in the neuronal circuits of the American cockroach.
- Halperin's neuroconnector network (Hallam, Halperin, and Hallam, 1994), a non supervised neural network organized in layers.
- Negrete's neuro-humoral model (Negrete and Martinez, 1996), a non-hierarchical distributed network of nodes, where each node is a neuron with neuronal and humoral capacities.
- Goetz's recurrent behaviour network (Goetz and Walters, 1997), a network of nodes, where a node can represent a behaviour, a sensor or a goal; the network converges to a particular behaviour (attractor), in a similar way that a Hopfield's network (Hopfield, 1982) converges to a certain pattern.

Table 1 shows a comparison among the different ASMs before mentioned, taking into account the most relevant aspects from these.

ASM	Disciplines	Architecture	Combination of stimuli	Learning schemes
Tinbergen	ethology	hierarchical network of nodes, where each node represents a kind of behaviour	summed	none
Lorenz	ethology, psychology and hydraulic engineering	psycho-hydraulic model	summed	none
Baerends	ethology	hierarchical network of nodes, where each node represents a kind of behaviour	unstated	none
Brooks	robotic	distributed network of finite state machines	unstated	none
Rosenblatt and Payton	robotic and artificial neural networks	connectionist, feed-forward network. Behaviours are defined by connections among processing elements	can be any function of weighted inputs	none
Maes	ethology and behaviour-based systems	non-hierarchical, distributed network, where each node represents a type of behaviour	summed	none
Beer	ethology, neuroethology and artificial neural networks	semi-hierarchical network, where each node is a neural network implementing a particular kind of behaviour	summed	none
Halperin	ethology and artificial neural networks	non-supervised, hierarchical, feed-forward network	summed	classical, secondary, and postponed conditioning
Negrete	neurophysiology ethology	non-hierarchical, distributed network of neuro-humoral neurons	summed	none
Goetz	artificial neural networks and attractors theory	recurrent distributed network	summed	none

Table 1. Different action selection mechanisms.

We can see that ASMs have been inspired in many different areas, and that they present many diverse properties. There has not been proposed a "best" ASM, since different systems have different requirements. We can say that each ASM is the best for what it was created for: for controlling an artificial creature in the context it was proposed.

3.2. Behaviours Production Systems

"It is the nature of the mind that makes individuals kin, and the differences in the shape, form, or manner of the material atoms out of whose intricate relationships that mind is built are altogether trivial"
—Isaac Asimov

Through this chapter, we will discuss and illustrate the building, in an evolutionary fashion, of a behaviours production system (BPS), that exhibits many of the principles and properties present in animal behaviour, following an evolutionary bottom-up approach. We define a BPS as a system that **produces** adaptive behaviours to control an autonomous agent. A BPS must solve the well known action selection problem (ASP), but it needs to be more than an action selection mechanism (ASM). A BPS is characterized by the following features: (1) **adaptiveness** to the environment (preprogrammed, learned, and/or evolved), (2) a set of autonomous and independent modules **interacting** among them, (3) behaviours are **produced** emergently through the interaction among the different modules that compose the system, also giving opportunity to other properties to emerge, (4) behaviour patterns **emerge** from the execution of simple behaviours through time, (5) new behaviours can be incorporated over the existing repertoire of behaviours, (6) new principles or properties to improve the behaviour production can be added taking into account the existing structure and functioning, and (7) several parameters regulate the behaviour production, and if they are fixed by an observer through an interface, the results that are originated of this adjustment can be observed (such as in a virtual laboratory). In this sense, the neuroconnector network of Halperin (Hallam, Halperin and Hallam, 1994) may be considered as an example of a BPS.

The behaviours production system presented here has been structured from a network of blackboard nodes (González and Negrete, 1997; Negrete and González, 1998). We believe that the blackboard architecture constitutes an ideal scenario for the implementation of behaviours production systems, due to its capacity of coordination and integration of many activities in real time. Also, it provides a great flexibility in the incorporation of new functionality, and it handles the action selection as knowledge selection in the solution of the problem. Another property of the blackboard architecture is the opportunism in the problem solving, which is a property of the behaviour production in animals desirable in autonomous systems.

The evolutionary bottom-up approach followed by us can be described in the following terms: we will first try to solve one problem, and once we have a BPS that solves this problem, we will strive to co-evolve the BPS alongside the problem as itself evolves and becomes more complex, but without losing the capabilities of solving the previous problem(s). In this way, and taking into account the scheme shown in Figure 1, we will first build a BPS for the problem of reflex behaviours, which constitutes an initial layer. Then, we will add a second layer to model reactive behaviours. Next, we will add another layer dealing with the problem of motivated behaviours, but without losing the functionality of the two previous ones. Finally, we will refine these layers, incorporating learning schemes to obtain a higher adaptiveness in the behaviour production.

With this work we have intended to reach two goals: (1) to map the main principles and properties that characterize animal behaviour onto a bottom-up, evolutionary construction of behaviour-based systems, and (2) to use the BPS to experiment with animal behaviour properties that this one is able to reproduce, also providing a better understanding of adaptive behaviour. This implies a journey, from biology to behaviour-based systems and back (Maes, 1991).

3.3. Blackboard Node Architecture

The concept of blackboard architecture (Nii, 1989; Engelmore, Morgan and Nii, 1988) was conceived by AI researchers in the 1970's. The goal of this architecture was to handle the problem of shared information among multiple expert agents involved in problem solving. The blackboard architecture was implemented for the first time in the language understanding system Hearsay II (Engelmore, Morgan and Nii, 1988), and later it has been used in a great variety of problem domains, and abstracted in many environments for systems implementation. Figure 6 shows the basic components of the blackboard architecture.

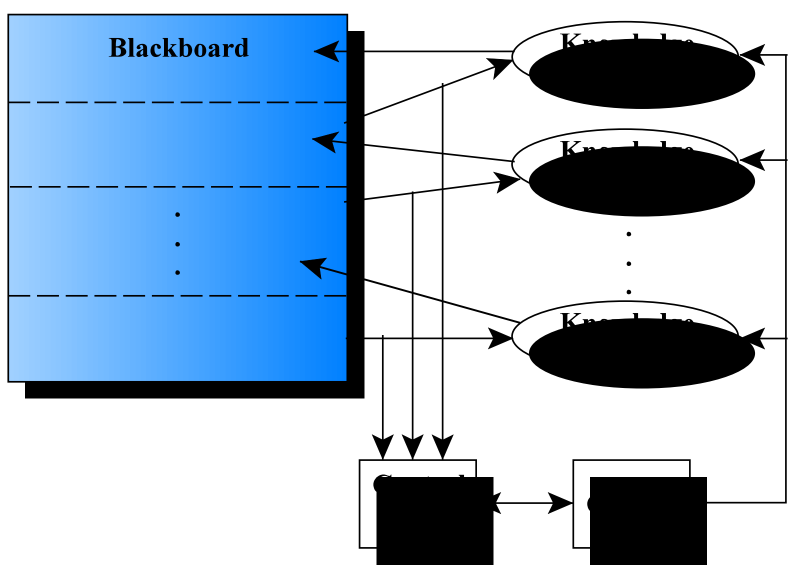

Figure 6. Components of the blackboard architecture.

The behaviours production system presented here has been structured from a network of blackboard nodes (González and Negrete, 1997; Negrete and González, 1998). A blackboard node is a blackboard system integrated by the following components: (1) a set of independent modules called **knowledge sources**, which have specific knowledge about the problem domain;

(2) the **blackboard**, a shared data structure through which the knowledge sources communicate with each other by means of the creation and modification of solution elements; (3) the **communication mechanisms**, which establish the interface between the nodes, and the interface between a given node and the external or internal media; and (4) a **control mechanism**, which determines the order in which the knowledge sources will operate on the blackboard.

The main characteristics exhibited by the **blackboard architecture** and desired in the implementation of behaviours production systems include the following: (1) a high capacity of coordination and integration of many activities in real time, (2) great flexibility in the incorporation of new functionality, (3) the handling of the action selection as knowledge selection in problem solving, and (4) the opportunism in problem solving. These characteristics support the evolutionary and bottom-up construction approach of our BPS discussed in the next sections.

3.4. Behavioural Columns Architecture: An Evolutionary Bottom-Up Approach

"Everything should be made as simple as possible, but not simpler"
—Albert Einstein

In this section we will present the basic components of our BPS, which we refer to as Behavioural Columns Architecture (BeCA) (González, 2000): the set of internal behaviours, the blackboards and their levels, the interface/communication mechanisms, the emergent behavioural columns, and the blackboard-nodes.

Internal behaviours are information processing mechanisms that operate within the BPS, whose function involves the creation, combination, and modification at different blackboard levels[16]. An internal behaviour in BeCA is equivalent to a knowledge source in the blackboard node architecture or a hidden layer in an artificial neural network. Internal behaviours can also be seen as agents embedded within node agents, and composed of elementary agents. Internal behaviours are constituted by **elementary behaviours**, which can be seen as the rules that are packed in a knowledge source in the blackboard architecture, or an artificial neuron in a neural layer. An elementary behaviour has three elements: a list of parameters, a condition component, and an action component. The **list of parameters** specifies the condition elements, the action elements, and the coupling strengths related with the elementary behaviour. The **condition** of an elementary behaviour describes the configuration of signals that is necessary on the blackboard, so that the elementary behaviour contributes to the solution processes of the problem. The way in which an elementary behaviour contributes to the solution of the problem is specified in its **action**, which can consist in the creation or modification of solution elements in certain blackboard levels. A **coupling strength** is represented by a vector $Fa = (Fa_{i1}, Fa_{i2}, ..., Fa_{in})$ of n real components, where each of these components represents the efficiency with which an elementary behaviour can satisfy a

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[16]The names of internal behaviours in BeCA will be typed with *italics* throughout the text.

particular condition. Depending on the nature of the elementary behaviour, the components of the vector Fa may be of a fixed or modifiable value. The existence of modifiable coupling strengths is important because it allows the **refinement** of previously defined layers, incorporating learning schemes. The vector Fa of coupling strengths of an elementary behaviour is equivalent to a weight vector in an artificial neuron.

The **blackboard** acts as an internal memory, where the internal behaviours read, create, and modify information at different blackboard levels. Each blackboard level contains information at a different processing stage[17]. The actions of the internal behaviours on the blackboard incrementally lead to the solution of a given problem. The blackboard can itself be seen as the environment of the internal behaviours.

On the blackboard, the **interface/communication mechanisms** can also read and create signals. They provide the interface between a blackboard node, and other media, such as the external medium, internal medium (needs or goals), and other nodes. The interface/communication mechanisms are also structured by elementary behaviours[18].

The **control** mechanism is distributed in the functionality of the elementary and internal behaviours.

Different types of elementary behaviours are organized forming **emergent behavioural columns**, which vertically cross different blackboard levels. They emerge when the signal created by an elementary behaviour constitutes the condition of an elementary behaviour of a different type, and the signal created by this one is in turn the condition of another elementary behaviour, until reaching the last blackboard level. Elementary behaviours from different internal behaviours and communication/interface mechanisms interact with each other through the blackboard. The result is the behavioural columns which thus emerge from this interaction, and represent the route that signals follow through different blackboard levels. Behavioural columns might converge or diverge.

BeCA has two defined **blackboard nodes**: a node that receives signals from the external medium and determines which action should be taken upon it, and a node for processing signals from the internal medium. Different internal behaviours, blackboard levels, and mechanisms will be defined in these blackboard nodes as we incrementally build our BPS.

We define our BPS separated from the perceptual system, the internal medium (needs, motivations or goals), and the motor system. This allows BeCA to be defined in a generic way, making possible its implementation in different environments and problem domains (perceptual and motor systems are dependent on their environment).

In the next sections, we will build our behaviours production system (BPS) following an evolutionary bottom-up approach. We will first try to solve one problem, and once we have a BPS that solves this problem, we will evolve the BPS as the problem evolves and becomes more complex, but without losing the capabilities of solving the previous problem(s). In this way, we will first build a BPS for the problem of reflex behaviours, which constitutes the initial layer.

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[17]The names of the blackboard levels will be written starting with capitals.

[18]The names of interface/communication mechanisms will be also typed with *italics*.

Then, we will add a layer to our BPS for reactive behaviours. Next, we will add another layer dealing with the problem of motivated behaviours. Finally, we will refine these layers, incorporating learning schemes to obtain a higher adaptiveness in the behaviour production. We will illustrate each layer and refinement process with experiments using our Behaviours Virtual Laboratory in Chapter 6.

3.5. Modelling Reflex Behaviours

Reflex is one of the simplest forms of behaviour exhibited in animals. In this type of behaviour a fast action is triggered when a particular external stimulus is perceived. The key characteristic of a reflex is that the intensity and duration of the triggered action completely depend on the intensity and duration of the stimulus. There is a rigid relationship between the stimuli and the action executed (Manning, 1979; McFarland, 1981; Anderson and Donath, 1990). Duration and intensity of reflex behaviours might depend on internal states, but for one type of stimuli, the triggered action will be of a specified type. This means that in reflex behaviours there is no action selection problem, because for every stimulus perceived, the corresponding behaviour will always be executed.

In BeCA we will model reflex behaviours in the following way: for every signal received from the perceptual system, a corresponding signal will be sent to the motor system.

In the initial approach of our BPS, the reflex behaviours are modelled as a first layer, which includes the definition of the following components: the External Perceptions, Actions, and Internal Perceptions blackboard levels, the *reflex actions* internal behaviour, and the interface mechanisms *exteroceptors, interoceptors,* and *actuators*. These last elements will allow us to establish connections between the perceptual and motor systems.

From this first layer, we will assume the existence of an internal medium (needs/goals), although it does not play a role in the control of reflex and reactive behaviours. This is the reason why the connections between the nodes will appear only at the third layer, for the modelling of motivated behaviours.

At the External Perceptions level the signals from the external medium are projected, first sensed and processed by a perceptual system. At the Actions level signals that indicate which external behaviour must be executed are created. When a signal is created at this level, the external behaviour associated with this element will be invoked, and the action will be executed by a motor system. At the Internal Perceptions level signals from the internal medium are projected, which are sensed by the *interoceptors* mechanisms.

The *exteroceptors* mechanisms establish the interface between the perceptual system and BeCA. Once they receive signals from the perceptual system, they process them (multiplying them by a specific coupling strength) and register the resulting signals in the External Perceptions level. In a similar way the *interoceptors* establish the interface between the internal medium and BeCA, registering signals in the Internal Perceptions level.

The role of the *reflex actions* internal behaviour is to allow the immediate activation of the behavioural columns representing reflex actions, which do not require an internal input for the execution of the external action associated with this column. The winners of a competition among the elementary behaviours, which were previously activated by corresponding signals in the External Perceptions level representing reflex behaviours, will register the specified signal in their action component directly at the Actions level.

The *actuators* establish the interface between BeCA and the motor system. When a signal is created at the Actions level, the *actuators* send it to the motor system, executing the motor action of the signal.

At this first construction stage we assume the existence of a default external behaviour executed by the motor system, when no stimuli have been perceived, which could be, for example, "stand by" or "wander". A diagram of our BPS at the stage of reflex behaviours is shown in Figure 7.

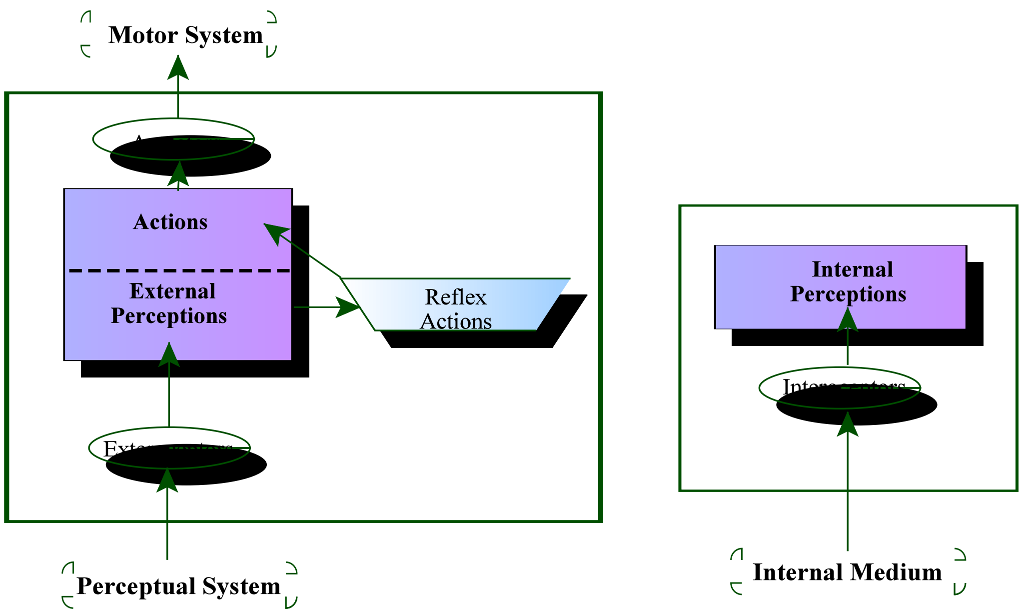

Figure 7. BeCA at the stage of the modelling of reflex behaviours

3.6. Modelling Reactive Behaviours

"Desiring without measure is a matter of children, not of a man"
—Democritus

Reactive animal behaviours are those behaviours that show a rigid and complete dependence on external stimuli (Manning, 1979; McFarland, 1981). In Section 3.5 we discussed and modelled the simplest of this type of behaviour: the reflex response. Other two types of reactive behaviours are the taxes and fixed-action patterns, which involve more specific and complex external stimuli and more elaborated response patterns than reflex behaviours.

Taxes or orientation responses consist in the orientation of an animal towards or away from some external stimulus, such as light, gravity, or chemical signals. A fixed-action pattern is an increased and stereotyped response to an external stimulus (Lorenz, 1981; Manning, 1979; McFarland, 1981). This response comprises an elaborated temporal sequence of component actions. Unlike reflex behaviour, the intensity and duration of a fixed-action pattern is not controlled by the presence of a given stimulus. In other words, the execution of the fixed-action pattern could continue even if the stimulus is removed. The escape response in animals is an example of fixed-action patterns. This type of reactive behaviour involves a sequence of evasive actions, and requires a **persistence** of the environmental signals.

The reactive behaviours are modelled in our BPS by incorporating a new layer over the first one. The creation of this second layer includes the definition of the following components: the Perceptual Persistents blackboard level, and two new internal behaviours: *perceptual persistence* and *external behaviour selector*. The inclusion of these components in BeCA allows us to model reactive behaviours by taking into account two new elements not present in the first layer: the persistence of external signals and a process of behaviour selection among different reactive behaviours.

The Perceptual Persistents level models a type of short term memory. At this level, the strongest external signals, initially projected onto the External Perceptions level, persist for more time. The signals at the Perceptual Persistents level are created or modified by the *perceptual persistence* internal behaviour. The condition of an elementary behaviour of this type is satisfied when at least one of the following facts has taken place: at the External Perceptions level there has been created an external signal specified in the condition of an elementary behaviour, and/or at the Perceptual Persistents level there has been created a signal specified in the condition of an elementary behaviour, or the intensity of this signal has been modified. The elementary behaviours that have satisfied their condition enter into a competition process. The activation level of each elementary behaviour is specified by expressions (1) and (2). The new O_i^T signal created on the Perceptual Persistents level by the *perceptual persistence* internal behaviour will be the activation level A_i^T in expression (2), if it is greater than a threshold θ^T, and zero otherwise. The time during which this signal will be active in the Perceptual Persistents level will depend on the value of parameter κ, which is a decay factor, in expression (1):

$$Atmp_i^T = (1-\kappa)O_i^T + Fa_{ii}^S O_i^S + \sum_{i \neq j} + Fa_{ij}^T O_j^T \qquad (1)$$

where O_i^T is the strength of the previous signal on the Perceptual Persistents level, Fa_{ii}^S is the coupling strength related to the signal O_i^S on the External Perceptions level, and Fa_{ij}^T is the negative coupling strength with which the signal O_j^T laterally inhibits the signal O_i^T. The final activation level A_i^T is calculated by hyperbolically converging the temporary activation level $Atmp_i^T$ to a value Max_i^T using expression (2):

$$A_i^T = \begin{cases} \dfrac{-1}{Atmp_i^T + \dfrac{1}{Max_i^T}} + Max_i^T \ if\ Fa_i^S C_i^S \ and\ Atmp_i^T > 0 \\ Atmp_i^T \ in\ other\ cases \end{cases} \quad (2)$$

Another internal behaviour required by this layer is *external behaviour selector*. The role of *external behaviour selector* is to decide which external behaviour will be executed in the current moment, a process which occurs by taking into account the signals recorded at the Perceptual Persistents level, through a competition process.

A diagram of our BPS at the stage of the modelling of reactive behaviours can be appreciated in Figure 8. As it can be seen, at this stage of the modelling, two types of external behaviours can be produced by BeCA: reflex responses, modelled as direct pathways between the External Perceptions and the Actions levels; and reactive behaviours, mediated by the internal behaviours *perceptual persistence* and *external behaviour selector* and involving a simple type of action selection.

If no external signals have been perceived, the motor system will execute a default behaviour (*e.g.* stand by or wander).

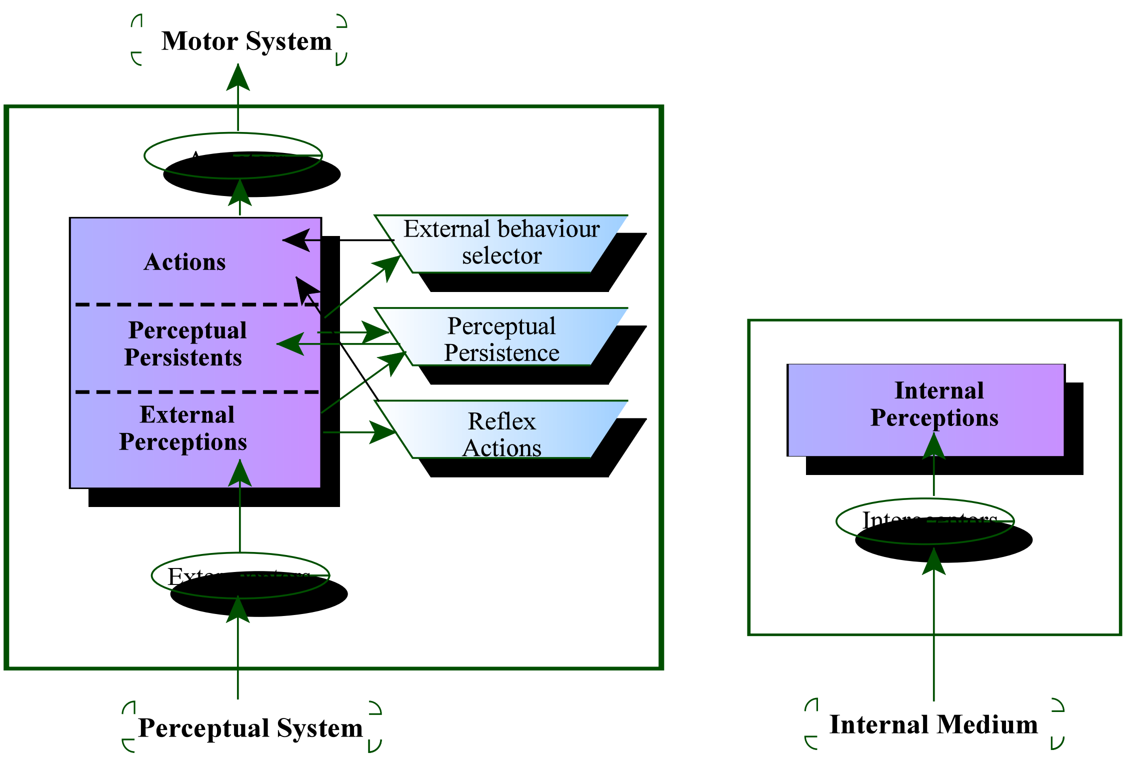

Figure 8. BeCA at the stage of the modelling of reactive behaviours.

3.7. Modelling Motivated Behaviours

"When ruling, rule yourself beautifully"
—Thales of Miletus

Motivated behaviours are those that by necessity require an internal state in order to be executed (Manning, 1979; McFarland, 1981). That is to say, unlike reflex and reactive behaviours, which show a rigid dependence of external stimuli, motivated behaviours are controlled mainly by the internal state of the animal. For example, that an animal executes the consummatory behaviour drink water depends not only on the presence of the external stimulus water, but also on the internal need thirst. The absence of a stimulus might also be itself an external stimulus capable of triggering a motivated behaviour. For example, the exploratory behaviour in animals is a motivated behaviour, exhibited when the external signal appropriate for the actual internal need is not present in the surrounding environment. Motivation is hence a class of internal process that produces changes in the behaviour (McFarland, 1981). Motivated behaviours are commonly characterized by: sequencing of component behaviours in time, goal-directedness, spontaneity, changes in responsiveness, persistence in the execution of behaviours, and several types of learning (Kupfermann, 1974; Beer, 1990).

Motivated behaviours are modelled in our BPS by incorporating a third layer over the two previous ones. The creation of this third layer can be seen as a process of improvement and refinement of the node related with the processing of external signals and of the node responsible for processing of internal signals or motivations.

The process of improvement and refinement of the node related with the processing of external signals includes the definition of three new blackboard levels: Consummatory Preferents, Drive/Perception Congruents and Potential Actions, the refinement of internal behaviours *perceptual persistence* and *external behaviour selector*, the definition of two new internal behaviours: *attention to preferences* and *reactive response inhibition*, and the further definition of the communication mechanisms *receptor* and *transmitter*. On the other hand, the node responsible for processing internal signals will grow functionally and structurally from the inclusion of the following components: three new blackboard levels, External Perceptions, Intero/Extero/Drive Congruents and Drive; the *intero/extero/drive congruence* and *consummatory preferences selector* internal behaviours that carry out the processing of internal signals, and the communication mechanisms *receptor* and *transmitter.* We will begin the construction of this layer improvement and refinement of the first node, assuming that it receives signals coming from the node related with the internal states, which indicates the internal need that should be satisfied.

At the Consummatory Preferents level, signals coming from the node responsible for the processing of internal signals are recorded. These signals indicate which internal need should be satisfied. The signals placed in the Drive/Perception Congruents level are derived from the combination of signals recorded at the Perceptual Persistents and the Consummatory Preferents levels. If a signal has been recorded at the Potential Actions level, then one of the two following things will occur: this signal will reinforce the external behaviour firing, initiated by a signal on the Drive/Perception Congruents level; or this signal by itself will be able to invoke an external behaviour.

The role of the *perceptual persistence* internal behaviour continues to be the representation of the external signals in the Perceptual Persistents level, although its activity has been refined. This means that for the persistence of a signal in Perceptual Persistents, this will be taken into account if a signal associated with this one has been created at the Drive/Perception Congruents level. This last signal participates in the competition among the *perceptual persistence* elementary behaviours, reinforcing the persistence of the corresponding signal at the Perceptual Persistents level. Expression (3) shows this refinement in the *perceptual persistence* internal behaviour.

$$Atmp_i^T = (1-\kappa)O_i^T + Fa_{ii}^S O_i^S + Fa_{ii}^I O_i^I + \sum_{i \neq j} + Fa_{ij}^T O_j^T \qquad (3)$$

where Fa_{ii}^I is the coupling strength of the signal O_i^I of the Drive/Perception Congruents level. The rest of the notation is the same as used in expression (1), and A_i^T is still determined by expression (2).

The signals placed at the Consummatory Preferents level are combined with signals placed at the Perceptual Persistents level to decide the possible external actions to execute. This task is carried out by the *attention to preferences* internal behaviour. At this level, we can see how the internal needs mediate the selection of the external behaviour to be executed. The elementary behaviours encapsulated in this internal behaviour work as operators AND or operators OR depending of the value of γ_i in expression (4). This parameter is used to modulate the reactivity degree in the observed behaviour of the entity. The final action of the elementary behaviour i consists in the creation of the solution element O_i^I at the Drive/Perception Congruents level. The value of solution element O_i^I is given by expression (4).

$$O_i^I = Fa_i^T O_i^T \left(\gamma_i + \phi \frac{\sum_j Fa_j O_j^C}{O_i^T} \right) \qquad (4)$$

where O_i^I is the value to be inscribed in the Drive/Perception Congruents level; O_i^T is the signal from the Perceptual Persistents level and Fa_i^T its corresponding coupling strength; O_j^C is the signal from the Consummatory Preferents level and Fa_j^C its corresponding coupling strength; and γ_i and ϕ modulate the reactivity degree in the observed behaviour of the agent.

When the value of ϕ equals one, the total value of the signals from the Consummatory Preferents level, representing the most imperative internal needs, is taken. This makes the external behaviour motivated. As ϕ decreases, less importance is given to the signals from the Consummatory Preferents level, making the external behaviour less motivated. If ϕ is equal to zero, there will be no flow of signals from the Consummatory Preferents level, and the agent will not have any knowledge of its internal needs. Therefore, by modifying the value of ϕ we can produce a motivational lesion in the BPS.

For a value of γ_i greater than zero, greater importance is given to the external stimuli, represented by the signals on the Perceptual Persistents level, than to the signals from the motivational node, found in the Consummatory Preferents level. This makes that even in the absence of motivation for an external behaviour, the behaviour might be executed reactively. Behavioural columns modelling reactive behaviours would have a γ_i value greater than zero, while pure motivated behaviours require their γ_i to be equal to zero.

The role of the *reactive response inhibition* internal behaviour is to establish the following hierarchical organizational principle: the activation of internal behaviours perceiving external signals from the Perceptual Persistents level that have a corresponding congruence with the internal needs, represented in the Drive/Perception Congruents, will have a higher opportunity to be activated, and hence inscribe their signal in the Potential Actions level, than the internal behaviours without a corresponding congruence with the internal needs. A competition takes place among the elementary behaviours, and the value of the signal created at the Potential Actions level (O_i^H) will be equal to the activation level A_i^H (determined by expression (5)) if the activation is greater than zero, and zero otherwise.

$$A_i^H = Fa_{ii}^T O_i^T + \sum_j Fa_{ij}^I O_j^I \qquad (5)$$

where O_i^T is the signal read from the Perceptual Persistents level, and Fa_{ii}^T is its corresponding coupling strength; and O_j^I is the signal from the Drive/Perception Congruents, and Fa_{ij}^I its corresponding coupling strength, which is negative for $i \neq j$ and positive for $i=j$.

The activity of *external behaviours selector* has been modified to take into account the internal needs in the selection of an external behaviour. Now, the *external behaviours selector* decides which external behaviour will be executed in the current moment taking into account both signals recorded in the Drive/Perception Congruents and Potential Actions levels. The elementary behaviours that structure *external behaviours selector* behave as OR operators. But, when for a signal recorded in the Potential Actions level, there is a corresponding signal recorded at the Drive/Perception Congruents level, the strength of the *external behaviours selector* elementary behaviour will be greater than those of elementary behaviours with signals represented at only one of the blackboard levels. After this, a competition takes place, in order to decide which signal(s) calculated with expression (6) will be inscribed at the Actions level.

$$A_i^M = \sum_j Fa_{ij}^H O_j^H + \sum_j Fa_{ij}^I O_j^I \qquad (6)$$

where O_j^H is the signal read from the Potential Actions level, and Fa_{ii}^H is its corresponding coupling strength; O_j^I is the signal read from the Drive/Perception Congruents level, and Fa_{ii}^I is its corresponding coupling strength; and A_i^M is the intensity of the signal to be created by *external behaviour selector*.

The node responsible for the processing of internal signals or motivations receives signals from the internal medium through the *interoceptors*, and from the node related with the processing of the external signals through the *receptor* mechanism, and it sends signals to this node through the *transmitter* mechanism. The role of the node responsible for the processing of internal signals includes the representation of internal signals, the combination of internal and external signals, and the competitive processes among motivationally incompatible behaviours. This produces the observed final external behaviour to be strongly dependent on the internal states. All the internal states registered by the *interoceptors* compete among them to determine which external behaviour will be executed. This competition is of the type *winner-take-all*.

The blackboard of this node organizes the signals in four levels of abstraction: Internal Perceptions, External Perceptions, Intero/Extero/Drive Congruents, and Drive. The signals recorded at Internal Perceptions correspond to the current values of the internal states, sensed and preprocessed by the *interoceptors* mechanism, multiplied by a coupling strength. At the External Perceptions level the values of the external signals, still represented at the Perceptual Persistents level of the node related with the external signals, are recorded (these signals are transmitted and received by the communication mechanisms). The signals placed at the Intero/Extero/Drive level are derived from a combination of signals at the Internal Perceptions, External Perceptions and Drive levels. The signals created at the Drive level represent the strongest internal needs that should be satisfied.

The signals at both the Internal Perceptions and External Perceptions levels are combined by the *intero/extero/drive congruence* internal behaviour. This combination may be increased if a corresponding signal has been created at the Drive level. The model for the combination of internal and external signals is given by expression (7).

$$A_i^C = Fa_i^E O_i^E \left(\alpha + \tau \sum_j Fa_{ij}^S O_j^S \right) + Fa_i^D O_i^D \qquad (7)$$

where A_i^C is the intensity of the signal to be created at the Intero/Extero/Drive Congruents level of the motivational node; O_i^E is the signal from the Internal Perceptions level and Fa_i^E its coupling strength; O_j^S is the signal from the External Perceptions level and Fa_{ij}^S its coupling strength; O_i^D is the signal from the Drive level and Fa_i^D its coupling strength; τ is a lesion factor; and α regulates the combination of the internal and external signals. This combination model is discussed in detail in (González *et. al.*, 2000).

For a value of α equal to zero, the internal signal and external signals interact in a multiplicative way. If one of the signals (internal or external) is very small, it decreases the importance of the other signal. In this way, external signals that contribute to weak motivations, will make the corresponding external behaviour to have little chance of being selected. The same occurs with small external signals for strong motivations. If we consider a value of α greater than zero, then the internal state will have more importance than the external signal. In this way, external signals that contribute to strong motivations, will make the corresponding external behaviour to have a strong chance of being selected, even in the total absence of external signals. This results in the external behaviour being a motivated one.

Once the external and internal signals are combined by the *intero/extero/drive congruence* internal behaviour and the resulting signals are placed on the Intero/Extero/Drive Congruents level, a competition process takes place in order to select the consummatory preferent signal which will be finally placed on the Drive level and sent to the other node. The first of these two processes is carried out by the *consummatory preferences selector* internal behaviour, whereas the second process is executed by the *transmitter* mechanism.

The *consummatory preferences selector* internal behaviour is composed of a set of specific elementary behaviours associated with specific needs and a default elementary behaviour. The condition of an elementary behaviour is satisfied when at the Intero/Extero/Drive Congruents level has been created the signal C_i or its value or intensity A_i^C has been actualized; and further, when for any of these two cases the value A_i^C surpasses a threshold θ previously established. All elementary behaviours that have satisfied this condition enter a competition of the type *winner-take-all*, which decides which elementary behaviours will execute their final action on the Drive level. The final action consists in the creation of the signal D_i with intensity O_i^D, the last value being calculated from expressions (8) and (9).

$$A_i^D = O_i^C + \sum_j Fa_{ij}^C * O_j^C \qquad (8)$$

$$O_i^D = \begin{cases} A_i^D & if \quad A_i^D > \theta \\ 0 \; in \; other \; cases \end{cases} \qquad (9)$$

where A_i^D is the intensity of the signal to be inscribed on the Drive level, O_i^C is the value of the signal from the Intero/Extero/Drive, inhibited by the rest of the signals O_j^C multiplied by a negative coupling strength $Fa_{ij}^{C.}$

If no element fulfills the condition $O_i^D > \theta$, then there will be no winner behaviour and the competition ends without a specific behaviour executing its final action on the Drive level. When more than one elementary behaviour has satisfied the condition $O_i^D > \theta$, then the competition takes place until it converges to a state in which only one elementary behaviour will be the winner. This happens by successive actions of the *intero/extero/drive congruence* and the *consummatory preferences selector* internal behaviours.

The communication between both nodes is carried out by the *receptor* and *transmitter* mechanisms. Each node has a *receptor* and a *transmitter*.

As part of the construction of this third layer, a new default external behaviour is incorporated: the *explore* external behaviour, preserving the default external behaviour defined in the second layer. The *explore* external behaviour is oriented towards searching a specific external signal that is required to satisfy an imperative internal need. The *explore* external behaviour might be executed when for a signal received from the Drive level and placed on Consummatory Preferents, there is not a corresponding signal at the Perceptual Persistent level. This is, when there is an internal need to be satisfied for which the corresponding external signal has not yet been perceived.

Reflex behaviours are still controlled by *reflex actions*, and reactive behaviours can be implemented in columns with a γ_i greater than zero.

Figure 9 shows the components of BeCA once the improvement and refinement processes concerning the construction of the third layer is concluded. At this stage of the bottom-up construction, BeCA is able to model three types of external behaviours: reflex, reactive and motivated, the last two of these mediated by action selection. As it can be appreciated in Figure 9, we have named cognitive to the node related with the external medium, and motivational to the node related with the internal medium. The **cognitive node** interacts directly with the external medium through its sensors and actuators. The **motivational node** responds to the different processes related with the motivations that take place at the level of this node.

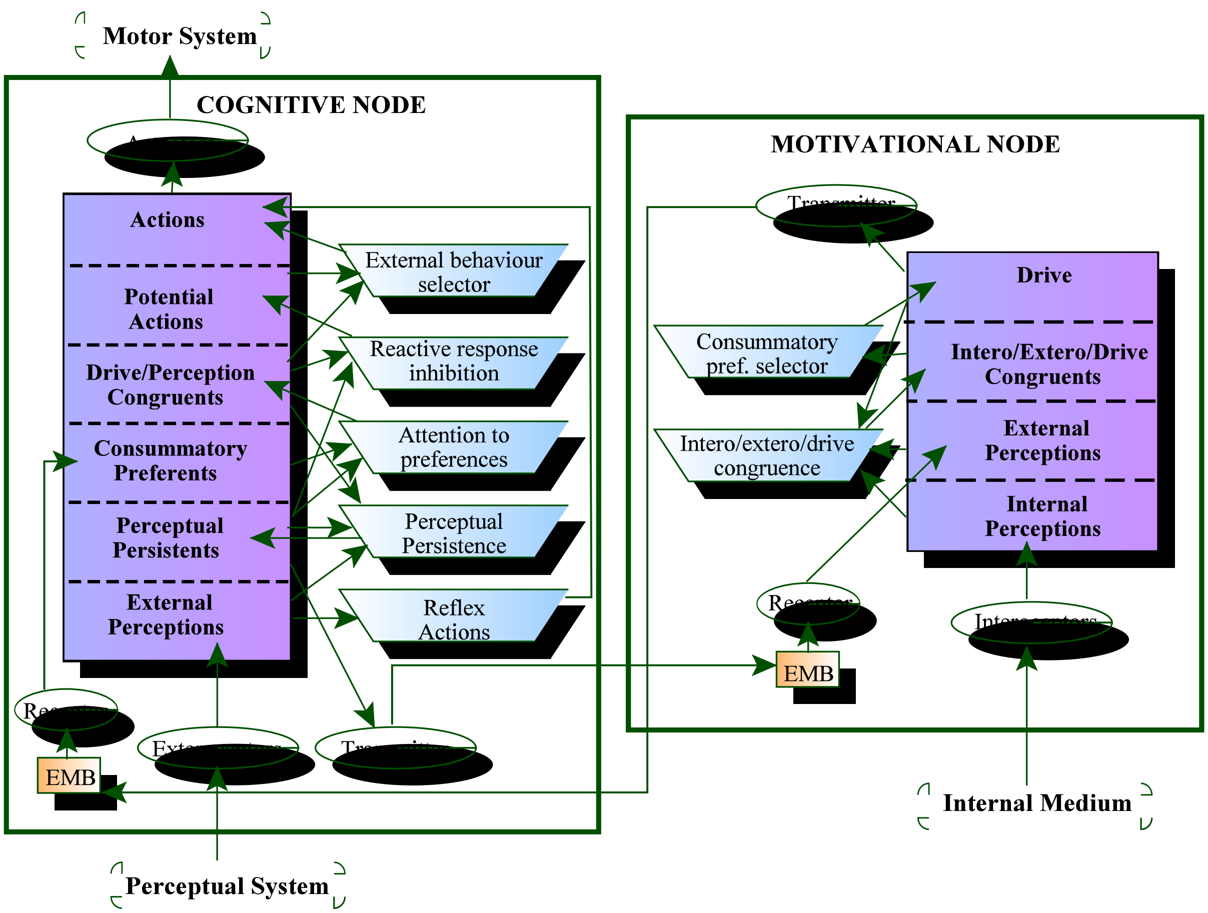

Figure 9. BeCA at the stage of the modelling of motivated behaviours.

3.8. Modelling Learning

Adaptation is one of the desirable characteristics in behaviour production. Adaptation in a behaviours production system can be obtained from three main approaches: preprogrammed adaptive behaviours, learned adaptive behaviours, and evolved adaptive behaviours (Meyer and Guillot, 1990). In our BPS, the preprogrammed adaptive behaviours were obtained from the construction of the three layers discussed in Sections 3.5, 3.6 and 3.7, whereas the learned adaptive behaviours can be seen as a refinement process of these layers. In this sense, we will refine the functionality of the BPS to provide it with two types of adaption by learning: (1) associative learning, which allows new behaviours and emergent properties to arise within BeCA, thus increasing its level of adaptiveness, and (2) a simple reinforcement learning approach, which allows the motivation degree in the behaviour to be adjusted dynamically.

3.8.1. Associative learning

All external signals sensed and preprocessed by the perceptual system are projected at each instant on the External Perceptions level of the cognitive node. Several of these external signals represent environment stimuli that are able to trigger the execution of either a reflex, reactive, or motivated behaviours; whereas other external signals are not associated to the execution of external behaviours. The last type of external signal is frequently known as neutral stimuli, because these signals do not have an initial meaning for the agent (*i.e.* they are not able to produce a behaviour). The associative learning is concerned with the acquisition of meaning by these stimuli under certain conditions explained below. The two forms of associative learning to be incorporated in BeCA are classical primary conditioning and classical secondary conditioning.

Classical primary conditioning can be explained in the following terms: if an initially neutral stimulus appears before each presentation of an unconditioned stimulus (US), the neutral stimulus will be associated with the unconditioned stimulus, and this is why now the first one will be able to produce the same answer produced by the unconditioned stimulus. This stimulus, initially neutral, is now called conditioned stimulus (CS) (Kandel, 1976; Kandel, 1985).

In BeCA, neutral stimuli initially are not able to form behavioural columns through all the levels crossed by unconditioned stimuli. In this sense, the principle to model associative learning in BeCA consists in the modification of the coupling strength values (Fa) of determined elementary behaviours, in order to form behavioural columns. In this way, the trajectory through the different levels of the two blackboards initiated by a neutral stimulus projected on the External Perceptions level of the cognitive node will be able to reach the Actions level.

The modification of the coupling strengths of elementary behaviours takes place when the following things occur: (1) a neutral stimulus is projected on the External Perceptions level of the cognitive node before each projection of an unconditioned stimulus (for example, water source, food source, etc.), and (2) a signal (representing an internal need) associated with the unconditioned stimulus from the Drive level of the motivational node was projected to the Consummatory Preferents level of the cognitive node. These modifications of the coupling strengths can be seen as learning processes, and they are similar to the adjustment of the connection weights in an artificial neural network.

The classical conditioning in BeCA is expressed in terms of three types of learning, which are referred to as: (1) learning of the motor action pattern, consisting in the modification of coupling strengths of the *external behaviour selector* elementary behaviours, (2) learning of the biological meaning, which consists in the modification of the coupling strengths of the *intero/extero/drive congruence* elementary behaviours, and (3) learning at a motivational level, which consists in the modification of coupling strengths of the *attention to preferences* elementary behaviours. The rule for the modification of the coupling strengths used by the three types of learning is given by expression (10).

$$Fa_{ij}(t+1) = \begin{cases} (1-\beta)Fa_{ij}(t) + \left(f\left(O_j^{in}(t)\right) f\left(O_i^{out}(t)\right)\right)\lambda & if\ f\left(O_j^{in}(t)\right) > 0 \\ (1-\mu)Fa_{ij}(t) & inother\ case \end{cases} \tag{10}$$

where: Fa_{ij} is the modifiable coupling strength of the elementary behaviour i with respect to the signal j; O_j^{in} is the value associated to the condition signal j; O_i^{out} is the value associated to the action signal i; β is a parameter that determines the proportion taken from the coupling strength corresponding to the previous instant, $(0 \leq \beta \leq 1)$; λ is a factor regulating the speed of the conditioning; and μ determines the speed of the extinction of conditioning $(0 \leq \mu \leq 1)$. The first part of expression (10) regulates the conditioning, whereas the second part regulates the extinction of the conditioning. For values of β equal to μ, the two parts of this equation could be reduced to the first.

The coupling strengths will be modified when O_i^{out} is greater than zero. If O_j^{in} is also greater than zero, the coupling strength will be increased, while if O_j^{in} is equal to zero, the coupling strength will be decreased.

As it can be seen in Figure 10 and Figure 11, each of these learning processes is able to form or reinforce a segment in the corresponding behavioural column to a neutral stimulus. Figure 10 shows the crossed trajectory segments by neutral stimuli (grey solid circles) and unconditioned stimuli (black solid circles) before classical conditioning. Figure 11 shows the crossed trajectory segments by the neutral stimulus (now, a conditioned stimulus) when the three types of learning have occurred.

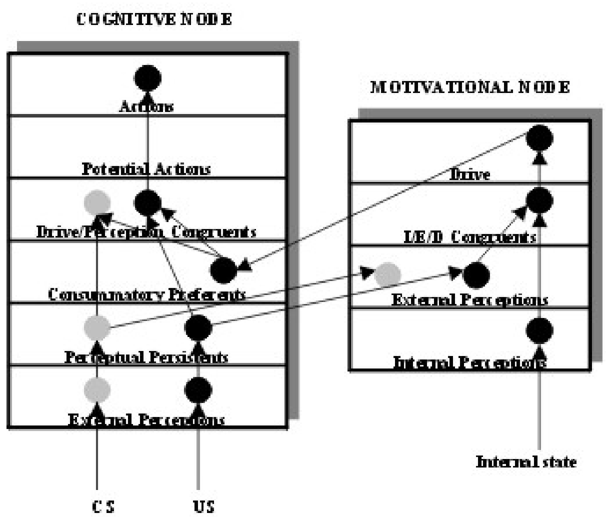

Figure 10. Trajectory of a neutral stimulus before the conditioning.

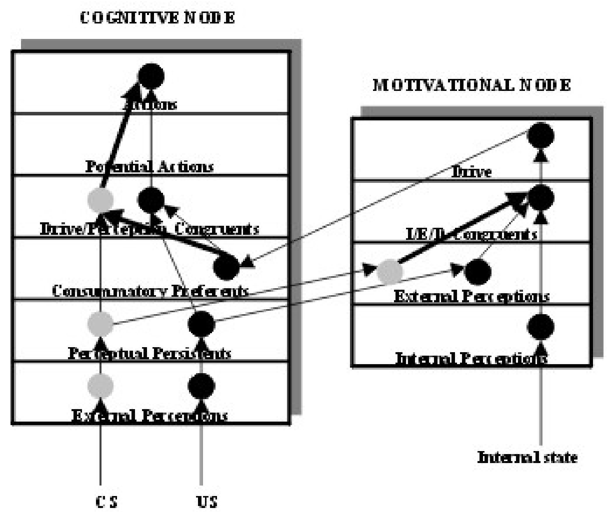

Figure 11. Trajectory of a conditioned stimulus.

The secondary conditioning is another type of associative learning incorporated in BeCA, as a part of the refinement process of the three created layers. This type of conditioning can be described in the following terms: if a stimulus that initially is neutral appears before each presentation of a stimulus that already was conditioned (CS), the neutral stimulus will become a conditioned stimulus. Thus, the neutral stimulus will be able to evoke the external behaviour that before evoked the CS, becoming itself also a CS. In other words, in the secondary conditioning the role of an unconditioned stimulus (US) is played by the previously conditioned stimulus (CS) (Kandel, 1976; Kandel, 1985).

In BeCA, the events that originate the secondary conditioning process are the same as the ones already described in the primary classical conditioning. The main difference between both processes of conditioning can be explained in the following terms: In primary classical conditioning, the stimulus that plays the role of the conditioner is by nature an US. This US is able to evoke an external behaviour without the need of a previous learning process (conditioning). This means that the behavioural columns have been previously established. The trajectories of the columns are given by the high values of the coupling strengths of the elementary behaviours associated with each column. In the secondary conditioning, the stimulus that plays the conditioner role is a CS, this is, a stimulus that initially was neutral but that was conditioned by an US in a previous process of primary classical conditioning. Although for this CS the behavioural columns have already been created as well, these were not preestablished, but were created through the process of primary classical conditioning instead (learning of the motor action pattern, learning of the biological meaning and learning at a motivational level). In this way, the second neutral stimulus would be able to form a behavioural column. The main properties of classical and secondary conditioning in BeCA are mentioned in Section 3.9.

3.8.2.Dynamic adjustment of the motivation degree

The other type of learning included in BeCA consists in the dynamic adjustment of the parameter α in the model for combination of internal and external stimuli, used by the *intero/extero/drive congruence* internal behaviour, presented in Section 3.7. This parameter allows to regulate the dependence degree of the external behaviour executed by the agent from his internal state. We have named this parameter "motivation degree". The effects produced by values of α equal to zero or α near to one in the observed external behaviour were already discussed in Section 3.7. We will rewrite again expression (7) taking into account that there is a different parameter α for each *intero/extero/drive congruence* elementary behaviour. Expression (11) incorporates this change.

$$A_i^C = Fa_i^E O_i^E \left(\alpha_i + \tau \sum_j Fa_{ij}^S O_j^S\right) + Fa_i^D O_i^D \qquad (11)$$

The learning model that controls the dynamic adjustment of the motivation degree (parameter α_i in expression (11)) can be explained in the following terms: when for a strong internal state (*e.g.* need, goal), if the external signal able to satisfy this need is not present, then parameter α_i is reinforced, so that the external behaviour related with column i begins to be more motivated. Therefore, after this adjustment, the BPS will begin to attach more importance to the internal state which has not been satisfied. In this case, the default exploratory behaviour can be activated for not so strong values of the internal need, although other external signals may have already been perceived. When an external signal is perceived and the value of the associated internal state to this signal is irrelevant, then the parameter α_i of expression (11) is decreased, and the behaviour production begins to become less motivated. Therefore, in later situations with this adjustment, the BPS will begin to give more importance to the available external signal, although the associated internal state is not a strong one. In this case, the default exploratory behaviour will need stronger values of the internal need to be activated. In any other case the parameter α_i is not modified. These cases are represented in expression (12).

$$\alpha_i(t+1) = \begin{cases} f^+(\alpha_i(t)) & \text{if } O_i^E > \theta \text{ and } \sum\limits_j Fa_{ij}^S O_j^S = 0 \\ f^-(\alpha_i(t)) & \text{if } O_i^E \le \theta \text{ and } \sum\limits_j Fa_{ij}^S O_j^S > 0 \\ \alpha_i(t) & \text{in other case} \end{cases} \qquad (12)$$

where O_i^E is the value of the internal signal from the Internal Perceptions blackboard level, $\sum_j Fa_{ij}^S O_j^S$ represents the value of all the external signals that are associated to the internal state i, and θ is a threshold value.

The increase in the value of parameter α_i is determined by expression (13). This increase can be seen as a hyperbolic divergence from αmin, as seen in Figure 12. In expression (13), δ determines the length of the divergence (how much time it will take α_i to go from αmin to αmax), and ρ determines the speed of the divergence. This smooth modification behaviour simulates a historic memory of the environment (remembered scenario), so that the value of α_i is increased only after several iterations within a certain environment.

$$f^{+}(\alpha) = \begin{cases} \left[-\frac{1}{x1(\alpha) - \delta} + \alpha\mathbf{min} - \frac{1}{\delta} \right] & \mathit{if}\,[\;] < \alpha\mathbf{max} \\ \alpha\mathbf{max} & \mathit{in\ other\ case} \end{cases}$$
$$x1(\alpha) = -\frac{1}{\alpha - \alpha\mathbf{min} + \frac{1}{\delta}} + \delta + \rho \tag{13}$$

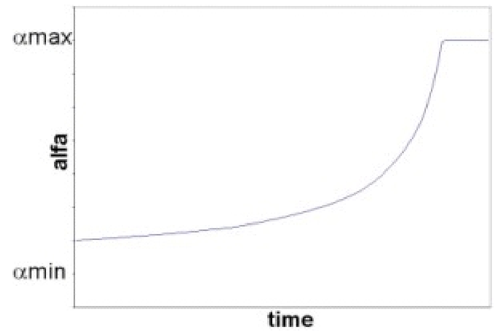

Figure 12. Increase of α_i.

The decrease of the parameter α_i is determined by expression (14). This is similar to the increase described by expression (13), only that it hyperbolically diverges from αmax, as seen in Figure 13.

$$f^{-}(\alpha) = \begin{cases} \left[\frac{1}{x2(\alpha) - \delta} + \alpha\mathbf{max} + \frac{1}{\delta} \right] & \mathit{if}\,[\;] > \alpha\mathbf{min} \\ \alpha\mathbf{min} & \mathit{in\ other\ case} \end{cases}$$
$$x2(\alpha) = \frac{1}{\alpha - \alpha\mathbf{max} - \frac{1}{\delta}} + \delta + \rho \tag{14}$$

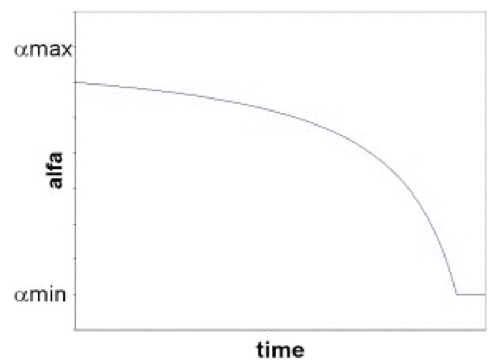

Figure 13. Decrease of α_i.

In Figure 14, we can see an example of the behaviour of the parameter α_i, as it is increased, decreased, or remains constant, in dependence of the perceived scenario and the internal needs. Note that the increase is faster than the decrease, because the values of α_i are closer to αmax than they are to αmin.

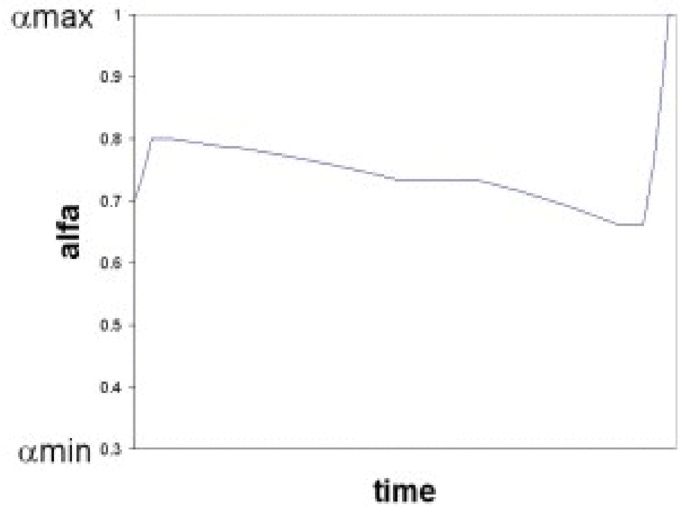

Figure 14. Example of the behaviour of parameter α_i

A detailed discussion related to the learning of the motivation degree in BeCA can be found in (Gershenson and González, 2000).

3.9. Properties of BeCA

"... and many are not amazed because they do not know about it"
—José Luis Mateos

One of the most notable properties of a behaviours production system like BeCA, is that, although it is formed of elemental behaviours, each of which does not have a significance in the survival of the creature it is controlling, the elemental behaviours interact in such a way that from this very interaction emergent behaviours are **produced**. In a similar way, words in a spoken language may have little meaning by themselves. But, since they have enormous possibilities of **combination**, almost an infinity of meanings can be created with these words. The articulation of different elemental behaviours in behavioural columns gives the possibility to the BPS to **produce** a wide variety of behaviours and behaviour patterns, which are not selected, but emergent.

BeCA is a **context-free** BPS. This means that it can be implemented in different environments and problem domains. This is possible because BeCA is defined in a general way and it is independent of the motor and perceptual systems. If BeCA is desired to be used as the behaviour production system of an artificial or virtual creature, the developers need only to connect the signals from the perceptual system and from the internal medium to BeCA, then define behavioural columns by setting appropriate coupling strengths, and finally connect the output to the motor system. The creature should present the properties of animal behaviour described in this section. Refinements on the resulting system would lead to still more emergent properties.

Our BPS is **robust**. While lesioning different components of BeCA (Gershenson, González and Negrete, 2000b), its functionality degrades "gracefully".

BeCA is able to model **reflex behaviours**. External signals perceived by the *reflex actions* internal behaviour will be directly sent to the Actions level of the cognitive node.

BeCA presents **regulated reactive behaviours**. The parameter γ_i in the *attention to preferences* internal behaviour regulates how reactive a behavioural column will be. If γ_i is equal to zero, then the behavioural column will not be reactive.

Our BPS has **motivated behaviours: regulated and/or learned by reinforcement** (Gershenson and Gonzalez, 2000). The parameter α_i in the *intero/extero/drive congruence* internal behaviour regulates the degree of the motivation of an external behaviour. If α_i is near zero, the behaviour will be less motivated than if it is near one. The wealth or scarcity of the environment is taken into account in the learning of this parameter. If the environment is scarce, α_i will be increased. If the environment is rich, then α_i will be decreased.

BeCA has **associative learning** implemented within it. At this stage, **primary and secondary conditionings** are present, and the following properties emerge from the interaction of the different components of BeCA: **blocking**, **decreasing of the stimulus activity in time**, **overshadowing**, **extinction of the conditioning**, **reacquisition of the conditioning**, **temporal interruption of the conditioning**, **inhibition of the conditioning**, and **the stronger conditioning occurs for intermediate values of inter-stimuli intervals** (González, 2000). BeCA also exhibits **delay conditioning**, in its two variants, and **trace conditioning**. The first variant of delay conditioning consists in the length of the neutral stimulus (or the stimulus in conditioning process) being equal to the inter-stimulus interval, whereas the second variant establishes that the length of the neutral stimulus is equal to the inter-stimulus interval plus the length of the unconditioned stimulus. In trace conditioning, the presentation of the neutral stimulus terminates before the arrival of the unconditioned stimulus (Balkenius, 1994).

The following properties of BeCA are **emergent**:

Opportunism. The blackboard architecture allows the possibility of opportunistic behaviour to arise. The elementary behaviours take the *opportunity* to execute their actions when their conditions allow it.

Preactivation of internal behaviours. Once a competition is carried out at a motivational level, the winning signal will be sent to the Consummatory Preferents level of the cognitive node. If there is no external signal corresponding for the internal need represented by the winning signal, then the *attention to preferences* internal behaviour will be "preactivated", focussing *attention* on the satisfaction of the need. If a corresponding signal appears, the corresponding external behaviour will be executed, without the need for waiting for signals from the motivational node.

Goal-directedness. If a behaviour is motivated, we can say that it is directed by the goals (or needs) of the entity.

Non indecision in the action selection. The different competition processes assure that there will be no indecision, or randomness, in the action selection. For example, if a creature controlled by BeCA has the same degree of hunger and the same degree of thirst, and has food and water in the same amount at the same distance, he will not decide randomly which behaviour will be executed. The motivations will compete until only one will be able to execute its corresponding behaviour.

Satiation. When a creature controlled by BeCA executes a consummatory behaviour to satisfy one of its needs, this need will decrease. Once the need is satisfied, it will not motivate the execution of the behaviour any longer.

Changes in responsiveness. When an internal need is satiated, the entity controlled by BeCA will have a change in its responsiveness, selecting a different behaviour.

Persistence in the execution of a consummatory behaviour. The feedback from the Drive/Perception Congruents level to the *perceptual persistence* internal behaviour allows the consummatory behaviour previously executed to have a higher possibility to be executed, as long as the external and internal signals corresponding to the behaviour are still strong. For example, if an agent controlled by BeCA is hungry and thirsty, and he finds food and water, there will be no switching from eating to drinking and back with every time step. The agent will execute a consummatory behaviour until the corresponding internal need is adequately satisfied.

Interruption in the execution of a consummatory behaviour. If a creature controlled by BeCA is executing a consummatory behaviour, this can be interrupted in the presence of a sudden need or a reflex or more imperative reactive behaviour. For example, if the creature is drinking, and he perceives a predator nearby, he might interrupt the satiation of his thirst in order to run away.

Varying attention. This property is defined by ethologists as the less importance that an animal gives to danger (*e.g.* a predator) when the animal has an extreme motivation (*e.g.* starvation) (McFarland, 1981). This property emerges from the competition at a motivational level. If an agent controlled by BeCA is very hungry, even if he is perceiving a predator, he may try to satisfy his hunger, because of the intensity of the signal representing the internal need.

3.10. About the Behavioural Columns Architecture

"All things are what one thinks of them"
—Metrodorus of Chius

The BeCA evolutionary bottom-up style of engineering, and many of its properties, were facilitated by the blackboard architecture, which provides a great flexibility and capacity of integration and of being intrinsically opportunistic.

There are many reasons to think that the BPS presented and discussed in previous sections is something more than a simple action selection mechanism. BeCA integrates in a single model an extensive repertoire of properties and principles desired in adaptive autonomous agents. Although different subsets of these properties can be found characterizing other ASMs and BPSs reported in the literature (Tinbergen, 1950; Tinbergen, 1951; Lorenz, 1950; Lorenz, 1981; Baerends, 1976; Brooks, 1986; Brooks, 1989; Rosenblatt and Payton, 1989; Maes, 1990; Beer, 1990; Beer, Chiel and Sterling, 1990; Hallam, Halperin and Hallam, 1994; Negrete and Martínez, 1996; Goetz and Walters, 1997), none of them present all of them as a whole, and the incorporation of all these properties in a single model provides great robustness in the behaviour production. The result is a BPS with a very high degree of adaptation.

The bottom-up and evolutionary approach followed in the construction of our BPS allows the increase of a given configuration of the BPS with the incorporation of new layers over existing layers, while preserving the capabilities of the previous ones. The new incorporated layers define types of behaviours that are more complex, which are required when the problem to solve also becomes itself more complex. In this sense, we could think that when the manipulation of concepts and logic is required in order to select behaviours, then cognitive behaviours could be incorporated into the BPS as a new layer over the layer of motivated behaviours, in the same way in which this last layer was incorporated over the layer of reactive behaviours, when the motivations were taken into account for the action selection. Of course, not only would the complexity of the BPS be increased, but we would need also to take into account other issues, such as societies, language, and culture. Therefore, our BPS is capable to be evolved when the problem to solve becomes more complex.

Our BPS is context-free, because it is independent of the motor and perceptual systems of the artificial creature to be controlled. Since the perceptual and motor systems are environment-dependent, our BPS can be easily used in different environments (robots, virtual animats, software agents, etc.), by just designing the appropriate perceptual and motor systems for the given environment of the artificial creature.

The two types of learning schemes present in the BPS, associative learning and dynamic adjustment of motivation degree, were obtained through a refinement process of the previously defined layers. Both types of learning have improved the behaviour production, doing it more adaptive. That is to say, our BPS is characterized by adaptation by learning (Meyer and Guillot, 1990). The associative learning allows new behaviours and emergent properties to arise, which increase the adaptive level of the BPS. The dynamic variation of parameter α_i in the model for combination of external and internal stimuli (expression (11)) allows the autonomous agent to contend with an environment from which the agent possesses certain knowledge, which is summarized in the value of this parameter.

We can also say that BeCA presents **emergent cognition**, in a Turing style (Turing, 1950). This is, an observer of an artificial creature controlled by BeCA (*e.g.* animats in our Behaviours Virtual Laboratory) may judge that the creature **knows** what he is doing. Our intention was not that BeCA would provide cognition to an artificial creature, not even the simple cognition that emerges for observers, but it does. Of course it is low cognition, present in animal behaviour. But we believe that this cognition is also emergent in animals, and that higher cognition should also be emergent. *Cognition is not a mechanism. It is an exhibition of capabilities.* And this exhibition must be perceived by an observer in order to be considered as cognition.

BeCA was implemented in the Behaviours Virtual Laboratory, to be presented in Chapter 5, providing the behaviour production of animats. In the next section we will present a simple model of social action, which allows complex social phenomena to emerge from the interactions of agents.

In Chapter 6 we will present experiments showing some properties and capabilities of BeCA, of our model for social action and of our Behaviours Virtual Laboratory.

4. Behaviour-Based Social Emergence

"Our brains make the world smart so that we can be dumb in peace!"
—Andy Clark

"Viajador en Megapteras". Carlos Gershenson, Mexico City, 1999. Ink on paper.

As we have seen in Chapter 2, in most theories involving artificial societies of agents, the agents are rational (Hogg and Jennings, 1997; Jennings and Campos, 1997), or at least cognitive (Castelfranchi, 1998). This means that their behaviour is guided by logic rules manipulating knowledge representations (Shoham and Tennenholtz, 1995).

In this chapter we will see that it is possible to **observe** intelligent[19] social behaviour without the need of knowledge representation. This is because we will use agents with emergent cognition, provided by BeCA. We will propose a model where complex social behaviour will emerge from simple social actions.

4.1. An I&I Model for Social Action[20]

"I knew they would follow us..."
—Nadia Bazlova

Our model for social action is very simple. It is based in the idea of imitation and induction (I&I) of behaviours. These will be the only social actions among individuals of a society. When an individual perceives another individual performing some kind of behaviour, he might imitate the other if the imitation is beneficial for him in some sense. On the other hand, an individual will try to induce the behaviour to the other individuals he is perceiving, who in turn might or might not imitate him. Induction, in this case, is an insinuation for imitation. An induced behaviour needs to be imitated to be executed by the induced individual. An imitation would be a **weak social action** (Castelfranchi, 1998), because the imitating individual bases his imitation in his beliefs about the behaviour of the imitated individual. An induction would be a **strong social action** (Castelfranchi, 1998), because the inducer tries to make the induced to execute the same behaviour that he is executing.

In animals, most imitated behaviours seem to be reactive behaviours: *e.g.* flock and school formations, stampedes, crowd behaviour. But motivated behaviours may also be imitated. For example, if an animal perceives another one with such a locomotion pattern that he knows that he is approaching food, if he is hungry, he will follow him, but if he is not, probably he will not pay attention to the other animal. Another example would be a Thompson's gazelle that sees other Thompson's gazelles speeding her way, presumably fleeing from a predator. She will not wait until she sees the predator, she will assume there is a predator coming and flee as the other gazelles. Of course this might lead to collective misbelief. We can see in animals examples of induced behaviour also. For example, honeybees induce other honeybees to follow their route to a food source. Some gregarious mammals might warn other members of their group when danger is near.

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[19]See Section 1.1.1.

[20]Part of this work was presented in the poster "Action Selection and Weak Social Action" in the Third International Conference of Complex Systems, in Nashua, NH, May 2000.

In animals, most induced behaviours seem to require a language, while imitated behaviours seem not to need one. This is because the inducer needs to send information to the individual(s) he is trying to induce; whereas perception gives the information required for imitation.

In natural systems, complex social behaviour may emerge from only imitation and induction of behaviour. For example, during a traffic jam, if one driver honks his horn, probably his action will be imitated, and the new honks will be also imitated (not *ad infinitum*), provoking a lot of noise, causing not much pleasure in the drivers. The clapping in audiences seems to work in a similar way. If one person begins to clap, then others tend to follow, and a general acclamation emerges in a chain reaction style. On the other hand, if no one claps, it is harder that someone will start clapping, or clap for a long time, because he is inhibited by the behaviour of the rest of the audience. So, mass approval or disapproval of events emerges in a complex way, depending on the imitation or non imitation of behaviours. Laughing also might be an induced behaviour. A joke is always funnier if there are a lot of people laughing around you. Or what for the recorded laughs in comic shows?

Induction and imitation of behaviour give individuals the possibility to socialize though some form of communication. Without communication, there is no society, only selfish individuals trying to survive by themselves, ignoring everyone else. And without society, no culture can evolve.

In our model, inspired in personal empirical observations, when another individual is perceived, his behaviour is taken into account in the action selection process, making equivalent the perceived behaviour to the external stimulus that motivated it. For example, if an individual perceives another approaching food or eating, it will be equivalent as if he had perceived food (which motivates the behaviours "approach food" and "eat"). If an individual perceives another one fleeing, it will be equivalent to the perception of an aversive stimuli (*e.g.* a predator). In Figure 15 we can see graphically this idea. We can formalize this as follows:

$$PR_i += BSk_j * \text{ל}k \qquad (15)$$

where PR_i is the perception of stimulus i by the receiver, which is increased by behaviour j related to stimulus i perceived in "sender" k, and לk (lamed) is the imitation factor related to individual k.

For induction the idea is very similar. When an individual perceives another, he will try to induce his behaviour to the other, as if the other would be imitating him. This is, the inducer will send to the induced a signal representing the stimulus that motivated the inducer's behaviours. We can formalize this as follows:

$$PR_i += BSk_j * \text{ל}k * \text{י} \qquad (16)$$

where PR_i is the perception of stimulus i by the induced receiver, which is increased by the behaviour j of inductor k related to stimulus i, לk (lamed) is the imitation factor related to the inductor k, and י (yud) is the induction factor of the inductor (sender) k. We can see graphically this idea in Figure 16.

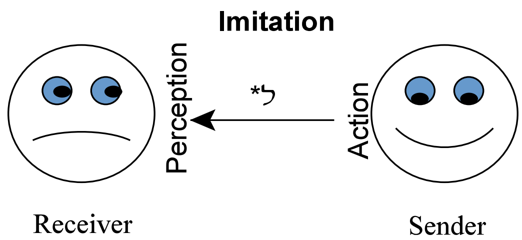

Figure 15. Imitation of behaviour

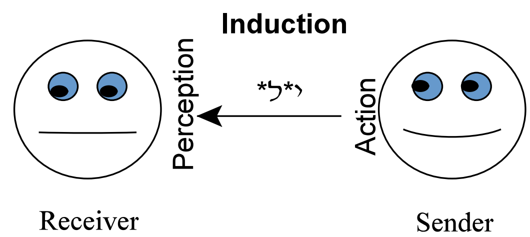

Figure 16. Induction of behaviour

An individual with a higher value of י will have a higher probability to induce his behaviour to others. In other words, he would be a leader (in comparison to individuals with a lower value of י). On the other hand, individuals with low values of ל will have a lower probability of imitating other individuals or being induced by other individuals. This makes them less social. Therefore, we can see ל as a sociality parameter.

The successful imitation and induction of behaviours depend on the ASM or BPS, the reactiveness and motivation degree of the behaviour, the internal state of the individual, and his perceived scenario. Our model only provides the information of the behaviour executed, but this information should go through a control process as any other information received by the perceptual system.

We can see that with this simple model, for different values of ל and י we can have a wide variety of complex social behaviours and systems, also depending on many other circumstances, such as the capabilities of the individuals, and the state of their environment.

4.1.1. The learning of the imitation factors

We have seen that in our I&I model the לk variables determine the strength of the imitation of the behaviours executed by individual k. So, if we increase the לk value, the individual will have a higher probability to imitate individual k, and if we decrease it, the individual will have a lower probability to imitate individual k, and he will never imitate him if the value of לk reaches zero. If לk is lesser than zero, we could say that the behaviour would tend to be antisocial towards individual k (the imitator would be inhibited in executing the behaviour that individual k is executing).

We will apply a simple modification criteria. First, the modification will only take place if there are internal needs in the individual. This is based on animal behaviour, where conditioning can only take place when there are internal needs (Pavlov, 1927). So, if the individual has internal needs, and he is perceiving individual k, לk will be modified. If he performs the same behaviour as the one perceived in individual k, לk will be increased. If he performs a different behaviour, לk will be decreased. The increase and decrease formulas are written in expressions (17) and (18).

$$f^{+}(\text{ל}) = \begin{cases} \left[-\dfrac{1}{x1(\text{ל}) - \text{ד}} + \text{ל}\,\mathbf{min} - \dfrac{1}{\text{ד}} \right] & \mathit{if} \left[\ \right] < \text{ל}\,\mathbf{max} \\ \text{ל}\,\mathbf{max} & \mathit{in\ other\ case} \end{cases} \quad (17)$$

$$x1(\text{ל}) = -\dfrac{1}{\text{ל} - \text{ל}\,\mathbf{min} + \dfrac{1}{\text{ד}}} + \text{ד} + \text{ר}$$

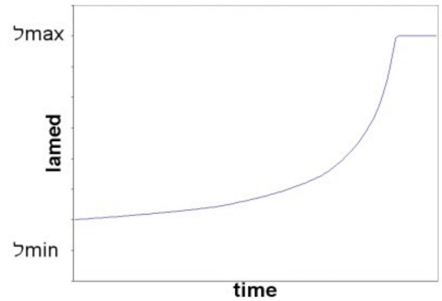

Figure 17. Increase of ל.

$$f^{-}(\text{ל}) = \begin{cases} \left[\dfrac{1}{x2(\text{ל}) - \text{ד}} + \text{ל}\,\mathbf{max} + \dfrac{1}{\text{ד}} \right] & \mathit{if} \left[\ \right] > \text{ל}\,\mathbf{min} \\ \text{ל}\,\mathbf{min} & \mathit{in\ other\ case} \end{cases} \quad (18)$$

$$x2(\text{ל}) = \dfrac{1}{\text{ל} - \text{ל}\,\mathbf{max} - \dfrac{1}{\text{ד}}} + \text{ד} + \text{ר}$$

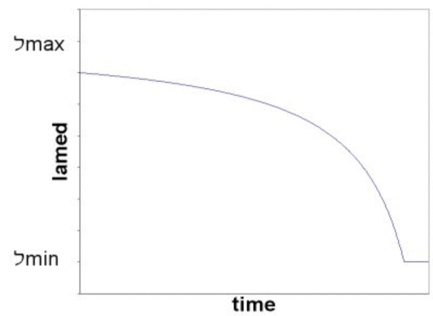

Figure 18. Decrease of ל.

where ד (dalet) determines the length of the divergence and ר (reysh) determines the speed of the divergence of ל bounded between לmin and לmax. Expression (17) can be seen as a hyperbolical divergence from לmin, as seen in Figure 17, and expression (18) as a hyperbolical divergence from לmax, as shown by Figure 18. The parameter α_i in BeCA is adjusted using similar expressions[21] (Gershenson and González, 2000). Because of the hyperbolical divergences, once a לk value reaches the neighbourhood of either לmax or לmin, it will be difficult that it will leave the neighbourhood. Therefore, for low values of ד and/or high values of ר, there is a strong dependence on the initial conditions.

The hyperbolical divergences simulate a persistence of the imitation factor over time, so that it does not jump linearly every time the individual imitates or not a behaviour. This gives a smoother transition of the values of לk, and it makes לmax and לmin to be attractors.

[21]See Section 3.8.2.

4.2. Properties of I&I.

"Now they were simple black dots, ordered in a capricious manner, animated with collective life"
—Boris Vian, in "L'arrache-cœur"

I&I is a very simple model for social action, where many social behaviours and processes **emerge** by the sole induction and imitation of behaviours.

Many properties emerge with I&I, depending on the ASM or BPS which controls the individuals in a society interacting through I&I. This is, if the BPS presents a lot of emergent properties, they will be able to be combined with the properties of I&I, providing a large number of specific emergent social behaviours, depending on the BPS and the social environment.

I&I is a **context-free** model for social action. Since it is defined in a generic way, it can be implemented in any group of adaptive autonomous agents, in order to make them social.

I&I models both **weak social action** and **strong social action** (Castelfranchi, 1998).

I&I can model emergent **social hierarchies**, by setting different imitation and induction parameters (ל and י, respectively).

The **degree of sociality** of an individual can be regulated with the imitation parameters (לk's).

There is emergence of **group beliefs** (Tuomela, 1992) and **misbeliefs** (Doran, 1998).

The learning of the imitation parameters (לk's) provides the model with **social adaptation**.

The wide repertoire of properties, mostly emergent, in such a simple model, allows us to try to understand and control better social processes and phenomena. When such a model is implemented in an artificial society, the possibilities of study and experimentation offer many advantages over natural societies, basically because in an artificial society one can control experiments in a much more precise way than in a natural one.

4.3. About I&I

"Every social regime creates problems"
—Kenneth Arrow

Our I&I model has very simple rules, but in experiments developed (to be shown in Section 6.2), we have seen that the social behaviours simulated are quite complex. Our artificial societies emerge from the imitation and induction of behaviours.

One of the main conclusions obtained after experimenting with I&I is that a society, as it evolves, is shaped more by its environment, than by the individuals themselves. Of course, the society can also influence individuals.

Another interesting property that emerges from our model is group beliefs (Tuomela, 1992) and misbeliefs (Doran, 1998). When an individual imitates another, he *believes* in the individual he is imitating. This can lead to group beliefs or misbeliefs.

Also, we were able to see with our model that if an individual A is not social towards individual B, most probably he will also not be social towards all the individuals of B's social group. This can lead to the emergent formation of different social groups.

In the next chapter we will introduce our Behaviours Virtual Laboratory, where the mentioned experiments were carried out.

5. A Behaviours Virtual Laboratory

"We have to be unmerciful without falling into cruelty"

"Les Trois Ombres". Carlos Gershenson, Hôtel Biron, Paris, 2000. Gel on paper.

In this chapter[22] we will present the properties our Behaviours Virtual Laboratory (BVL). We will first describe virtual labs and in the following sections we will describe the components of ours: the virtual environment, the animats, and the interface.

We programmed our BVL in Java, using its External Authoring Interface (EAI) to control objects on a VRML world. This allows users to access the BVL through the Internet.

Our BVL can be accessed and/or downloaded (source code included) in the URL http://132.248.11.4/~carlos/asia/bvl

5.1. Virtual Labs and Behaviours Virtual Labs

Virtual laboratories have been developed in different areas, to reproduce experiments that were made in physical laboratories. Virtual labs are useful for prepractice and postanalysis of experiments developed in physical labs, and in some cases they can replace the physical lab itself. Although virtual labs may have many limitations, they have many advantages over physical labs. For example, some physical labs have scarcity of resources (in equipment and staff), limiting the researcher's performance. Virtual labs have relatively low costs, experiments can easily be repeated, and there are no inconveniences in failing experiments, because the virtual environment is controlled, and there are no risks for natural systems. It is desirable that virtual labs exploit the advantages of virtual reality, multimedia, and the Internet. Virtual labs have been developed for different areas, such as physics, electronics, robotics, physiology, chemistry, engineering, economics, and ecology.

We believe that there should be also development of virtual labs in the area of ethology. We name these Behaviours Virtual Laboratories (BVL). This development would benefit both ethology and behaviour-based systems. To ethology, a virtual lab would help reproduce with ease experimental and natural conditions that could take even weeks to develop in a physical lab. For example, some kinds of conditioning in animals take days of training, while in a virtual lab, this process may be accelerated, saved, and recovered. For artificial intelligence researchers, a virtual lab would help design and test systems and mechanisms of robots, software agents, or animats.

A BVL should be capable of achieving the same conditions that are found in an ethology physical laboratory, and even provide better development of the experiments. A Behaviours Virtual Laboratory would be useful to design bottom-up autonomous agents or robots, propose and test animal behaviour theories, reproduce behaviour patterns from experimental data, and easily produce lesions in different structures and mechanisms of the animats, amongst other questions. Unlike other types of virtual labs, a BVL should be capable of producing unpredictable results, allowing emergent behaviours to arise. With all these properties, a BVL should induce researchers to "think adaptively". This is, to easily show the properties and characteristics of adaptive behaviour, without the need of complex experimentations or heavy research, in an interactive way.

[22]Parts of this chapter are a restructuration of Gershenson, González, and Negrete (2000b).

Examples of works related to behaviour virtual laboratories are the Simulated Environment developed by Tyrrell (Tyrrell, 1993), which tests different proposed action selection mechanisms; and Beer's Simulation of Cockroach Locomotion and Escape (Beer and Chiel, 1993), which allows to lesion different neuronal structures of the insect.

Following these ideas, we developed a Behaviours Virtual Laboratory, in which animats and simple animat societies can be simulated, having in mind three goals: First, to test and analyse the properties of the Behavioural Columns Architecture (BeCA) (González, 2000). Second, to test an analyse our Imitation and Induction (I&I) model for social action. And finally, to provide a useful tool for biologists, sociologist, and roboticists to experiment with the adaptive and social behaviours that BeCA and I&I, respectively, are able to simulate.

5.2. The Virtual Environment

"The environment is not best conceived solely as a problem domain to be negotiated. It is equally, and crucially, a resource to be factored in the solutions."
—Andy Clark

The virtual environment is defined by a plane (z, x) of a space (x, y, z), limited by a frame. In the area defined by this frame different objects can be created. These objects represent the following external stimuli: food (green spheres), water (blue circles), grass (texturized green circles), fixed obstacles (brown parallelepipeds), blobs (black ellipsoids), and other kinds of stimuli that initially have no specific meaning for the entity (red and yellow circles). The frame that defines the plane (z, x) is also considered as a fixed obstacle. The animats perceive these stimuli, and act upon them. Figure 19 and Figure 20 show aerial views of the simulated environment.

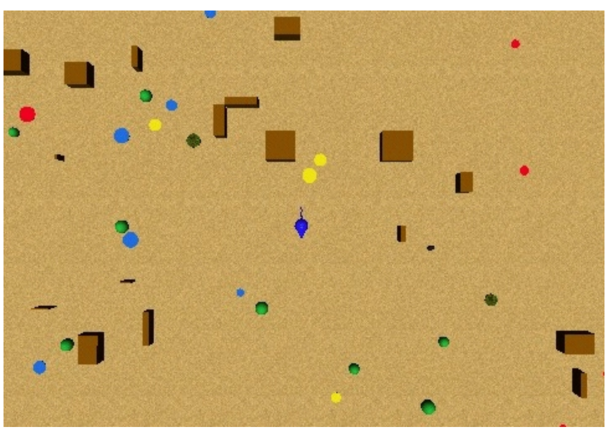

Figure 19. An environment seen from the top.

Figure 20. Another perspective of an environment.

5.3. The Animats

We developed animats of two kinds: predators and preys. Predators chase, kill, and eat preys, and preys run away from the predators. Our initial intention was not to reproduce the behaviour of specific species of animals, but to model general properties found in animal behaviour.

The internal structure of each animat can be described in terms of four basic components: the perceptual system, the internal medium, the behaviours production system (BeCA), and the motor system. Animats communicate and socialize using I&I.

5.3.1. The perceptual system

"The world is my representation"
—Artur Schopenhauer

The perceptual system first registers stimuli that are in the perceptual region (R_p) found in the plane (z, x) of the space (x, y, z) defined by the half-circle of expression (19):

$$R_p = \begin{cases} \left(\left(x > x_a + \tan\left(\left(\theta + \frac{\pi}{2}\right)(z - z_a)\right)\right) \cap \left((z - z_a)^2 + (x - x_a)^2 < r_p^2\right)\right) & \text{if } 0 < \theta \leq \pi \\ \left(\left(x < x_a + \tan\left(\left(\theta + \frac{\pi}{2}\right)(z - z_a)\right)\right) \cap \left((z - z_a)^2 + (x - x_a)^2 < r_p^2\right)\right) & \text{if } \pi < \theta \leq 2\pi \end{cases} \quad (19)$$

where (z_a, x_a) is the position of the animat, θ its orientation in radians, and r_p is the radius of the half-circle (the radius of perception). After this, the perceptual system eliminates the stimuli that are found behind obstacles, as shown in Figure 21, determining the "perceived scenario". The stimuli found in the perceived scenario are pondered as a ratio between the magnitude of the stimulus and its distance from the animat. If a stimulus leaves the perceived scenario, then the pondered value (Fe) decreases in terms of the parameter $\aleph$, as shown in expression (20):

$$Fe(t+1) = Fe(t) - \aleph \quad (20)$$

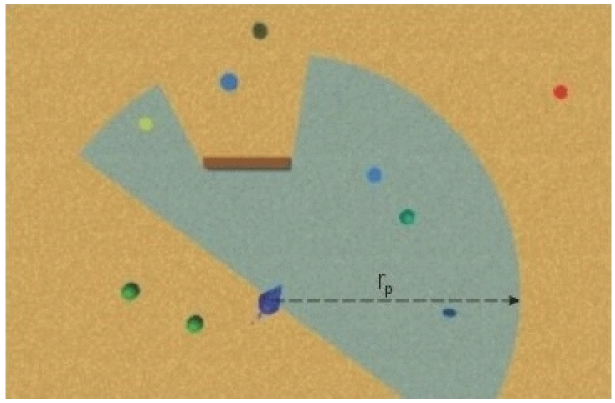

Figure 21. Perceived scenario of an animat.

Expression (20) simulates a short-medium term memory. The “remembered” stimuli conform the animat’s “remembered scenario”. All the stimuli found in the perceived and remembered scenarios are registered in BeCA by the *exteroceptors*.

5.3.2. The internal medium

The internal medium is defined by a set of variables which can take values between zero and one, representing strength, lucidity, safety, fatigue, thirst, and hunger. The size of the angular steps of the animat is proportional to his strength, while his radius of perception is proportional to his lucidity. The safety value does not change in time; but fatigue, thirst and hunger are increased in time (or decreased if a proper consummatory behaviour is executed). When these last three internal needs are high, strength and lucidity are decreased, and when they are low, strength and lucidity are increased. When strength is equal to zero, the animat dies. A prey animat might also be killed by a predator, which feeds himself decreasing the prey’s strength value. When this reaches zero, predators cannot longer feed themselves from the hunted prey.

The internal medium of the animats is perceived by the *interoceptors* of BeCA.

5.3.3. The motor system

The animat’s movement is commanded by angular steps α and β, with a centre in the extremes of the diameter of the projection of the sphere of the animat in the plane (z, x), as shown in Figure 22.

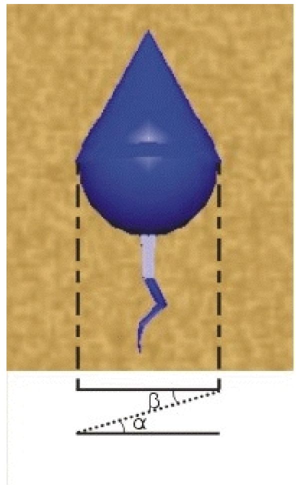

Figure 22. Angular
steps of an animat.

When the angular steps α and β are equal, the animat follows a straight trajectory.

The motor system receives signals from BeCA through the *actuators*, and can execute the next behaviours: wander, explore, approach (to different stimuli), eat, drink, rest, runaway (from different stimuli), and the reflex behaviour avoid obstacle.

5.3.4. The behaviours repertoire

Each animat has a behaviours repertoire. This is the set of behaviours that BeCA is able to select depending on the internal state and on the perceptions. **Table 2** shows the external and internal signals required by each behaviour.

Behaviour	External Signal	Internal Signal	Type of behaviour
Wander	None	none	default
Explore	None	thirst and/or hunger and/or fatigue	default oriented to the search of a specific signal
Avoid obstacle	Obstacle at range, *Prey at range*, Predator at range	none	reflex
Runaway	*Predator perceived*, Blob perceived	safety	motivated
Approach food	*Food perceived*, Prey perceived	hunger	motivated, appettitive
Eat	*Food at range*, Prey at range	hunger	motivated, consummatory
Approach water	Water perceived	thirst	motivated, appettitive
Drink	Water at range	thirst	motivated, consummatory
Approach grass	Grass perceived	fatigue	motivated, appettitive
Rest	Grass at range	fatigue	motivated, consummatory
Approach food and water	*Food and water perceived*, Prey and water perceived	hunger and thirst	motivated, appettitive

Table 2. Behaviours repertoire of the animats. *Italics* are for preys, underlined are for predators, and normal are for both.

We can see that wander is a default behaviour, and explore is a default behaviour oriented to the satisfaction of an internal need, and avoid obstacle is a reflex behaviour. Runaway, although it can be seen as a reactive behaviour, it competes with the rest of the behaviours at a motivational level. Reactive behaviours depend mostly on the external signal, but this is sometimes because the motivation is implicit. In this case, safety is a constant parameter, adjusted by the user. The rest of the behaviours are motivated. Approach food, approach water, approach grass, and approach food and water are appetitive behaviours, while eat, drink, and rest are consummatory.

5.3.5. BeCA in the animats

We designed behavioural columns for the behaviours exposed in the previous sections in BeCA by simply setting the values of coupling strengths and connecting BeCA to the perceptual and motor systems and to the internal medium.

Figure 23 shows examples of possible signal trajectories through different blackboard levels in BeCA. The lines show the trajectories of some behavioural columns. Dotted lines indicate potential behavioural columns, that might be consolidated by associative learning (see Section 3.8.1.).

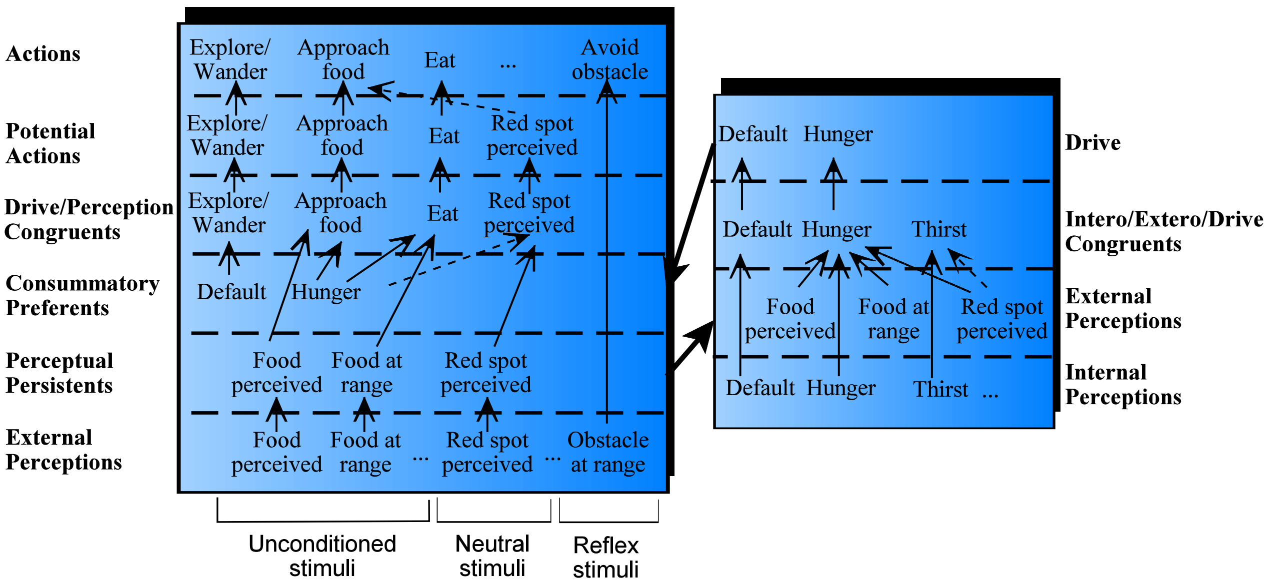

Figure 23. Signal trajectories in BeCA implemented as the BPS of an animat.

5.3.6. I&I in the animats

The imitation and induction (I&I) model presented in Section 4.1 is used by the animats to communicate and socialize by imitating and inducing their behaviours.

For example, if animat Paco is hungry, and he is perceiving no food sources, but he is perceiving animat Pepe executing the behaviour "approach food", he will imitate him by approaching to Pepe. Once he perceives the food source Pepe was approaching to, he will approach to it. Induction occurs in a similar way.

5.4. The Interface

The interface of the BVL allows to perform a wide variety of simulations and experiments. It consists of one window containing the general controls of the BVL and one window for each animat created in the BVL, as the ones shown in Figure 24 and Figure 25.

The general controls window allow the user to save, load, and reset animats, environments, and simulations. Animats are saved with all their properties (internal states, learning states, parameters, and attributes). Simulations handle animats and environments as one. This allows to save initial, partial, or final states of experiments easily. In this window, the user can add and remove external stimuli, randomly or with specific positions and magnitudes; pause and resume the simulation; adjust the refresh rate of the graphics (time steps / step painted); and set a delay for each simulation interval in milliseconds.

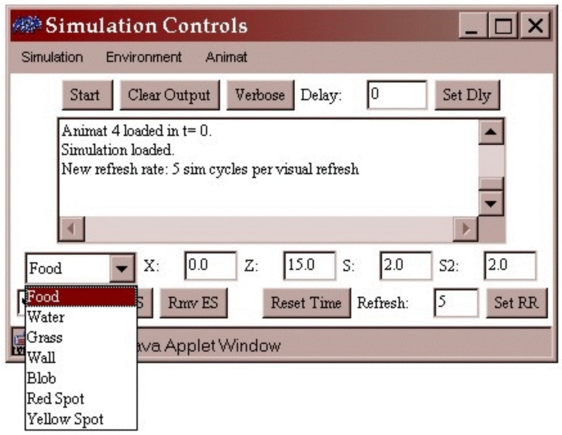

Figure 24. General controls window.

In the animat controls window, the user can set the name of the animat, its position and orientation, its radius of perception, and its type (predator or prey). The animat also can be set as immortal (not immoral!). The internal states of the animat are adjusted and shown in the same display, which is a set of scrollbars. The animat can leave a trail, which colour can be also selected to: a specific colour, the animat's colour, or the RGB colour of the magnitudes of fatigue, thirst, and hunger mapped to red, blue, and green, respectively. This allows to visualize the dynamics of the animat's internal states. The parameters α, β, γ, δ, κ, λ, μ, ρ, τ, and ϕ of BeCA; א and r_p of the perceptual system; and י, ל, ד, and ר of I&I; can be modified through this interface. **Table 3** shows the function of each parameter.

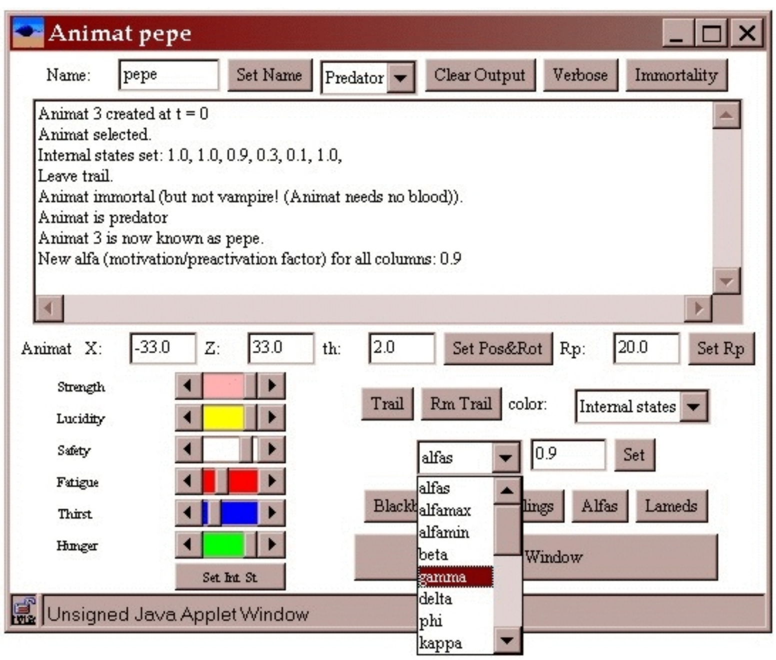

Figure 25. Animat controls window.

Parameter	Role	Defalut value	Equation
α	Motivation and preactivation factor. It is learned (Gershenson and González, 2000).	0.7	(7)
β	Learning factor.	0	(10)
γ	Reactivity factor.	0	(4)
δ	Alfa adjustment interval factor.	1000	(13,14)
κ	Perceptual persistence factor.	0.25	(3)
λ	Learning factor.	0.01	(10)
μ	Unlearning factor.	0.05	(10)
ρ	Speed of alfa adjustment factor.	0	(13,14)
τ	Motivational lesion factor.	1	(7)
ϕ	Reactivity/motivational lesion factor.	1	(4)
r_p	Radius of perception.	20	(19)
א	Forget rate.	0.1	(20)
י	Induction factor.	0.3	(16)
ל	Imitation factor.	0.5	(15,16)
ד	Lamed adjustment interval factor	1000	(17,18)
ר	Speed of lamed adjustment factor	0.05	(17,18)

Table 3. Parameters Modifiable in the BVL

Both controls have a display to inform of the states of the simulation, environment, or animat. The animat controls can display the actual state of the blackboard levels, of the coupling strengths involved in the learning processes, of the α's from the *intero/extero/drive congruence* internal behaviour, and of the ל's that regulate the imitation of behaviours.

5.5. About the BVL

All the presented properties of the BVL allow a wide variety of possibilities in order to produce interesting experiments and simulations.

As with real animals, the animats in the BVL often present non obvious behaviours. But, in difference with real animals, we can easily observe and change the internal states and mechanisms of the animats, providing understanding of their behaviours, and also about adaptive behaviour in animals. This is, not only it provides artificial adaptive behaviour, basing ourselves in ethology, but it gives ethology back a greater understanding of adaptive behaviour and its internal processes.

Our BVL at the present stage may be limited. But indeed it seems that you can never stop counting the small details of animal behaviour you can simulate. For our present purposes, all the properties of the BVL, enhanced by the ones of BeCA and the I&I model, seem to be a good start.

In the next chapter we will present some experiments carried out in our BVL, in order to show and test properties of BeCA, I&I, and our BVL itself.

6. Experiments

"To understand it you need not only to create it, but also to break it"
—José Negrete Martínez

"Яблокошки[23]". Nadia Bazlova and Carlos Gershenson, St. Petersburg, 2000. Gel on paper.

[23] Яблоко is apple, and кошки are cats.

In this chapter we will describe experiments carried out in our Behaviours Virtual Laboratory. In the first section, we will present experiments involving the emergent intelligence, opportunism, and lower cognition given by BeCA in the animats, while in the second section we will present experiments involving emergent social behaviours and structures in small animat societies. We encourage the readers to access our BVL through our web page http://132.248.11.4/~carlos/asia/bvl to execute the experiments presented here, and also to develop their own.

The goal of the experiments presented here is to show the properties and capabilities of BeCA, I&I, and our BVL.

In the first section, we will present experiments showing the simulation of reflex, reactive, and motivated behaviours. We will also show experiments involving primary and secondary classical conditionings, and the learning of the motivation degree. We will also present an experiment showing the non persistence of a consummatory behaviour in the presence of an aversive stimulus, and we will show experiments involving different motivation and reactive degrees through the adjustment of parameters in BeCA.

In the second section, we will first present simple experiments showing the imitation and induction of behaviours. Then we will expose the relevance of the environment in the sociality of the animats as they learn the imitation factors. Finally, we will present experiments concerning collective misbelief.

6.1. Intelligence in the BVL

"Intelligence is the art of getting away with it"
—Arturo Frappé

We will present here experiments related with the adaptive intelligence emerging from BeCA, which provides the control for the animats.

6.1.1. Modelling reflex behaviours

In this simple experiment, an animat is exploring following a straight trajectory. When an obstacle is perceived as too close, he reflexively avoids it. These behaviours can be appreciated in Figure 26. In animals, the behaviour "avoid obstacle" would be more reactive than reflex, but our animats have no planning, and this behaviour can then be seen as a reflex behaviour, because the signal to avoid the obstacle is inscribed on the External Perceptions level only when the obstacle is within a close range[24].

[24]See Section 3.5.

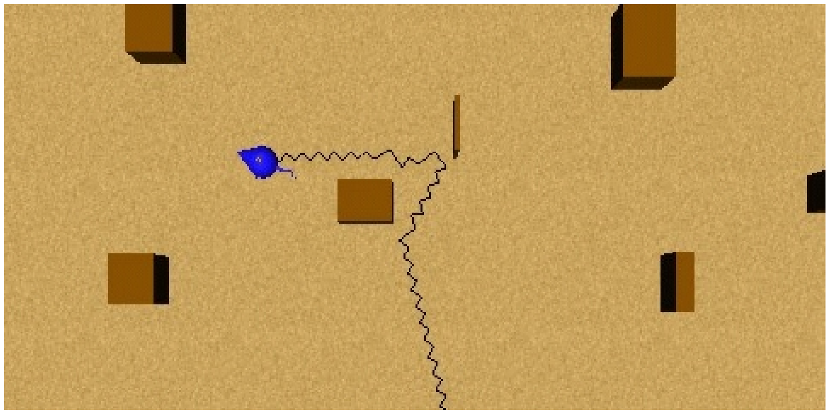

Figure 26. An animat avoiding obstacles reflexively.

6.1.2. Modelling reactive behaviours

In this experiment we have a wandering prey animat and a hungry predator, as shown in Figure 27. But when the prey animat perceives the predator, he reactively runs away, as seen in Figure 28. We can see that the presence of the predator was enough to trigger the runaway behaviour, but not as directly as with reflex behaviours. If there are other stimuli that may trigger reactive behaviours, BeCA will select the most imperative one, depending on the external signals, to be executed[25].

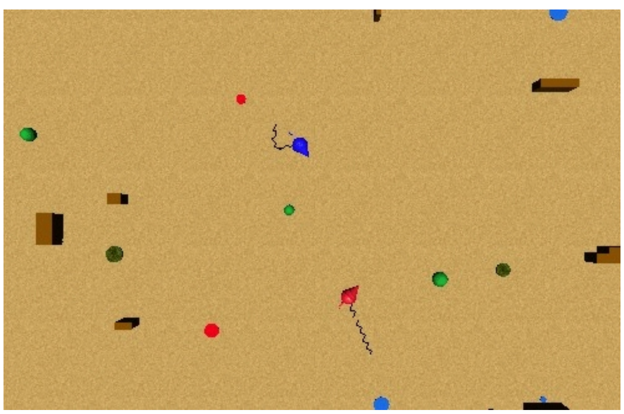

Figure 27. A wandering prey animat and an exploring hungry predator.

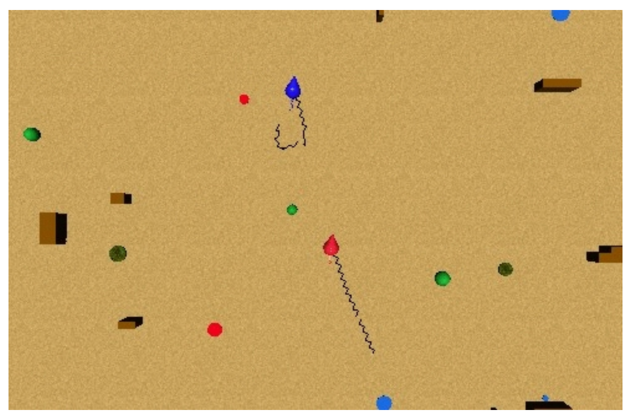

Figure 28. The prey animat runs away reactively after perceiving a predator.

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[25]See Section 3.6.

6.1.3. Modelling motivated behaviours

In this experiment we have an initial state as the one shown in Figure 29. We have an animat with some hunger and a lot of thirst. He is perceiving a food source. Since the thirst column wins the competition at the motivational level[26], he does not approach the food, but begins to explore. Once he perceives a water source, he approaches it and drinks until his thirst is satiated. After this, the hunger column wins the competition at a motivational level, so he approaches the food and eats until he satiates his hunger. After this, he wanders because he has no internal needs, nor are there any stimuli that trigger reactive or reflex behaviours. This behaviours patterns can be appreciated in Figure 30.

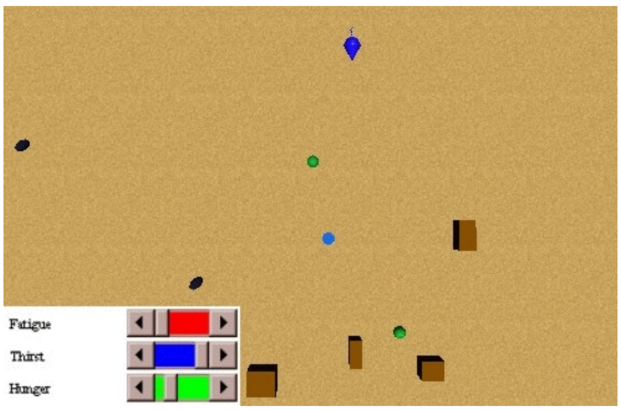

Figure 29. Initial state of the experiment.

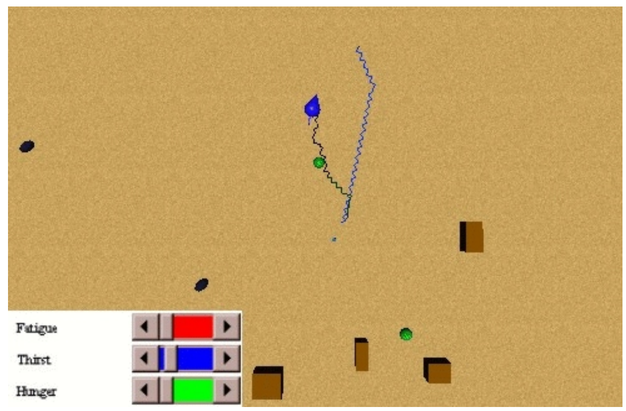

Figure 30. Animat after satiating his needs.

6.1.4. Primary and secondary classical conditionings

In this experiment we will test primary and secondary classical conditionings. In order to obtain the conditioning of a red spot with a food source, we make several presentations of the pair red spot - food source, when the animat is hungry. Figure 31 shows an initial stage of the conditioning: we can see that the coupling strengths related to the internal behaviours *external behaviours selector* (SCE4), *intero/extero/drive congruence* (CPED2), and *attention to preferences* (AP3), have still small values. Figure 32 shows an advanced stage of the conditioning, where the coupling strengths have higher values. The speed of the conditioning can be modulated in the BVL with the parameter λ of expression (10)[27].

[26]See Section 3.7.

[27]See Section 3.8.1.

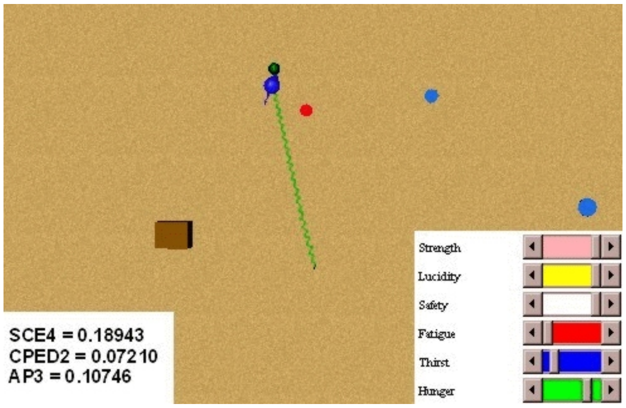

Figure 31. Initial stage of the primary conditioning

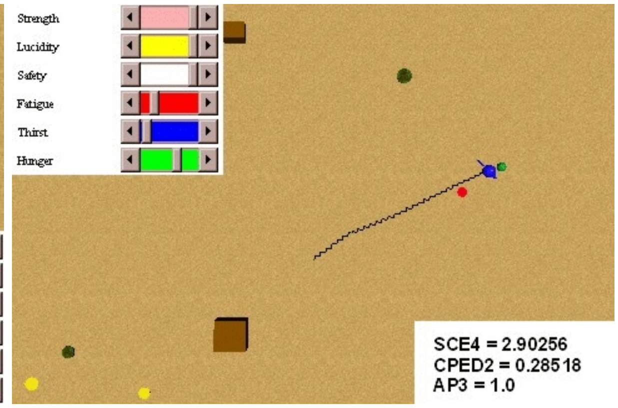

Figure 32. Advanced stage of the primary conditioning.

In Figure 33 we can see a behaviours pattern executed once the conditioning of the red spot with the food source was achieved. When the hungry animat perceived the red spot, he approached it, because the red spot was able to activate the same signal on the Actions level that a perceived food would have produced. That is to say, the modification of the coupling strengths allowed the red spot to complete a behavioural column, associated with the appetitive behaviour "approach food". Once the animat perceived a food source, he approached it, and satiated his hunger.

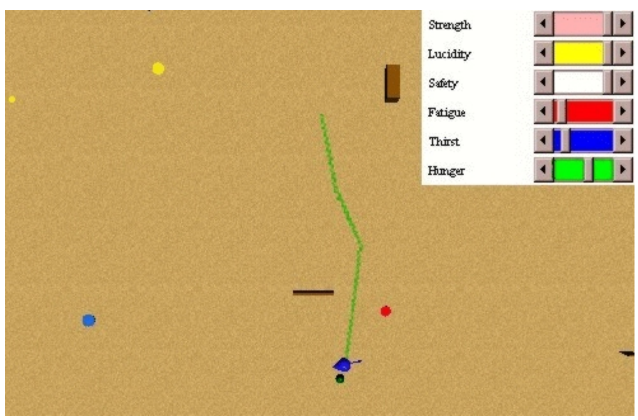

Figure 33. Behaviours pattern once achieved the conditioning.

Once the red spot is conditioned with the food source, we can use the red spot as a conditioner of another neutral stimulus. In this case, yellow spots. In Figure 34 we can see an initial stage of the secondary conditioning[28]. The values of the coupling strengths before the comma are the ones of red spots, while the others are the ones related with yellow spots. Before perceiving a red spot, the hungry animat perceives a yellow spot. If we repeat this situation, the

[28]See also Section 3.8.1.

coupling strengths will be reinforced, forming a behavioural column also for the yellow spot signal. In Figure 35 we can appreciate a behaviours pattern once the secondary conditioning was achieved. If the conditioned hungry animat perceives a yellow spot, he will approach to it, and once he perceives a food source, he will approach to this one, and thus satiate his hunger.

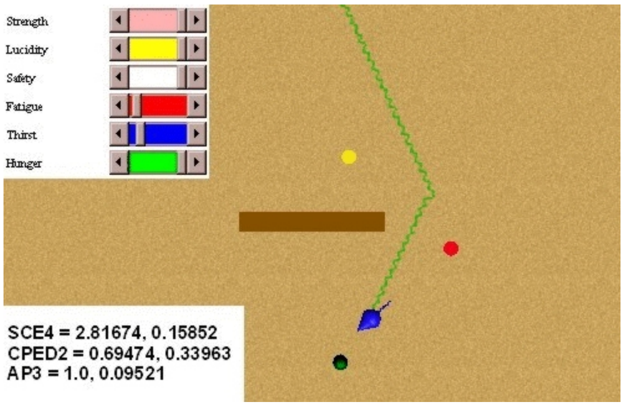

Figure 34. Initial stage of the secondary conditioning.

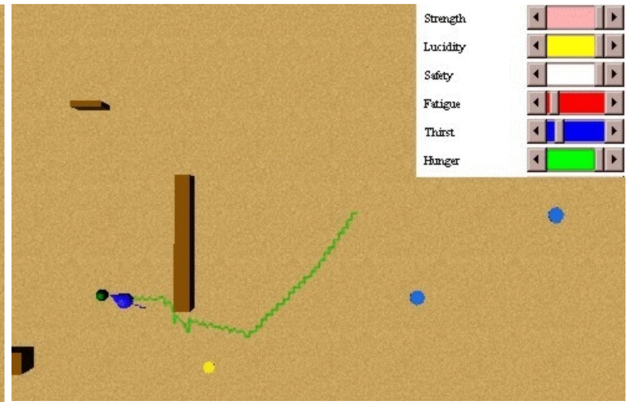

Figure 35. Behaviours pattern once the secondary conditioning was achieved.

6.1.5. Learning the motivation degree

For this experiment we considered an initial state as the one shown in Figure 36. We have two animats in separated environments: one with abundant sources of food, and the other one with none. Other stimuli are created in both environments. Both animats are initialized with the same parameters: a very high level of hunger, and no other internal need, with an initial value of α for the hunger column of 0.7. α_{max} has a value of 1.0, α_{min} of 0.0, δ of 1000, and ρ of 0.0005.

Figure 37 shows what occurred after 1000 simulation cycles. The animat in the scarce environment explored, searching for food, but finding none. This remembered scenario led to the incremental adjustment of his respective α_i until it reached α_{max}. On the other hand, the abundant environment allowed the animat in it to satisfy his hunger quickly. Once his hunger was satiated, the animat wandered, while his respective α_i decreased[29].

[29]See Section 3.8.2.

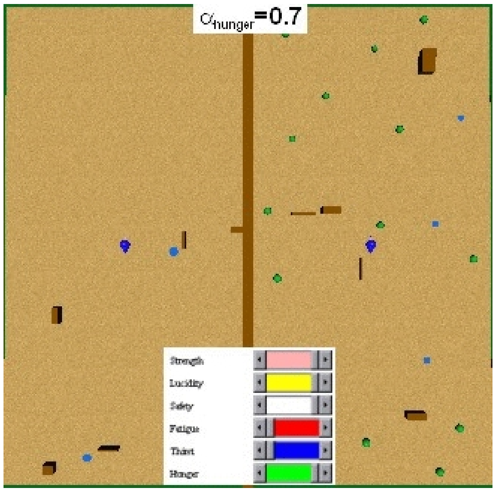

Figure 36. Initial state of the experiment.

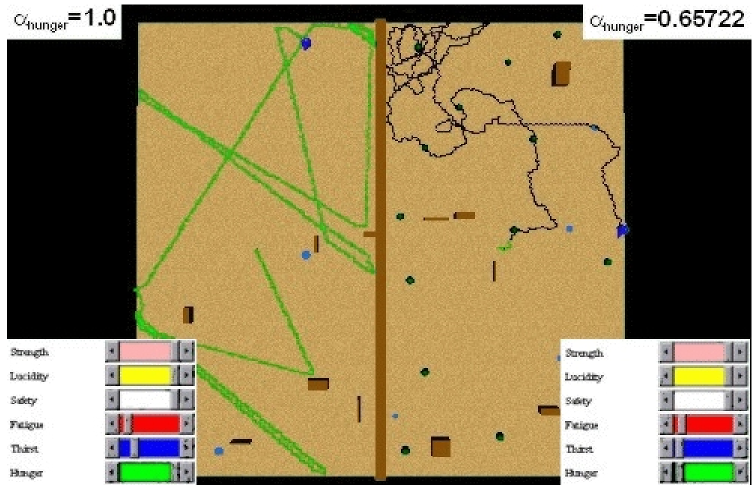

Figure 37. Behaviour patterns executed by the animats in their respective environments.

We now can set two animats with the same degree of hunger, but with different α_i values. The animat with a high α_i, since he learned that food is scarce and will be difficult to find, will begin to explore. Meanwhile, the animat with a low α_i will wander, because he learned that he will find abundant food with little effort, and thus allows himself to wander, and will not explore until his hunger level is higher. An example of these behaviours can be seen in Figure 38.

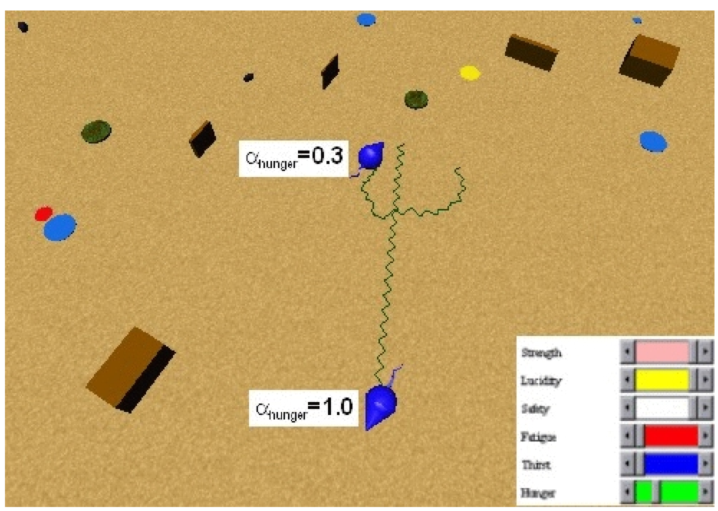

Figure 38. Behaviour patterns for animats with the same degree of hunger, but with different values of α_i for hunger.

6.1.6. Non persistence of a consummatory action in the presence of an aversive stimulus

In this experiment we will test the non persistence of a consummatory action (eat) of a prey animat in the presence of a predator. We have an initial state as the one shown in Figure 39: a hungry prey animat, perceiving a food source, but not perceiving a thirsty predator that is nearby. The prey animat perceives the predator while he is eating, and runs away before he satiates his hunger completely, as seen in Figure 40.

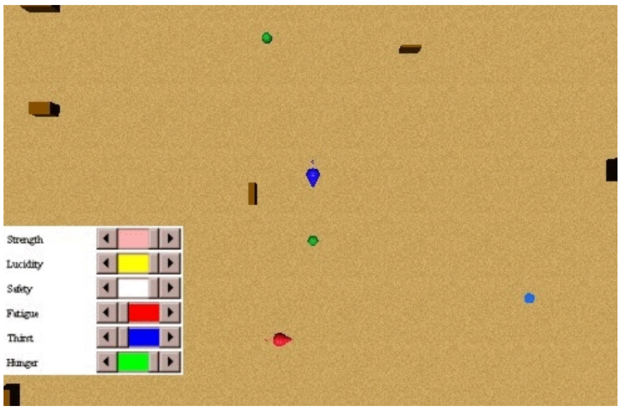

Figure 39. Initial state of the experiment.

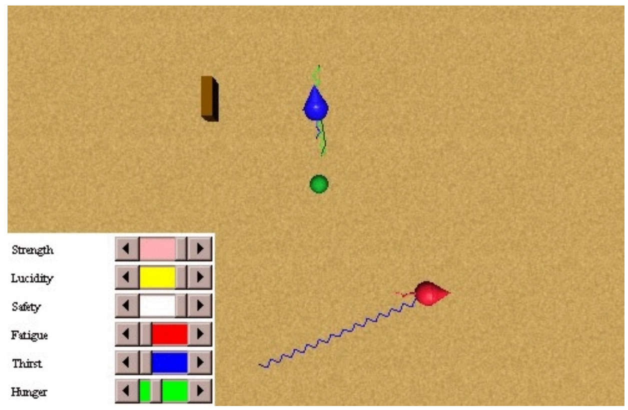

Figure 40. The prey animat runs away before satiating his hunger.

Afterwards, the prey animat perceived another food source, which he was able to satiate his thirst with, as seen in Figure 41. We used a value of κ equal to 0.9. Otherwise, the persistence would have been enough to satiate the hunger of the prey animat. If the prey animat would eat slower, with a usual value of κ we would have obtained similar results.

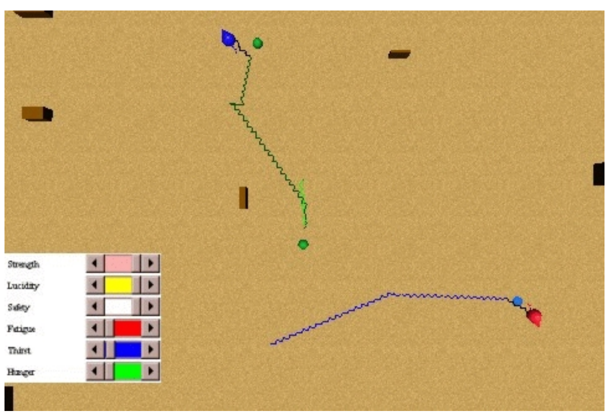

Figure 41. The prey animat was able to satiate his hunger with another food source.

6.1.7. Degrees of motivation and reactiveness

"We have to break things, but then we have to find out what to do with the pieces"
—Mafalda

In these experiments, we modified the values of the parameters α, γ, and ϕ of BeCA; in order to observe how motivated or reactive is the behaviour of an animat depending on these parameters. Some of the adjustments of these parameters can be seen as lesions in different mechanisms of BeCA.

We used for all experiments an initial environmental state as the one shown in Figure 42. The animat has little fatigue, much thirst, and some hunger. There are food sources near him, but the water sources are distant and the animat cannot perceive them at this stage. The BVL's interface allows the easy loading of this initial state for each experiment.

First, we took values of $\alpha=0.8$, $\gamma=0.0$, and $\phi=1.0$. These are the default values used in the BVL. The behaviours executed by the animat can be appreciated in Figure 43. Since the predominant need was thirst, the animat began to explore in the search of water, in spite of perceiving food sources. When he perceived a water source, he approached it, and drank until his thirst was satiated. After this, he approached a food source, and satiated his hunger by eating. These behaviours were motivated by the internal states of the animat.

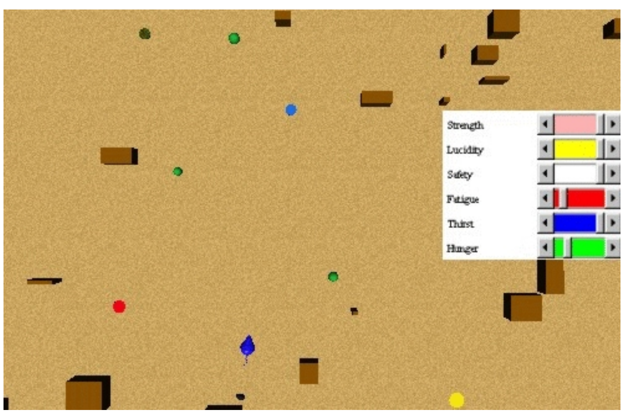

Figure 42. Initial state of the experiments.

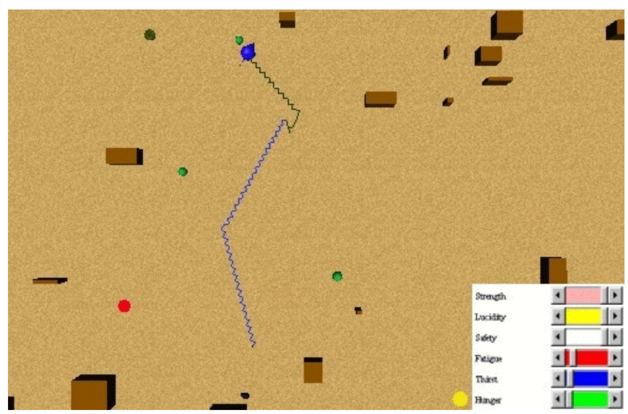
Figure 43. Behaviours executed with α=0.8, γ=0.0, and ϕ=1.0.

For the next experiment, we took values of $\alpha=0.0$, $\gamma=0.0$, and $\phi=1.0$. Since the internal and external signals are being combined multiplicatively (as it can be seen in expression (7)), the animat will need to perceive the water before the respective behavioural column may win the competition in the motivational node. So, since the animat was perceiving food and was hungry, he approached it and ate until his hunger was satiated. After this, he wandered until he finally perceived the water source, approached it, and satisfied his thirst by drinking it; as shown in Figure 44. These behaviours are less motivated, since the animat cannot execute the explore behaviour, and any internal need can fire its behaviour only if a corresponding external stimulus is perceived. This also affects the animat's survival performance, because he will need more time to find a stimulus to satiate a need than for higher values of α (González *et. al.*, 2000).

For the following experiment, we used values of α=0.8, γ=0.0, and ϕ=0.0. Since ϕ=0 causes that no signal from the motivational node reaches the cognitive node, the animat has no awareness of his internal needs. Because of this, he will wander independently of his perceptions or motivations, unable to perform motivated behaviours; as shown in Figure 45, until his death.

For values of α=0.0, γ=0.0, and ϕ=0.0 we had similar results. If there is no flow of signals from the motivational node, the value of α will not affect the external behaviour of the animat.

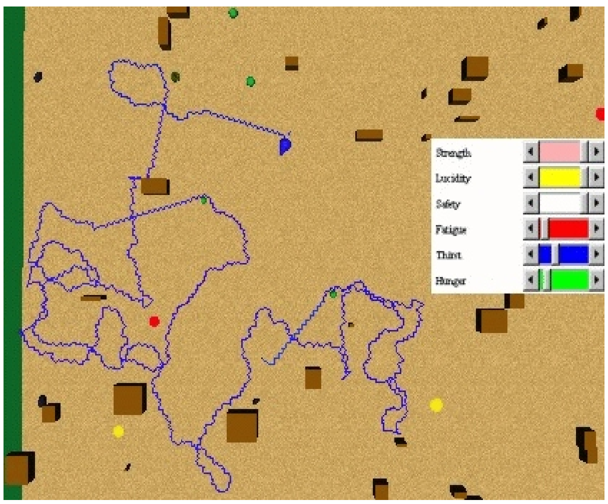

Figure 44. Behaviours executed with α=0.0, γ=0.0, and ϕ=1.0.

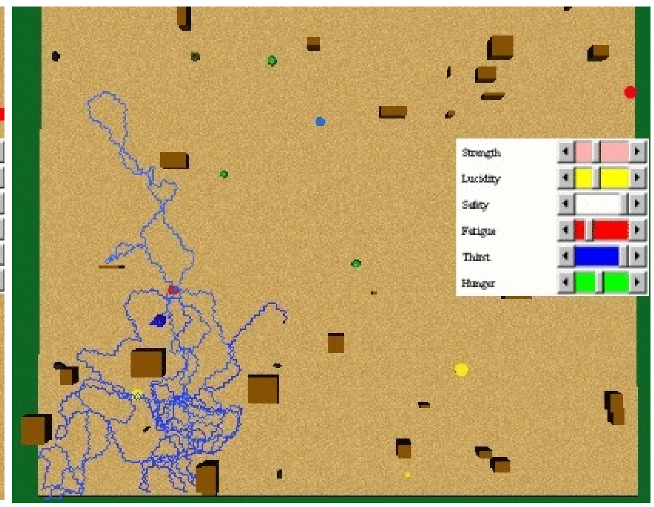

Figure 45. Behaviours executed with α=0.8, γ=0.0, and ϕ=0.0.

Next, we used values of α=0.8, γ=0.1, and ϕ=1.0. γ greater than zero in expression (4) allows a behaviour to be reactively executed, even in the absence of an internal need. Figure 46 shows the behaviours that the animat executed: First, he perceived food, approached it, and ate it completely, even when he had no more hunger. Then, he began to explore, until he perceived the water source, approached it, and drank it completely. Since he perceived a food source, he approached it in order to eat it reactively.

With values of α=0.0, γ=0.1, and ϕ=1.0 we had the same results.

Figure 47 shows the last experiment, where we first took values of α=0.8, γ=0.1, and ϕ=0.0. In this case, the animat has no awareness of his internal state, but his behaviour is reactive since γ is greater than zero. He is able to reactively satiate his hunger and thirst, but because the external signals were at hand. Otherwise, he would have wandered independently of his internal needs. In this situation, the animat would only survive if he finds by chance external stimuli for the needs he has in a precise moment. If he does not run into an appropriate external stimulus, he would die unknowingly.

With values of α=0.0, γ=0.1, and ϕ=0.0 we had similar results.

We can see that motivations are important for the survival of the animats. Although they could survive without them, being all the behaviours reactive, they have a higher probability to survive a scarce environment and adapt in it if their behaviours are motivated.

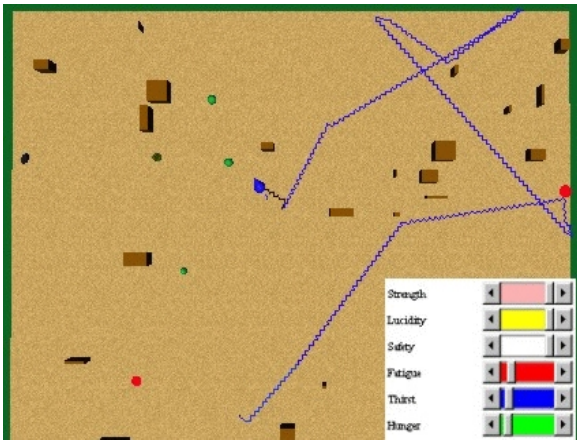

Figure 46. Behaviours executed with α=0.8, γ=0.1, and ϕ=1.0.

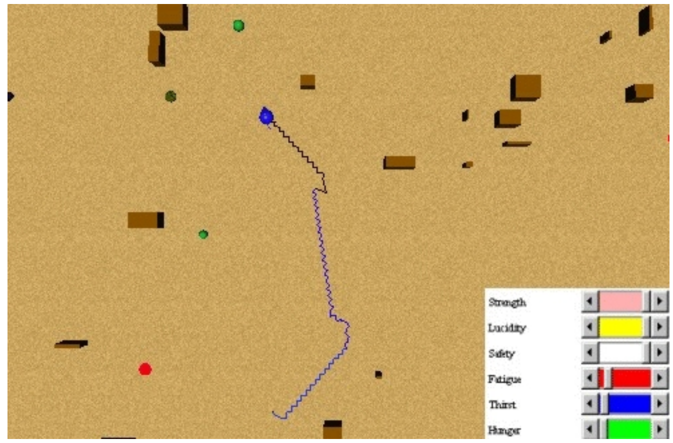

Figure 47. Behaviours executed with α=0.8, γ=0.1, and ϕ=0.0.

6.2. Social Emergence in the BVL

In this section we will present experiments involving small animat societies, and the complex social behaviour that emerges from their simple interactions, provided by our I&I model presented in Chapter 4.

6.2.1. Imitation of behaviour

In this experiment we will test the imitation of a behaviour provided by our I&I model. Figure 48 shows the initial state of the experiment: a thirsty animat perceiving a water source, and a second thirsty animat perceiving the first, but without perceiving the water source. The first animat approaches the water source obeying his thirst. When the second animat perceives the first one approaching water, he imitates his behaviour because he is also thirsty and approaches him (as if the first would represent a water source). Once he perceives the water source, he approaches towards it directly. He avoids the first animat, who while drinking water does not allow the second animat to approach enough to the water source to be able to drink. When the first animat finally moves and the water source is free, the second animat satiates his thirst. These behaviours are illustrated in Figure 49.

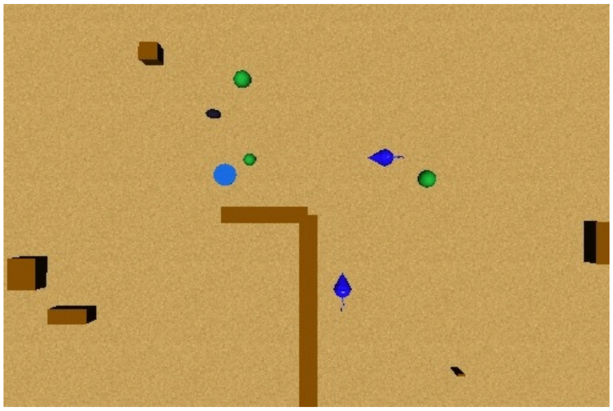

Figure 48. Initial state of the experiment.

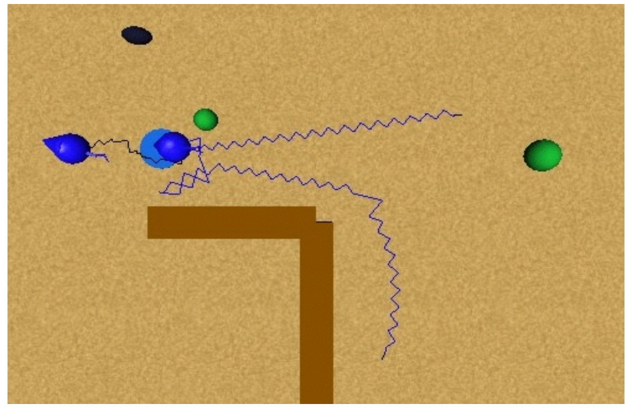

Figure 49. Behaviours after imitation.

The imitation of behaviours increases the adaptiveness of the animats, and also improves their chances of survival. For higher values of ל, the animats will be more social, and vice versa.

6.2.2. Induction of behaviour

In this experiment, we will test the induction of behaviour, provided by I&I. We have for the initial state a predator animat, and two prey animats, as seen in Figure 50. One prey is perceiving the second prey and the predator, while the second prey is not perceiving the predator nor the first prey. When te simulation begins, the first prey animat begins to run away, but also induces the second prey to run away. He imitates the induced behaviour because of his need for safety, and runs away from the predator, as shown in Figure 51.

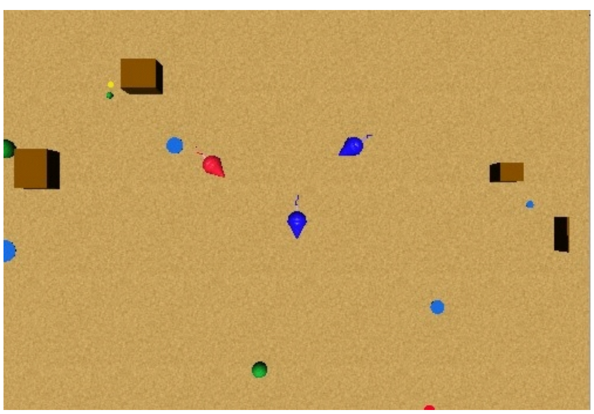

Figure 50. Initial state of the experiment.

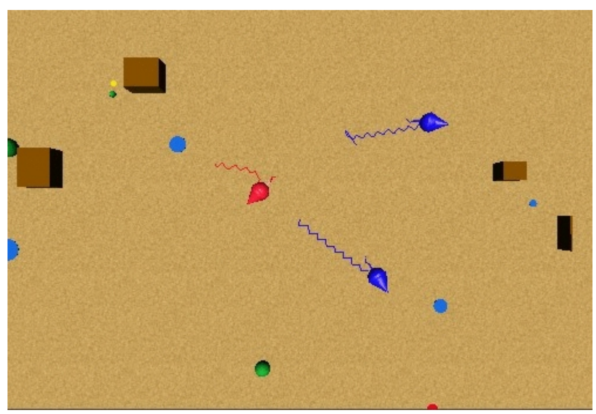

Figure 51. Prey animats running away from a predator.

The induction of behaviours also increases the adaptiveness in animats. Animats with a higher value of י will have a higher possibility to induce the rest of the animats. This may lead to the emergence of social hierarchical structures.

6.2.3. Learning of the imitation parameters

"Sometimes our intentions are not responsible for our possibilities"
—Nadia Bazlova

For these experiments, we created five prey animats with initial values of ל equal to 0.5, לmax equal to 0.8, לmin equal to 0.2, and י equal to 0.3.

First, we put the animats with some internal needs in a scarce environment, as seen in Figure 52. After more than ten thousand time cycles, half of the ל values for imitation were in the neighbourhood of לmax, and half in the neighbourhood of לmin. This was because, in a scarce environment, animats tend to have similar internal needs, and thus imitation of behaviours can be performed, and ל would be increased. We also made an experiment with the same initial state, only that one animat had a value of י equal to 1.0. This did not make much difference in the adjustment of the ל's, because other animats did not have a higher percentage of high values of ל for the animat with a high י than for others at the end of the experiment. The α_i values related with the internal needs that could not be satisfied were increased, increasing the motivation degree.

Next, we put the animats with no internal needs in an abundant environment, as shown in Figure 53. After more than ten thousand simulation cycles, all ל's were below their initial value, and most in the neighbourhood of לmin. This is because, in an abundant environment, animats are wandering most of the time (remember that the adjustment of ל's only takes place when the individual has internal motivations), and when one has internal needs enough to trigger an appetitive or consummatory behaviour, in most of the cases the animats he is perceiving are performing different actions, making all ל's to tend to לmin. For this case we also made an experiment putting an animat with a value of י equal to 1.0, but again this did not made a noticeable difference in the ל values. Because of the abundant environment, the α_i values related to the internal needs related to the abundant stimuli decreased, decreasing the motivation degree.

A high value of י does not make a big difference because the behaviours produced by BeCA were strongly motivated. For reactive behaviours, a high value of י makes a more noticeable difference.

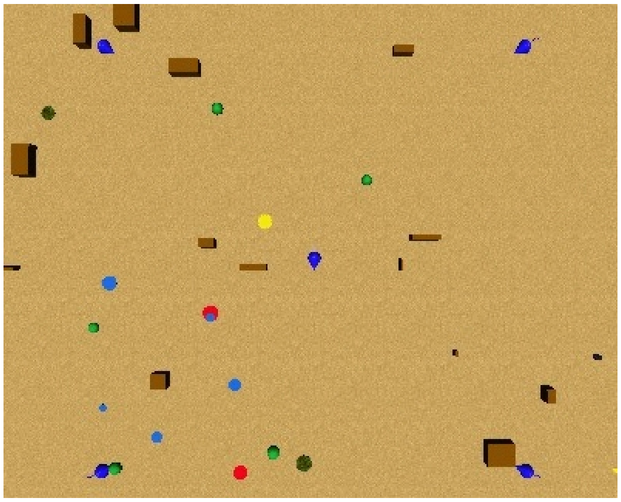

Figure 52. Animats in a scarce environment.

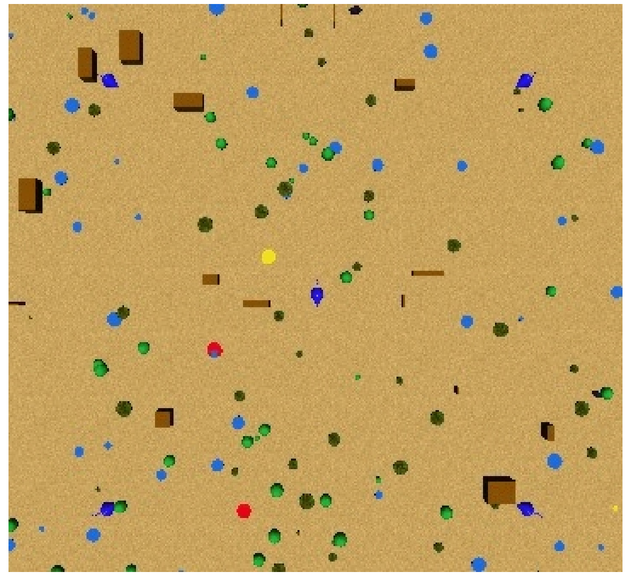

Figure 53. Animats in an abundant environment.

We could see by the previous experiments that a scarce environment makes the animats more social, while an abundant one makes them more selfish. Since the behaviour of the animats was motivated, this indicates that the environment shapes the society, more than its members do (if behaviours are motivated). This suggests sociology not to study only the individuals in order to study a society, but also their environment and context.

We also made experiments with an environment similar to the one shown in Figure 52, but with a non-homogeneous society of animats. We found that animats tend to be less social in such situations. Especially, reactive animats ($\gamma=0.1$) tended to be less social than animats with a degree of motivation (α) equal to zero, and these also tended to be less social than animats with a high degree of motivation. Also, animats with a higher radius of perception (r_p) tended to be less social than ones with a lower one. The perceptual persistence (κ, $\aleph$) seemed not to play an important role in the learning of the imitation parameters. Without taking into account sociality, animats with a higher degree of motivation (animats predisposed to be more social) have higher probability of survival , but animats with a higher radius of perception (animats predisposed to be less social) also have a higher probability of survival. This suggests that societies can tend to be more or less social (after some generations) depending on parameters that at first sight are not related with sociality. Of course, the environment also plays a very important role in the shaping of the society.

We could see that the shaping of a society is indeed complex, because it depends on so many elements: the behaviour of the individuals, their interactions, and their environment. A group can be more or less social because of several parallel reasons. Artificial societies and virtual laboratories are necessary tools in the understanding of such complex processes.

6.2.4. Collective misbelief

"All ideas are valid in the context they were created"

In these experiments we will study collective misbelief[30]. An example of collective misbelief follows: Sven believes that Thorfin is going for wine, so he is going along with him; but Thorfin believes that Sven is going for wine, so he is going along with him. In fact, no one has wine or money to buy wine, but they have misbeliefs that are reinforced mutually. So, we can say that collective misbelief is given when a group of individuals believes that the rest of the group is knowing what they are doing, and vice versa, when actually no one knows what to do. Quoting Immanuel Kant, "one milks the male and the other one holds the bucket".

In order to simulate this, we thought of a configuration as the one shown in Figure 54: we have four hungry predator animats in a closed space with only one exit, each one perceiving another, and the last perceiving the first. Using clock coordinates, the first animat is at nine o'clock, the second at six o'clock, the third at three o'clock, and the fourth at twelve o'clock. The first predator is perceiving a prey on the entrance of the corral where the predators are almost confined to. We used values of r_p equal to 30.0, $\aleph$ equal to 0.5, and י equal to 0.0 to avoid induction of behaviour (otherwise, the first animat would tell the fourth where the prey was, and the fourth the third, and so on).

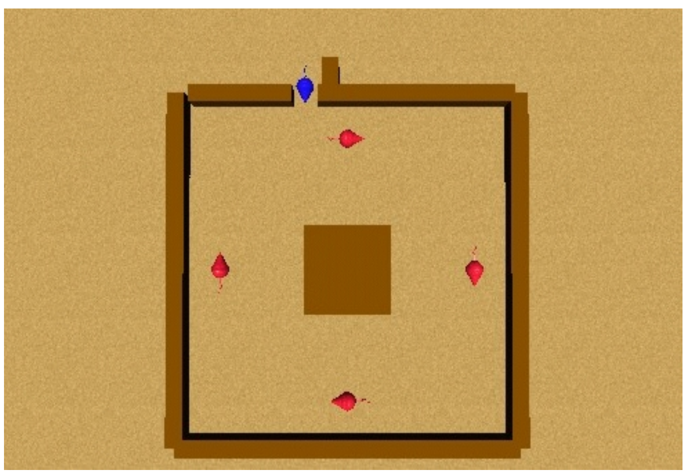

Figure 54. Four hungry predators in a corral, each one perceiving the next, and the first perceiving a prey.

When the simulation starts, the first predator perceives the prey, and he begins to approach him. Since the second animat is also hungry, and perceives the first one approaching a prey, he imitates his behaviour and approaches him. The same occurs with the third perceiving the second, and the fourth the third. But, soon after the prey leaves the sight of the first animat, he forgets where the prey was, because of his value of $\aleph$. So, since he is perceiving

[30] Doran (1998) presents an extensive discussion on collective misbelief in artificial societies.

the fourth and second animats approaching to a prey, he imitates their behaviour, and approaches the second animat. So, what occurred was that the first approached the second and vice versa, and the third approached the fourth and vice versa, as seen in Figure 55. When they collided, they avoided each other, so the misbelief was broken, and everyone began to explore, as shown by Figure 56.

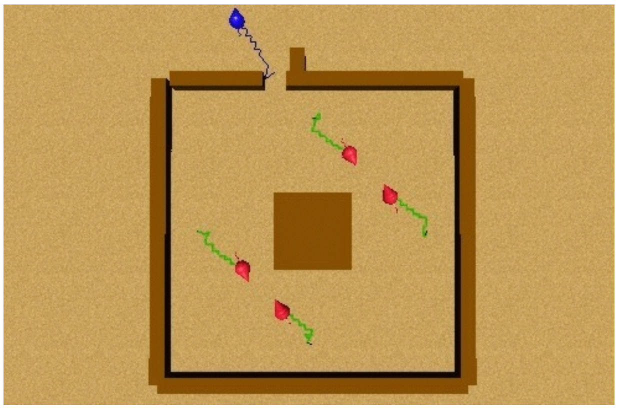

Figure 55. Collective misbelief begins.

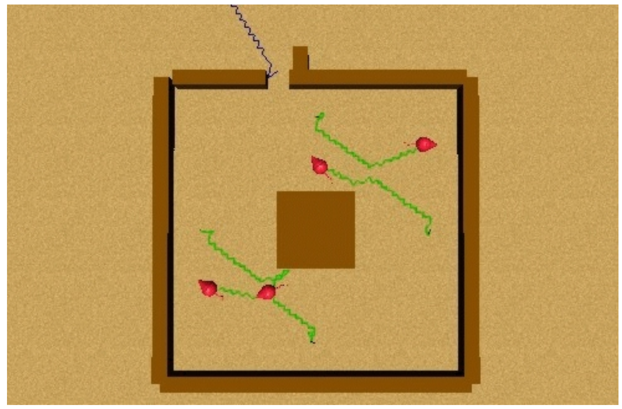

Figure 56. Collective misbelief was broken.

We thought about an experiment where the collective misbelief would not be broken, or at least not as easily as in the experiments just presented above, but none of our attempts were successful. Surprisingly, the situation was given by itself, when we were performing an experiment on the modification of the ל's in a scarce environment. This unexpected result (as others we have had, such as the emergence of a "nesting" behaviour) was possible because of the complexity of the BVL and its components: BeCA and I&I.

We observed the behaviours and internal variables of the animats, and concluded the following: At least one animat conditioned a red spot with grass. He had fatigue, so he approached a red spot, but without any grass nearby. Without sociality, there would be an extinction of the conditioning, but another animat with fatigue perceived the first one approaching grass (the red spot), and he approached him. The fact that both animats were perceiving each other approaching grass, made them, not only not to lose the conditioning, but even reinforce it. Another animat with fatigue could fall also in the misbelief. When they collided with each other, they moved away from the red spot, but since they remembered its location, they returned again and again. So, they were moving around the red spot, with the imitation and induction of the other animats keeping them in the area, as seen in Figure 57. We then put two more animats with fatigue in the vicinity, and they easily fell in the misbelief, as seen in Figure 58.

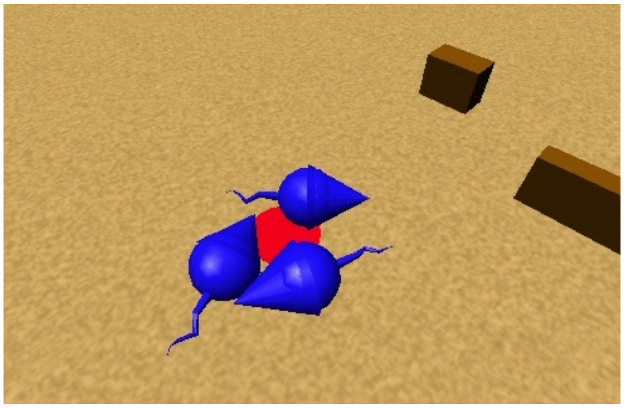

Figure 57. Three animats in collective misbelief.

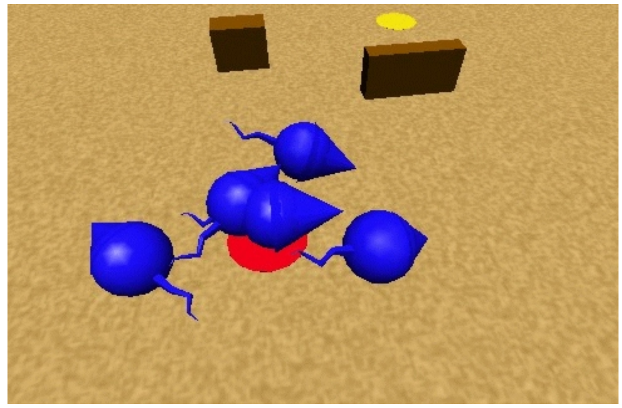

Figure 58. Five animats in collective misbelief.

Believing emerges from the imitation of behaviour (*i.e.* we can perceive beliefs in the behaviours of the animats, but there is no "belief module" containing them). This is, if one animat imitates another, it is because he *believes* in the correct behaviour of the imitated animat. Of course, as we could just see, beliefs are not always correct. They **should not** be always correct, which is why they are beliefs.

6.3. About the Experiments

"There are reasons of the heart, which the heart does not know"
—Blaise Pascal

As we could see in the this chapter, animats in their virtual environment behave *as* animals in a natural environment. Of course the analogy is not total, but the main characteristics of adaptive animal behaviour were able to be reproduced in the BVL, because of BeCA and I&I.

We say that intelligence emerges in the animats because we, as external observers, can judge that their behaviour is intelligent because by adapting to their environment they are able to survive (not always, of course), but they take every *opportunity* to achieve it. This is for us intelligence. We say that the animats have emergent cognition, because for external observers, they **know** their environment, and what to do in it in order to survive.

We say that social phenomena and structures emerge in animat societies because we can perceive social behaviours, such as leadership (given by a high value of י), organization (when animats perform the same behaviour to obtain a common goal, such as herd hunting), desocialization (low values of ל), and misbelief. We can also see that the behaviour of an individual might lead or mislead the behaviour of his whole society. These emergent behaviours were not designed in I&I, but emerge from the properties of the environment and interactions of the animats.

The developed experiments tried to show and illustrate the capabilities of our BVL, the intelligence and emergent cognition in BeCA, and the emergence of social phenomena in I&I. Since we have obtained unexpected results in our experiments, showing emergent properties also present in natural systems, we believe that further experimentation (probably also carried out by motivated readers) would lead to the discovery of more emergent properties, and suggestions for refining our models.

Also, our present computing capabilities limit us to societies of less than ten individuals. Experiments with a higher number of animats would also bring interesting results and understandings.

Conclusions

"We can only see a short distance ahead, but we can see plenty there that needs to be done"
—Alan M. Turing

"Found souls playground". Carlos Gershenson, Mexico City, 1999-2000. Oil on canvas, 150 x 100 cm. González Pérez collection.

Through this work we could see, not only that science is understanding how animals behave, preparing the road to understanding cognition; but also that we are able to simulate this adaptive behaviour, building artificial systems with the same properties than the ones present in animal behaviour.

Intelligent behaviour depends on the observer, and also the emergent low-level cognition exhibited by our animats. The animats *act as if they would know* what they are doing. Do they *really* know what they are doing? Do we *really* know what we are doing? If they perform in the same way, the rest is just a matter of interpretation, not important for their actions. The animats behave the way they do, independently of the names we put to the mechanisms that produce their behaviours.

The significance of the Behavioural Columns Architecture lies in its ability to model and simulate adaptive behaviour in such a complete way. The number and quality of the properties presented in BeCA is the highest of all the BPSs and ASMs proposed to date. Also, since it was designed in a *bottom-up* fashion, more functionality can be added to it in order to improve its performance and capabilities. The fact that it is a context-free BPS, allows it to be implemented in different environments, by designing only the perceptual and motor systems, which are dependent of the environment. Also, the production of behaviours emerging from the interactions among the elemental behaviours, each of which, by itself, is not important in the behaviours production, is noticeable.

Our Imitation and Induction model for social action shows that complex social behaviour might be described, and therefore, undestrood, with very simple rules. That the complexity of the behaviour of the system is determined not only by the complexities of the individuals, but also by the amount of individuals in the system, and the number of their interactions.

Our Behaviours Virtual Laboratory is quite a useful tool. It allowed us to test and validate BeCA and I&I, and now it is available for the community for understanding adaptive and social behaviour, or even just for playing with it. Also, since the source code has been made public for the community, programmers can adapt it and expand it. Students can learn properties of adaptive behaviour, behaviour-based systems, artificial societies, complex systems, object-oriented programming, and virtual reality with our BVL.

The experiments presented allowed us to exhibit the properties of BeCA and the I&I model using our BVL, showing the capabilities of the BVL at the same time.

We are able to create artificial adaptive autonomous agents. This paves the road for creating fully rational and conscious agents.

Understanding Societies

We believe that social structures of different animal species and different human cultures were evolved following certain rules of the interactions among the individuals with themselves and their environment. These rules would be certainly more complex than the only two in I&I, but we believe that they are similar, and understandable at a short-medium term following a similar approach as the one presented in this work.

With this, we could understand why some animals gather in herds, some are monogamous, others polygamous, societies where only the female raises the siblings (*e.g.* polar bears), or where they are raised by both male and female (*e.g.* penguins).

In a similar way, artificial societies and complex systems could help us understand the family structure, the role of the men and women, why some human cultures are monogamous or polygamous, etc.; issues which have a very important role in the development of human cultures and societies and their individuals.

Artificial societies, as the one presented here, have been very important for social sciences. This is because natural societies are very hard to control due to their high complexity, and thus, theories were contrasted with unprecise observations, and sometimes were judged as being mere speculations. Since in a virtual laboratory, one can adjust every parameter, repeat experiments easily, and control the environment and each situation, theories can be contrasted synthetically (Steels, 1995; Verschure, 1998; Castelfranchi, 1998) in order to be validated. Of course, natural societies are not less important, since artificial societies are inspired in them, and created among other things for understanding natural societies.

Future Work: The Path to Cognition

"Nature likes to hide itself"
—Heraclitus

We are interested in the research of the evolution of cognition. In a similar way that with animal adaptive behaviour, we plan to build artificial systems basing ourselves in ethology, neurophysiology, sociology, philosophy, psychology, and linguistics, not only to understand better cognition, but to build systems with cognitive capabilities in open environments.

The work presented in this thesis is very important for our future plans, because we argue that we need to model and understand first adaptive behaviour in order to attempt to understand cognition and its evolution.

Adaptive behaviour is a *behavioural basis of cognition*, in the sense that animals evolutionally developed cognition as an extension to adaptive behaviour.

We humans are not that far from other animals (Clark, 1997; Pepperberg, 1991). We are understanding animal behaviour. We are not that far from real artificial intelligence. But the step between adaptive behaviour and cognition is not small. If our brains are not that different from higher animals, our **tools** are. By tools I mean culture, language, and society. Our brains are not that evolved compared to other animals. We make the world around us smart (Clark, 1997). The structure of our culture, the ability to store information outside us using languages, and the way we interact with each other. We need to address these issues if we want higher cognition to emerge in artificial systems.

Future Culture: Artificial Cognition

"The only impossible thing is something to be impossible"

Biologically, we are not that different from men of six thousand years ago. Why we are so intelligent compared to them? Because of the accumulation of knowledge, provided by language and culture. Education provides the transmission of this knowledge to new generations. If we would isolate a small group of newborns in a closed society, they would not be that different from other primates. If we build a system **capable** of simulating human cognition, at the beginning the system would not be smarter than a neanderthal. In the same way we educate our children and transmit them our culture, we would need to educate such a system in order to be high-cognitive. This means that "intelligent machines" would need to depart from our culture. Once they would grasp their own culture based on ours, where would their culture go? Wherever we would direct them to lead it. And it seems it would be hard to make a distinction between *their* culture and *our* culture.

Beliefs and Misbeliefs

We believe that reason is based on beliefs. That beliefs are the axioms of reason. Thus, reason cannot be proven[31]... just believed[32]. We could say that most of our beliefs are learned by imitation. This implies that, since we cannot be sure of our beliefs, some of them could be collective misbeliefs.

With our experiments, we could see that some misbeliefs were broken by experience. But some did not. It seems that the more experience, the less misbeliefs we will have. But will all our experiences break all our misbeliefs?

[31]This is based on Gödel's incompleteness theorem (See Section 0.2).

[32]More completely speaking; reason, beliefs, and experience, are based each one on the others. The exposition of our philosophical system still needs to be made in another work.

Philosophical Implications

"Once you know the rules of the game, you can change them"

How could we be able to understand ourselves, when we use ourselves to understand ourselves? Because we have mirrors. Other people can be these mirrors. Artificial systems can be also these mirrors. But now we can control Artificial Societies, and cannot other people that easily. And once we understand our reflections, we will understand ourselves[33].

At the same time we are understanding human behaviour, intelligence, and mind, we are being able to simulate it. Cognitive science is widening our horizons, questioning many philosophical concepts. If we comprehend how, biologically and/or artificially, we are able to reason, know, imagine, believe; it will definitely shake philosophy from its roots, as it is already beginning to.

As we, on one hand, understand and manipulate nature, and on the other hand, we are able to simulate it; what would be the difference between artificial and natural systems? Only the ones determined by our prejudices.

But once we are able to comprehend cognition, we will be able to simulate it, imitate it, change it, improve it, and create it.

[33]We can see part of ourselves without reflections. But we need them if we want to understand ourselves more completely.

Glossary

action selection mechanism. (ASM) A mechanism that computes which action should be executed by a behaviour-based system in dependence of the internal state and the external perceptions. (See Section 3.1.)

adaptation. The act or process of adapting or fitting.

agent. An actor. We define an agent as a system which has goals to fulfill.

animat. Artificial animal. Simulated animal or autonomous robot (Wilson, 1985).

appetitive behaviour. An appetitive behaviour is one that leads indirectly to the satisfaction of a motivation (*e.g.* approach food in order to satiate your hunger).

autonomy. The ability of self control.

behaviour. The action or reaction of something (as a machine or substance) under specified circumstances.

behaviour-based system. (BBS) An ethologically inspired system which provides the control to an artificial creature.

behavioural basis of cognition. We believe that cognition has a basis in adaptive behaviour. In order to understand and reproduce cognition, we need to understand and reproduce adaptive behaviour first. (See Introduction and Conclusions.)

behaviours production system. (BPS) A system that produces behaviour in order to control an autonomous agent. This production in most cases will be emergent. (See Section 3.2.)

belief. Acceptance of a fact, opinion, or proposition.

cognition. Knowledge. Understanding. Faculty of understanding things, compare them, make judgements, and deductions.

collective misbelief. Mistaken belief, caused and reinforced by the reciprocal beliefs on the actions of others. (See Section 6.2.4.)

competition. Contest, strife.

complex system. A complex system is composed of several elements interacting among them. The complexity of a system depends on the number of elements that conform it, the number of interactions among the elements, and the complexities of the elements and the interactions. (See Section 2.1.)

conscious behaviour. Behaviour executed while being aware of it. (See Introduction.)

consummatory behaviour. A consummatory behaviour is one that leads directly to the satisfaction of a motivation (*e.g.* eat in order to satiate your hunger).

emergent property. Emergent properties arise from the interactions of the components of a system, but are not present in the components themselves.

ethology. Branch of biology that studies animal behaviour.

goal. Final purpose or aim. The end of an action.

induction. The act of introducing or bringing in.

intelligence. We need a being to perform an action in order to judge his/her/its intelligence. Intelligent actions are the ones people judge to be intelligent. (See Section 1.1.1.)

imitation. The following or copying of a pattern, model or example.

motivation. The reason for the action.

motivated behaviour. A motivated behaviour requires an internal need (motivation) in order to be executed. (See Introduction and Section 3.7.)

opportunism. The art or practice of taking advantage of opportunities or circumstances.

plasticity. Adaptation ability of neural circuits by connection or disconnection of parts of the circuit. Ability of learning in neural circuits.

reactive behaviour. A behaviour that shows a strong dependence of an external stimulus. (See Introduction and Section 3.6.)

reasoned behaviour. Behaviour that is selected using of concepts. (See Introduction.)

reflex behaviour. A fast action triggered by the perception of a particular stimulus. (See Introduction and Section 3.5.)

robustness. A system is considered robust if its functionality degrades "gracefully" when components of the system stop working.

situatedness. An agent is situated in his environment if he can perceive it and act upon it.

social action. A social action is an action that deals with another entity as his *similar* (Castelfranchi, 1998). (See Section 2.2.)

sociality. The condition of a group when its members interact among them **socially** (*i.e.* through **social actions**).

society. A group of individuals exhibiting intelligence interacting among them through social actions.

vegetative behaviour. Internal actions in charge of the survival of the organism (*e.g.* metabolism). (See Introduction.)

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References

Anderson, T. and Donath, M. (1990). Animal Behaviour as a Paradigm for Developing Robot Autonomy. *Robotics and Autonomous Systems* 6, pp. 145-168.

Baerends, G. (1976). The functional organization of behaviour. *Animal Behaviour*, 24, pp. 726-735.

Balkenius, C. and Morén, J. (1998). Computational Models of Classical Conditioning: A Comparative Study. *Proceedings of the Fifth International Conference on Simulation of Adaptive Behavior*. MIT Press

Bar-Yam, Y. (1997). *Dynamics of Complex Systems*. Addison-Wesley.

Beer, R. D. (1990). *Intelligence as Adaptive Behaviour: an Experiment in Computational Neuroethology*. Academic Press.

Beer, R. D., Chiel, H. and Sterling, L. (1990). A biological perspective on autonomous agent design. *Robotics and Autonomous Systems*, 6, pp. 169-186.

Beer, R. D., H. Chiel, K. Quinn, S. Espenschield, and P. Larsson (1992). A distributed neural network architecture for hexapod robot locomotion. *Neural Computation* 4 (3), pp. 356-365.

Beer, R. D. and H. Chiel (1993). Simulations of cockroach locomotion and escape. In Beer, R., *et. al.* (Eds.), *Biological Neural Networks in Invertebrate Neuroethology and Robotics*. Academic Press.

Booch, G. (1994). *Object-Oriented Analysis and Design with Applications*. Addison-Wesley, Reading, MA.

Breazeal, C. (1999). Imitation as Social Exchange between Humans and Robots. *Proceedings of the 1999 Symposium on Imitation in Animals and Artifacts (AISB99)*, pp. 96-104. Edinburgh, Scotland.

Brooks, R. A. (1986). A robust layered control system for a mobile robot. *IEEE Journal of Robotics and Automation*. RA-2, April, pp. 14-23.

Brooks, R. A. (1989). A robot that walks: Emergent behaviour from a carefully evolved network. *Neural Computation*, 1, pp. 253-262.

Brooks, R. A., (1990). Elephants Don't Play Chess, *Robotics and Autonomous Systems* Vol. 6, pp. 3-15.

Brooks, R. A. (1991). Intelligence without reason. *Proceedings of the 12th International Joint Conference on Artificial Intelligence*. Morgan Kauffman.

Brooks, R. A. (1993). A robot that walks: Emergent behaviors from a carefully evolved network. In Beer, R., *et. al.* (eds.), *Biological Neural Networks in Invertebrate Neuroethology and Robotics*. Academic Press.

Castelfranchi, C. (1997). Individual Social Action. In Holmstrom-Hintikka, G. and R. Tuomela (eds.), *Contemporary Theory of Action* Vol. II, Kluwer, Dordrecht, pp. 163-192.

Castelfranchi, C. (1998). Modelling social action for AI agents. *Artificial Intelligence* 103, pp. 157-182.

Clark, A. (1997). *Being There: Putting Brain, Body, and World Together Again*. MIT Press. Cambridge, Massachusetts.

Connell, J. (1989). A Colony Architecture for an Artificial Creature. Technical Report II 5 1, MIT AI Lab.

Conway, J. (1970). *The Game Of Life*.

Dennet, D. C. (1987). *The Intentional Stance*. MIT Press, Cambridge, MA.

Doran, J. (1998). Simulating Collective Misbelief. *Journal of Artificial Societies and Social Simulation* 1 (1).

Engelmore, R., Morgan, A.J. and Nii, H.P. (1988). Hearsay II. In R. Engelmore and T. Morgan (Eds.) *Blackboard Systems*. Addison-Wesley Publ. Co., London.

Epstein, J. M. and R. L. Axtell (1996). *Growing Artificial Societies: Social Science from the Bottom Up*. The Brookings Institution Press, Washington, D. C. & The MIT Press, Cambridge, Massachusetts.

Genesereth, M. R. and S. P. Ketchpel (1994). Software agents. *Communications of the ACM*, 37 (7), pp. 48-53.

Gershenson, C. (1997). El Juego de la Vida en Tres Dimensiones. *Memorias X Congreso Nacional Sobre Informática y Computación, ANIEI.* Monterrey, México.

Gershenson, C. (1998a) Lógica multidimensional: un modelo de lógica paraconsistente. *Memorias XI Congreso Nacional ANIEI,* pp. 132-141. Xalapa, México.

Gershenson, C. (1998b). Control de Tráfico con Agentes: CRASH. *Memorias XI Congreso Nacional Sobre Informática y Computación, ANIEI*, pp. 122-130. Xalapa, México.

Gershenson, C. (1999). Modelling Emotions with Multidimensional Logic. *Proceedings of the 18th International Conference of the North American Fuzzy Information Processing Society (NAFIPS '99)*, pp. 42-46. New York City, NY.

Gershenson, C., P. P. González, and J. Negrete (2000a). Action Selection Properties in a Software Simulated Agent. In Cairó, O. *et. al. MICAI 2000: Advances in Artificial Intelligence*, Lecture Notes in Artificial Intelligence 1793, pp. 634-648, Springer-Verlag.

Gershenson, C., P. P. González, and J. Negrete (2000b). Thinking Adaptive: Towards a Behaviours Virtual Laboratory. In Meyer, J. A. *et. al. SAB2000 Proceedings Supplement*. Paris, France. ISAB Press.

Gershenson, C. and P. P. González (2000). Dynamic Adjustment of the Motivation Degree in an Action Selection Mechanism. *Proceedings of the International Systems and Applications Conference, ISA 2000*. Wollongong, Australia.

Goetz, P. and D. Walters (1997). The dynamics of recurrent behaviour networks. *Adaptive Behaviour*, 6 (2), pp. 245-282.

Gode, D. and S. Sunder (1992). Allocative Efficiency of Markets with Zero Intelligence (ZI) Traders: Markets as a Partial Substitute for Individual Rationality. Working Paper No. 1992-16. Carnegie Mellon Graduate School of Industrial Administration.

Gödel, Kurt (1931). Über formal unentscheidbare Sätze der Principia Mathematica und verwandter Systeme, I. *Monatshefte für Mathematik und Physik*, vol. XXXVIII, pp. 173-198.

Goldspink, C. (2000). Modelling Social Systems as Complex: Towards a Social Simulation Meta-model. *Journal of Artificial Societies and Social Simulation* 3 (2).

González, P. P. (1995). Sistemas expertos facultativamente asociados en red cooperativa con arquitecturas de pizarrón: una aplicación en la consulta e interconsulta médica. *MSc Thesis*. Instituto de Investigaciones Biomédicas/UNAM, México.

González, P. P. (2000). Redes de Conductas Internas como Nodos-Pizarrón: Selección de Acciones y Aprendizaje en un Robot Reactivo. *PhD. Dissertation*, Instituto de Investigaciones Biomédicas/UNAM, México.

González, P. P. and J. Negrete (1997). REDSIEX: A cooperative network of expert systems with blackboard architectures. *Expert Systems*, 14 (4), pp. 180-189.

González, P. P., J. Negrete, A. J. Barreiro, and C. Gershenson (2000). A Model for Combination of External and Internal Stimuli in the Action Selection of an Autonomous Agent. In Cairó, O. *et. al. MICAI 2000: Advances in Artificial Intelligence*, Lecture Notes in Artificial Intelligence 1793, pp. 621-633, Springer-Verlag.

Hallam, B. E, J. Halperin and J. Hallam (1994). An Ethological Model for Implementation in Mobile Robots. *Adaptive Behaviour*, 3 (1), pp 51-79.
Hogg, L. M. and N. R. Jennings, (1997) Socially Rational Agents, in *Proc. AAAI Fall symposium on Socially Intelligent Agents*, Boston, Mass., November 8-10, pp. 61-63.
Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the National Academy of Sciences*, 79, pp. 2554-2558.
Jennings, N. R. (2000). On agent-based software engineering. *Artificial Intelligence* 117, pp. 277-296.
Jennings, N. R. and J. R. Campos (1997). Towards a social lever characterization of socially responsible agents. *IEE Proc. Software Engineering* 144 (1) pp. 11-25.
Kandel, E.R. (1976). *Cellular Basis of Behaviour*. W.H. Freeman, San Francisco.
Kandel, E.R. (1985). Cellular mechanisms of learning and the biological basis of individuality. In E.R. Kandel and J.H. Schwarts (Eds.), *Principles of Neural Science*. Elsevier, New York.
Kupfermann, I.J. (1974). Feeding Behavior in Aplysia: A simple system for the study of motivation. *Behavioural Biology* 10, pp. 1-26.
Lorenz, K. (1950). The comparative method in studying innate behaviour patterns. *Symposia of the Society for Experimental Biology*, 4, pp. 221-268.
Lorenz, K. (1981). *The Foundations of Ethology*. Simon and Schuster, New York.
Manning, A. (1979). *An Introduction to Animal Behavior*. Third edition. Addison-Wesley Publ. Co.
Maes, P. (1990a). Situated agents can have goals. *Journal of Robotics and Autonomous Systems*, 6 (1&2).
Maes, P. (1990b). A bottom-up mechanism for behaviour selection in an artificial creature. In J. A. Meyer and S.W. Wilson (ed.), *From Animals to Animats: Proceedings of the First International Conference on Simulation of Adaptive Behaviour*. MIT Press/Bradford Books.
Maes, P. (1991) (ed.). *Designing Autonomous Agents: Theory and Practice From Biology to Engineering and Back*, MIT Press.
Maes, P. (1993). Modelling Adaptive Autonomous Agents. *Journal of Artificial Life*, 1 (1-2), MIT Press.
McFarland, D. (1981). *The Oxford Companion to Animal Behavior*. Oxford University Press.
Meyer, J.A. and Guillot, A. (1990). Simulation of adaptive behavior in animats: Review and Prospect. *Proceedings of the First International Conference on Simulation of Adaptive Behavior*. MIT Press.
Minsky, M. (1985). *The Society of Mind*. Simon & Schuster. New York, NY.
Negrete, J. and M. Martínez (1996). Robotic Simulation in Ethology. *Proceedings of the IASTED International Conference: Robotics and Manufacturing*, Honolulu, Hawaii, USA, pp. 271-274.
Negrete, J. and P. P. González (1998). Net of multi-agent expert systems with emergent control. *Expert Systems with Applications*, 14 (1) pp. 109-116.
Nii, H. P. (1989). Blackboard Systems. In A. Barr, P. R. Cohen and E. A. Feigenbaum (Eds.) *The Handbook of Artificial Intelligence*, volume IV. Addison-Wesley Publ. Co., Stanford, California.
Pavlov, I. P. (1927). *Conditioned Reflexes*. Oxford University Press.
Pepperberg, I. M. (1991). Referential communication with an African Grey parrot. *Harvard Graduate Society Newsletter*, Spring, 1991, pp. 1-4.
Pfeifer, R. and C. Scheier. (1999). *Understanding Intelligence*. MIT Press.
Priest, G. and Tanaka, K. (1996). Paraconsistent Logic, *Stanford Encyclopedia of Philosophy*.
Resnick, M. (1994). *Turtles, Termites, and Traffic Jams: Explorations in Massively Parallel Microworlds*. MIT Press.
Reynolds, C. W. (1987) Flocks, Herds and Schools: A distributed Behavioral Model. *Computer Graphics*, 21(4) (SIGGRAPH '87 Conference Proceedings), pp 25 - 34.

Rosenblatt, K. and D. Payton (1989). A fine-grained alternative to the subsumption architecture for mobile robot control. *Proceedings of the IEEE/INNS International Joint Conference on Neural Networks*, IEEE.

Rosenblueth, A. and N. Wiener (1968). Purposeful and non-purposeful behaviour, in Buckley, W. (ed.), *Modern Systems Research for the Behavioural Scientist*, Aldine, Chicago.

Russel, S. and P. Norvig (1994). *Artificial Intelligence: A Modern Approach*. Prentice Hall, Englewood Cliffs, NJ.

Searle, J. R., (1980). Minds, brains and programs. *Behavioral and Brain Sciences* 3:417-57.

Shannon, C. (1948). A Mathematical Theory of Communication. *Bell System Technical Journal*, Vol. 27 (July and October 1948), pp. 379-423 and 623-656. Reprinted in D. Slepian, (ed), *Key Papers in the Development of Information Theory*, IEEE Press, NY, 1974.

Shoham, Y. (1993). Agent-oriented programming. *Artificial Intelligence*, 60 (1), pp. 51-92.

Shoham, Y. and M. Tennenholtz, (1995). On Social Laws for Artificial Agent Societies: Off-Line Design. *Artificial Intelligence* 73 (1-2): 231-252.

Sims, K. (1994). Evolving 3D Morphology and Behavior by Competition. In Brooks, R. and P. Maes (Eds.) *Proceedings of Artificial Life IV*, MIT Press.

Steels, L. (1995). Building Agents out of Autonomous Behavior Systems. In Steels, L. and R. Brooks (eds.). *The Artificial Life Route to Artificial Intelligence. Building Embodied Situated Agents.* Lawrence Arlbaum Ass. Hillsdale, NJ.

Steels, L. (1996). The Origins of Intelligence. In *Proceedings of the Carlo Erba Foundation Meeting on Artificial Life.* Fondazione Carlo Erba. Milano.

Tinbergen, N. (1950). The hierarchical organization of mechanisms underlying instinctive behaviour. *Experimental Biology*, 4, pp. 305-312.

Tinbergen, N. (1951). *The Study of Instinct.* Claredon Press.

Tuomela, R. (1992). Group Beliefs. *Synthese* 91, pp. 285-318.

Tuomela, R. (1993). What is Cooperation? *Erkenntnis* 38, pp. 87-101.

Turing, A. M. (1936-7). On Computable Numbers, with an Application to the Entscheidungsproblem. *Proc. London Math. Soc.* (2), 42, pp. 230-265.

Turing, A. M. (1950). Computing Machinery and Intelligence. *Mind*, LIX (236), pp. 433-460.

Tyrrell, T. (1993). Computational Mechanisms for Action Selection. *PhD. Dissertation.* University of Edinburgh.

Verschure, P. F. M. J. (1998). Synthetic Epistemology: The acquisition, retention, and expression of knowledge in natural and synthetic systems. *Proceedings of the 1998 World Conference on Computational Intelligence, WCC '98*, Anchorage, Alaska. IEEE. pp. 147-152.

Wakefield, J. (2001). Complexity's Business Model. *Scientific American*, January, 2001, pp. 24,25.

Wiener, N. (1948). *Cybernetics; or, Control and Communication in the Animal and the Machine.* MIT Press.

Wilson, S. W. (1985). Knowledge growth in an artificial animal. *Proceedings of the First International Conference on Genetic Algorithms and Their Applications.* Lawrence Erlbaum Assoc.

Wooldridge, M. (1997). Agent-Based Software Engineering. *IEEE Proc. Software Engineering* 144 (1), pp. 26-37.

Wooldridge, M. and N. R. Jennings (1995). Intelligent agents: Theory and practice. *The Knowledge Engineering Review*, 10 (2), pp. 115-152.

"There is no such thing called "a finished thesis"..."