# Hybridization of cognitive models using evolutionary strategies

Óscar J. Romero López, Angélica de Antonio Jiménez

*Abstract*— **Incorporating different kinds of micro-theories of cognition and modulating several mechanisms to unify all the recommended actions and outputs of an Intelligent System when a huge amount of environmental variables are changing continuously with increasing complexity, may become a very comprehensive task. The presented framework proposes an Hybrid Cognitive Architecture that relies on integrating of emergent systems approaches —connectionist and autopoietic systems—, and cognitivist approaches, in order to combine implicit and explicit processes necessary in developing cognitive skills. The proposed architecture includes different kinds of learning capabilities at each cognitive level which grant to the architecture a big plasticity. In addition, the propounded attention module includes an evolutionary mechanism based on gene expression programming to evolve a set of eligibility conditions in charge of modulating the coalition/ subordination of specialized behaviours, taking into consideration the theatre metaphor for consciousness. Finally, a co-evolutionary mechanism is proposed to propagate behaviours and knowledge between cognitive systems —Agents— on the basis of memetic engineering. The proposed architecture was proved in an animat environment using a multi-agent platform where several emergent properties of self-organization arose.**

## I. Introduction

In the last decades, artificial cognitive systems have been an area of study that collects disciplines as artificial intelligence, cognitive science, psychology and more, to determine necessary, sufficient and optimal distribution of resources for the development of agents exhibiting emergent intelligence.

There are several positions about cognition, each taking a meaningfully different posture on the nature of cognition, what a cognitive system should do, and how a cognitive system should be analyzed and synthesized. Among these, however, it is possible to discern three broad classes: the cognitivist approach based on symbolic information processing representational systems, the emergent systems approach, embracing connectionist systems, dynamical systems, and enactive systems, all based to a lesser or greater extent on principles of self-organization [1], [2], and hybrid approach which combine the best of the emergent systems and cognitivist systems [3].

Some of the most relevant cognitive architectures which follow a cognitivist approach are: SOAR [4], ACT-R [5], ICARUS [3], and EPIC [3]. On the other hand, some emergent approach architectures with major importance are: GW [6], SASE [3], and DARWIN [3]. As hybrid approach architectures are known CEREBUS [3], KISMET [7], CLARION [8], Polyscheme[9], and LIDA[10]. Some of these architectures deal with aspects about cognitive modeling and representation, some others include learning modules, inference and knowledge generalization, and there are others that try to go further and add motivational and meta-cognition components. However, the attempts of hybrid approach to unify all the different dichotomies of symbolic vs. subsymbolic models, explicit vs. implicit learning, and cognitive vs. emergent approach, it is a complex but very interesting topic. A common feature in hybrid approach architectures is they usually enclose the emergent component to knowledge representation and learning, narrowing the system functionality to a rigid structure of symbolic and subsymbolic component with poor ability to self-organize and adapt to new environments. This feature is often present in pure emergent approaches.

The present research focuses on developing an hybrid architecture for cognitive agents based on symbolic representation approach and three biologic approaches about organization in emergent systems [11]: Epigenesis which refers to heritable changes in phenotype (appearance) or gene expression caused by mechanisms other than changes in the underlying DNA sequence; Ontogenesis, which describes the origin and development of an organism (agent), and defines the history of structural change in a unity without the lost of organization that allows that unity to exist; and Phylogenesis, which describes the evolutionary relatedness among various groups of organisms (agents). Additionally this work proposes an attention module which has the responsibility of arbitrate all the interaction among specialist behaviours through relations of coalition, subordination, competition, inhibition, and aggregation which are coordinated by an evolutionary mechanism.

The remainder of the paper is organized as follows. The description of the proposed architecture is detailed in Section 2. Sections 3, 4, and 5 describe in more detail each module according to three main biologic principles and how it is computationally designed into the architecture. Section 6 outlines and discusses the experimental results and emergent properties obtained. Finally concluding remarks are shown in Section 7.

## II. Proposed Hybrid Cognitive architecture

Fig. 1 outlines an overview of the architecture which has

Manuscript received November 14, 2008. This work was supported by the Programme Alban, the European Union Programme of High Level Scholarships for Latin America and Politécnica de Madrid University.

Óscar J. Romero is with the Software Engineering Department, Universidad Politécnica de Madrid, Spain (e-mail: ojrlopez@hotmail.com).

Angélica de Antonio is with the Software Engineering Department, Universidad Politécnica de Madrid, Spain (e-mail: angelica@fi.upm.es).

six main modules: Attention module, Procedural module, Intentional module, Motor module, Motivational module, and co-evolutionary module. Every module is composed by sub-modules that have more specific functionalities which are communicated to each other by mechanisms of knowledge broadcasting.

In the following, a brief description of architecture's modules is done, and a more detailed description of the developed modules is explained. Initially, our work focuses on developing the procedural and co-evolutionary modules, and their interaction with attention and motor modules. The remainder modules will be considered in subsequently research stages.

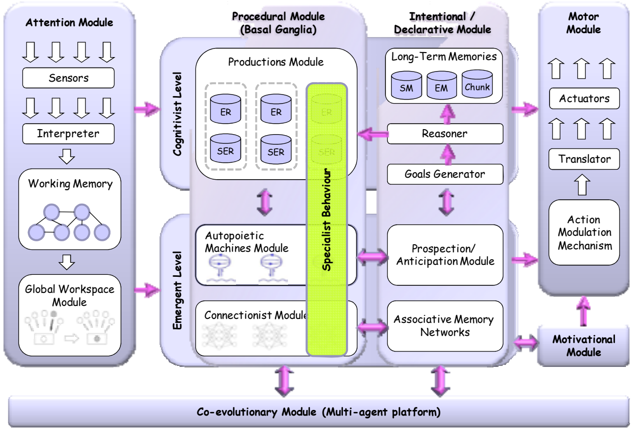


Fig. 1. Hybrid Cognitive Architecture. Components are distributed in two dimensions: horizontally, modules belong to either emergent level or cognitivist lever; vertically, modules are distributed on attention, procedural, intentional or motor modules.

*Procedural module* corresponds with a mammalian brain area called Basal Ganglia [5] which is in charge of functions as motor control, conflicts resolution, and selection and execution of actions. The Procedural module is composed of three sub-modules as follows: connectionist module and autopoietic machines module are contained in emergent level, productions module is included in cognitivist level. These levels are distributed vertically.

*Connectionist module* keeps the bottom-level representations using bakcpropagation neural networks (BNN). The main purpose of connectionist module is modeling "innate skills" which require lesser processing time in comparison with other process of deliberation, being appropriate to represent reactive reasoning.

*Autopoietic Machines (AM)* module is formed by multiple self-organized and self-regulated systems, where each one models a set of sub-symbolic rules which bases on autopoietic principles [11]. The purpose of AMM is to model an agent's specialized skill which is refined through evolutionary process.

*Productions module* keeps different sets of symbolic rules. The different kinds of rules are as follows:

- *Expert Rule (ER)*: this kind of rule simulates either the innate knowledge passed on genetically by an evolutionary process, or the acquired knowledge by a previous experience.
- *Sub*-symbolic *Extraction Rule (SER)*: this kind of rule represents the acquired rules through knowledge extraction using a bottom-up learning process, and therefore they will go refining by means of experience, generalization, and specialization processes.

Procedural module is distributed in two dimensions: vertically and horizontally. Vertical dimension contains a set of Specialist Behaviour (SB), where each one is composed by one component of every sub-module (i.e., one BNN, one AM, one set of ERs, and one set of SERs, as in Fig. 1). Each SB specializes the set of symbolic and sub-symbolic representations, producing a modular and scalable architecture, where each hybrid SB attends either a specific task or a set of specific stimuli. Accordingly, each SB is able to model the conjunction between elements from sub-symbolic to symbolic representations and which can be formalized as follows:

$$\langle SB\rangle = \langle ER_{set}\rangle \cup \langle SER_{set}\rangle \cup \langle AM\rangle \cup \langle BNN\rangle$$

Finally, main architectonic features of Procedural module are parallelism, behaviour specialization, and autonomy.

*Intentional module* pretends to lead the agent's intentionality through goal and planning generation in cognitivist level, as well as prospection strategies and internal simulation in emergent level. This module will have a declarative knowledge representation composed by chunk, semantic, and episodic memories which are accessed indirectly as in [8]. This module will be provided by skills to predict the actions outcomes, construct a model of events for controlling perception through stimuli anticipation, react emotionally to potential sceneries, and refine/generalize the reactive knowledge acquired by each SB.

*Attention module* has the responsibility of interpreting the information which is perceived through the sensors and transformed in percepts (sensory inputs translated into dimension/value pairs). This module constructs a network of nodes which makes up the working memory in charge of keeping information of agent's current state, including elements of external perception, internal motivational states, and the agent's goal and intentions sets.

Furthermore, Attention module includes a mechanism that takes the main principles of Global Workspace theory and Theatre Metaphor for Consciousness [6]. This mechanism is in charge of, on the one hand, coordinating the execution of SBs which compete and form coalitions in order to get the attention focus (conscious process), and on the other hand, feedback and broadcast those SBs that have not been selected to obtain the attention focus but they has the responsibility of generating new inferences, consolidating acquired knowledge, and inferring anticipatory signals. The most innovative aspect of this module is the incorporation of an evolutionary computation mechanism called Gene Expression Programming (GEP) proposed by Ferreira [12]. This will be discussed later in section 4.

## III. Epigenetic Approaches: Connectionist and Autopoietic Modeling

Epigenetic approach makes reference to mechanisms ehich allow to specific individual to modify some aspects of its either internal or external structure as a result of interacting with its environment. Therefore, epigenesis represents the final tuning process by means of each individual adapts efficiently to its environment from the abilities included in its genetic code. In our work, we propose two main approaches which intend to simulate the most evident epigenetic systems observed in nature: the central nervous system and the natural immune system.

In the following sections, we describe the proposed computational model for each one of these systems and their functionality inside the architecture.

### *A. Connectionist Module*

Rumelhart [13] and Sun [8] have provided support in regards to the argument that a backpropagation networks can represent the subsymbolic, distributed representation of implicit knowledge. A backpropagation network is a type of neural network in which the connections between nodes are adjusted to produce the optimal output.

Sun [8] explains that the units in a backpropagation network are capable of accomplishing computations but are subsymbolic and not individually meaningful; that is, they generally do not have associated semantic labels. Just like neurons, nodes are not individually useful. Since implicit knowledge represents the lower-level, almost automatic processing of information, it is easy to see why backpropagation networks are used.

In our work, Connectionist module is organized in groups of BNN, each one of these represents the sub-symbolic specialization of a task. Every specialized BNN is classified according to its purpose, filtering in this manner the perceived stimuli from environment and selecting the respective actions.

On the other hand, Reinforcement is a factor of learning in the procedural module and is used to modify the agent’s future responses. This is achieved through adjusting the connections in the backpropagation networks (in emergent-level) and modifying the production rules (in cognitivist-level). Several approaches has been proposed, often, reinforcement learning can be used, especially Q-learning as in [14]. In this learning setting there is no need for external teachers providing desired input/output mappings.

### *B. Autopoietic Machines Module*

An autopoietic machine is a machine organized (defined as a unity) as a network of processes of production (transformation and destruction) of components which: (i) through their interactions and transformations continuously regenerate and realize the network of processes (relations) that produced them; and (ii) constitute it (the machine) as a concrete unity in space in which they (the components) exist by specifying the topological domain of its realization as such a network [11].

A good example of autopoietic machines however, is the immune system's ability to distinguish between self and non-self. Varela [11] has been pointing out for some time that this is an observed behaviour, produced by the operational dynamics of the immune system in its environment, and that it is wrong to look for some discriminatory recognition mechanism within the immune system.

Artificial Immune Systems (AIS) [15] are adaptive systems inspired by immunological theory and immune functions, models and principles observed in nature as defense mechanisms.

The AIS which we propose, start with an input data set (sensors) that will correspond to a set of antigens that stimulate an immune network, which goes through a dynamic process, until it reaches some type of stability. Therefore, each autopoietic machine is based on AiNet [15], a model which implements a discrete immune network that has been developed for data compression and clustering and later for optimization.

On the one hand, each AIS incorporates an evolutionary mechanism that uses GA in order to discover new knowledge as rules (antibodies), and on the other hand, each AIS uses a credit assignment method which is able to resolve the antibody selection given an specific antigen (sensory input). Some of the developed immunological mechanisms include clonal selection, clonal maturation, diversification, and different kind of meta-dynamics.

## IV. Ontogenetic Approach: Specialist Behaviour Orchestration using GEP

Ontogenetic principles involve all the mechanisms in charge of developing an agent on the basis of stored information in its own genetic code without interposing the environment influence. Some outcomes of these principles as self-replication and self-regulation properties can be valued.

In our work, the ontogenetic approach is simulated through the interaction between different modules: Attention module, Goal module, and SBs in procedural module. The main idea in this approach is that Attention module leaded by Global Workspace theory, orchestrates the different SBs in such a way that either cooperate among them or generate hierarchical relations of activation between them (inhibition, coalition, aggregation, subordination, etc.).

Each SB has a intentional label which indicates the goals it will satisfy, the associated exèctation, and a the set of stimuli and working memory item that will activate the execution threshold of such specialist.

As a result, the question is how the Attention module will be able to arbitrate and orchestrate the set of SBs given a set of stimuli, expectations, goals, and emotions of the agent in an autonomous manner?, this question is solved next.

The internal structure of each agent is decomposed in atomic components which can be estimated and used to find the optimal organization of SBs during the agent's lifetime. The main goal is that the agent self-configures its own SBs interaction. So, in our work, the evolutionary model proposed by Ferreira in [12] called GEP, is used to evolve the eligibility conditions set of each agent to generate an appropriate orchestration of behaviours.

GEP uses two sets: a function set and a terminal set. Our proposed function set is: IFMATCH, AND, OR, NOT, INHIBIT, SUPRESS, AGGREGATE, COALITION, and SUBORDINATION. The AND, OR and NOT functions are logic operators used to group and exclude subsets of SBs. The conditional function IFMATCH is an applicability predicate that matches with specific stimuli. This function has three arguments; the first argument is the rule's antecedent and it is a set of eligibility conditions which correspond with a subset of sensory inputs, a subset of motivational indicators (internal states, moods, drives, etc.), and a subset of working memory elements which model the agent's current state. All elements of these subsets are connected with logic operators. If the whole set of conditions exceeds a threshold, then the second argument, the rule's consequent, is executed, otherwise the third argument is executed. Second and third argument should be a set of functions like INHIBIT/ SUPPRESS/ AGGREGATE/ COALITION/SUBORDINATION, or maybe an AND/OR function connecting more elements if necessary.

The INHIBIT, SUPPRESS and AGGREGATE functions have two arguments ($SB_A$, $SB_B$) and indicate that $SB_A$ *inhibits/suppresses/aggregate* $SB_B$.

On the flip side, COALITION/SUBORDINATION functions, instead of binomial functions mentioned above, perform a set of SBs. COALITION function describes a cooperation relationship between SBs where actuators may activate multiple actions. SUBORDINATION function defines a hierarchical composition of Sbs which are activated in a specific sequence.

On the other hand, the terminal set is composed by the SB set, the motivational indicators, the goal set, and the working memory elements. Additionally "do not care" elements are included so whichever SB, motivational indicator, goal, or working memory item can be referenced.

Each agent has a chromosome with information about its self structure, e.g. one agent might have a chromosome, as in Fig. 2, which is a valid eligibility rule because both the antecedent and the consequent of IFMATCH function match to each required argument type, as follows:

*IFMATCH:*
$mi_1$ *AND* $mi_2$ *AND* $g_1$ *AND* $wmi_1$
*THEN:*
$sb_1$ *INHIBIT* $sb_2$
*ELSE: COALITION* $sb_3$ *AND* $sb_4$ *AND* $sb_5$

Analyzing this eligibility rule we can infer that the agent has five SB: $sb_1$, $sb_2$, $sb_3$, $sb_4$, and $sb_5$, the first inhibit the second one, and the last three make a coalition when agent has an specific stimuli, motivational indicator $mi_1$, goal $g_1$, and working memory item $wmi_1$. However, these chromosomes (eligibility rules) do not have always a valid syntax, so the GEP mechanism is used to evolve the chromosome until it becomes in a valid syntactic rule.

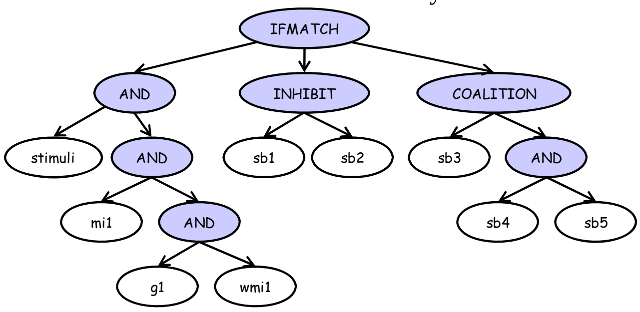


Fig. 2. Tree structure representation of a chromosome example (eligibility rule). From Karva notation [17] this chromosome would be: [IFMATCH] [AND] [INHIBIT] [COALITION] [stimuli] [AND] [sb1] [sb2] [sb3] [AND] [mi1] [AND] [sb4] [sb5] [g1] [wmi1], where $mi_n$ is the motivational indicator n, $sb_n$ is the specialist behaviour n, $g_n$ is the goal n, and $wmi_n$ is the working memory item n.

Each individual (agent) has a multigenic chromosome, that means, each chromosome has a gene set where each gene is an eligibility rule like the example, so the agent has several rules (genes) as part of its genotype and each one is applied according to the situation that matching the rule antecedent. Each gene becomes to a tree representation and afterwards a genetic operator set is applied between genes of the same agent and genes of other agents as in [12]: selection, mutation, root transposition, gene transposition, two-point recombination and gene recombination, in order to evolve chromosomal information.

After certain number of evolutionary generations, valid and better adapted agent's configurations are generated. A roulette-wheel method is used to select individuals with most selection probability derived from its own fitness. Fitness represents how good interaction with environment during agent's lifetime was.

## V. Phylogenetic Approach: Co-evolutionary Strategy Based on Memetics

In biology, phylogenesis (evolution) collects all those mechanisms which, leaded by natural selection, have given place to the broad variety of species observed in nature. Evolutionary mechanism operates in populations and as a result, it gets a genetic code which allows individuals of a concrete population to adapt to the environment where they live in.

In the basis of phylogenetic theory [11], a co-evolutionary mechanism is proposed to evolve fine-grained units of knowledge among the multi-agent society, and which take the foundation of Meme and memetic algorithms. The term "meme" was also introduced and defined by Dawkins [16], in 1976 as the basic unit of cultural transmission, or imitation that may be considered to be passed on by non-genetic means. The term Memetic Algorithm (MA), inspired by both Darwinian principles of natural evolution and Dawkins' notion of a meme, was first introduced by Moscato[17] where he viewed MA as being close to a form of population-based hybrid genetic algorithm coupled with an individual learning procedure capable of performing local refinements.

In our work, each meme contains a symbolic and sub-symbolic unit of knowledge representation, and also a set of variables like demotion level, reliability, rule support and fitness. Most evolutionary approaches use a single population where evolution is performed; instead, in our co-evolutionary approach, the SBs are discriminated in categories and make them evolve in separate pools without any interaction.

Each agent has a specific configuration of SBs which will allow it to interact with the environment and learn a set of rules in order to generate its own knowledge base.

Finally, after certain period of time a co-evolutionary mechanism is activated. For each behaviour pool is applied a stochastic selection method where those SBs that had the best performance (fitness) in each agent, will have more probability to reproduce. Then, a crossover genetic operator is applied between each pair of selected SBs, and some memes are selected and interchanged with other ones.

## VI. Experimentation

In order to evaluate the proposed cognitive model, following aspects were considered:

- Learning and Generalization skills,
- Analysis of eligibility rules generated by GEP,

An artificial life environment called Animat (animal + robot) is proposed to test the experiments. The environment simulates virtual agents competing for getting food and water, avoiding obstacles, etc. Each animat driven by an agent in the environment disposes a set of 8 proximity sensors around itself.

Some environmental changes were introduced during the experimentation in order to validate the generalization and adaptation ability.

Thus, some experiments designed to evaluate the performance aspects mentioned above are described next.

### *A. Learning and Generalization skills*

In this experiment we chose three types of environments gradually increasing in complexity. The purpose was to validate the adaptation and generalization level acquired by the agent through learning. First, the agent was configured with two SBs:

$SB_1$: *looking for food*

$SB_2$: avoiding obstacles

In Fig. 3 is depicted the three environments and the desired paths that the agent should cross. Environment in Fig. 3a. is a basic learning scenario where agent had to follow a simple path. In Fig. 3b. the environment is a little bit different changing the position of some elements, and in Fig. 3c. the environment is more complex including more elements and a new path of food.

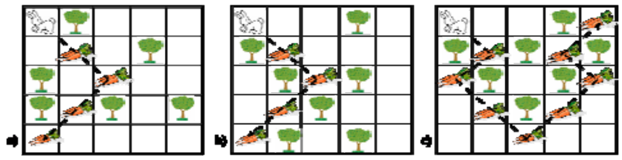

Fig. 3. Animat environments. a) basic environment, b) modified environment, and c) complex environment.

In the first environment, the agent was trained from emergent to cognitivist levels. In the other two environments the agent was tested using the previous knowledge acquired in the first environment. Table I shows the learning parameters used for training.

TABLE I
LEARNING PARAMETERS OF ARCHITECTURE

| Parameter | AIS | BNN |
|---|---|---|
| Life Tax | 0.005 | - |
| Bid Tax | 0.003 | - |
| Cloning Rate per rule | 4 | - |
| Mutation Rate per rule | 2 | - |
| Similarity Threshold | 0.8 | - |
| Alpha $\alpha$ | - | 0.1 |
| Beta $\beta$ | - | - |
| Delta $\delta$ | - | 0.02 |
| Gamma $\gamma$ | - | 0.8 |
| Lamda $\lambda$ | - | 0.8 |
| Layers in NN | - | 3 |
| Number of epochs | 40 | |
| Num. runs per epoch | 20 | |

Fig. 4 illustrates the learning curve of agent in the three different environments. It is important to notice how the agent took more time training in the basic environment but the learning curve decreased when the agent was tested in the other two environments. This demonstrated the agent had generalized the knowledge acquired in training and it was able to adapt quickly to new environments.

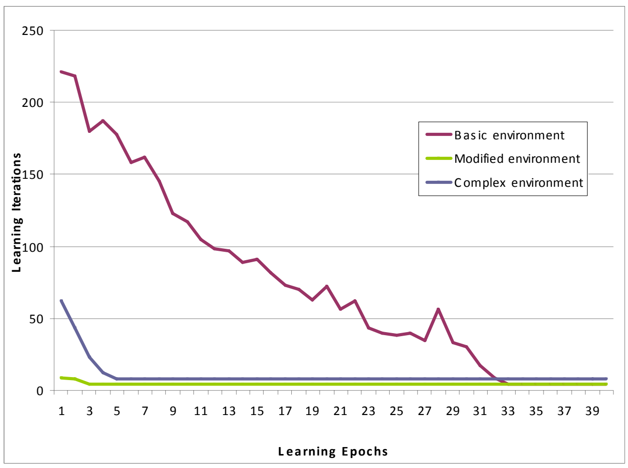


Fig. 4. Learning curves in three different environments

### B. Analysis of eligibility rules generated by GEP

After the whole system has evolved during a specific number of generations, we have analyzed the final structures of the best adapted agents where emergent properties arose.

First, we present some initial eligibility rules which have syntax conflicts; therefore an evolved set of eligibility rules syntactically well-formed emerges from GEP.

This is an initial eligibility rule of a test agent in epoch 0:

```
IFMATCH
  {food},{tree},{empty},{empty},{empty},{empty},
  {empty},{tree} AND {goal-is-eat}
THEN
  {SB-eat} INHIBIT {SB-avoid-obstacles} AND
  {SB-avoid-obstacles} SUPRESS {SB-eat}
ELSE
  SUBORDINATION
  {SB-avoid-obstacles} AND {SB-eat}
```

The above eligibility rule is contradictory because `{SB-eat}` cannot inhibit `{SB-avoid-obstacles}` behaviour and at the same time to be inhibited by this behaviour. So, the evolved rule consequent of the eligibility rule after 17 epochs is:

```
  …
THEN
  COALITION {SB-eat} AND {SB-avoid-obstacles} AND
ELSE
  {SB-avoid-obstacles} INHIBIT {SB-eat}
```

It is important to notice that evolved eligibility rule does not present any syntax conflict and is a valid rule when the agent reads food and obstacles around it. Otherwise, the agent always will execute the rule: `{SB-avoid-obstacles}` inhibiting `{SB-eat}`, because `{SB-eat}` behaviour has a lower priority.

## VII. Conclusion

The experimentation demonstrates that specific parameter configurations in AIS, BNN, GEP and Co-evolutionary mechanism are required to reach certain robustness, adaptability and learning capacities in the overall system. Nevertheless, emergent properties did not arise always or in a fast way, in several experiments animats died quickly and they could not learn to survive, but this allows appearing more robust individuals later.

The evolutionary mechanisms used in this work, provided a plasticity feature allowing the agent to self-configure its own behaviour-based architecture; thus it can avoid creating exhaustive and extensive knowledge bases, pre-wired behaviour-based structures and pre-constrained environments. Instead of this, a cognitive agent using our architecture only needs to interact with an arbitrary environment to adapt to it and take decisions in a reactive and deliberative fashion.

In the experimentation, the emergent properties were difficult to discover because it takes a lot of time to evolve the overall system despite of using a multi-agent platform in a distributed configuration. Maybe, it can be similar to the natural evolution where adaptation occurs slowly and sometimes produces poor adapted creatures.

In our future work we expect to continue working on designing more adaptive and self-configurable architectures, using fuzzy techniques in the RMLSs to improve the sensors readings and to manipulate motivational levels (moods). One concrete application of this research will be the development of a cognitive module for Emotive Pedagogical Agents where the agent will be able to self-learn of perspectives, believes, desires, intentions, emotions and perceptions about itself and other agents, and the present approach will be responsible of driving the cognitive architecture.

## Acknowledgment

Supported by the Programme Alban, the European Union Programme of High Level Scholarships for Latin America, scholarship No. E05D056455CO”.

## References

[1] M. L. Anderson, “Embodied cognition: A field guide,” Artificial Intelligence, vol. 149, no. 1, pp. 91–130, 2003.
[2] A. Berthoz, The Brain’s Sense of Movement. Cambridge, MA: Harvard Univ. Press, 2000.
[3] D. Vernon, G. Metta, and G.Sandini, “A survey of artificial cognitive systems: Implications for the autonomous development of mental capabilities in computational agents,” *IEEE Trans. Evolutionary Computation,* vol. 11, No. 2, April 2007.
[4] P. Rosenbloom, J. Laird, and A. Newell, Eds., The Soar Papers: Research on integrated intell. Cambridge, MA:MIT Press, 1993.
[5] J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin, “An integrated theory of the mind”, Psy. Rev., vol. 111, no. 4, pp. 1036–1060, 2004.
[6] M. P. Shanahan and B. Baars, “Applying global workspace theory to the frame problem,” Cognition, vol. 98, no. 2, pp. 157–176, 2005.
[7] C. Breazeal, “Emotion and sociable humanoid robots,” Int. J. Human-Computer Studies, vol. 59, pp. 119–155, 2003.
[8] R. Sun, E. Merrill, T. Peterson, “From implicit skills to explicit knowledge: A bottom-up model of skill learning”. Cognitive Science, vol. 25, pp. 203-244, 2001.
[9] N.L. Cassimatis, Adaptive Algorithmic Hybrids for Human-Level Artificial Intelligence. Advances in Arti. Intell., 2007.
[10] S. Franklin, “The LIDA architecture: Adding new modes of learning to an intelligent, autonomous, software agent”. In Proc. of the Int. Conf. on Integrated Design and Process Technology, 2006.
[11] H. R. Maturana and F. J. Varela, “Autopoiesis and Cognition: The Realization of the Living”, ser. Boston Studies on the Philosophy of Science. Dordrecht, Holland: D. Reidel Publishing Company, 1980.
[12] C. Ferreira, Gene Expression Programming: A new adaptive algorithm for solving problems, Complex Systems, vol. 13, pp. 87-129, 2001.
[13] D. Rumelhart and J. McClelland, “Parallel Distributed Processing: Explorations in the Microstructures of Cognition”, MIT Press, 1986.
[14] C. Watkins and P. Dayan, Q-learning. Machine Learning, vol. 8, num. 3, pp. 279-292, 1992.
[15] L. N. de Castro, J. “Timmis, Artificial Immune Systems: A New Computational Intelligence Approach”, Ed. Springer, 2002.
[16] R. Dawkins. "The Selfish Gene". Oxford University Press. 1989
[17] P. Moscato, "On Evolution, Search, Optimization, Genetic Algorithms and Martial Arts: Towards Memetic Algorithms". 1989.