Emergence analysis in a Multi-robot System

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***Abstract*— In this paper, we study the emergent behaviors in a multi-robot system. The multi-robot system uses a model for decision making that is composed of three levels: one individual, one collective, and another for the knowledge and learning management. In particular, the individual level, the base of the emergent behavior of the system, is composed of a module of perception/interpretation, an executing module and a behavioral module that has an emotional component, a reactive component, a cognitive component and a social component. In this paper, we analyze the robot performance, in order to produce an emergent behavior in the system. We present an example of an emergent scenario, and study its instantiation in our multi-robot architecture.**

***Index Terms*—Multi-robot Systems, Emergent Systems, Swarm architecture.**

I. Introduction

In this work is studied the effect of a multi-robot architecture in the emergent behavior of the system. Multi-robot systems have been studied through different approaches: control architectures, cooperation mechanisms, among others [1, 2]. There are different works for these kind of systems: in [3] is proposed a multi-robot system for hunting tasks under a swarm approach; in [4] is described a robot swarm that implements an algorithm based on the bee hive for food gathering; in [5] is defined a hybrid approximation for multi-robot systems; [6] proposes an algorithm based on the human immunological system for the cooperative objects transportation. Other works have added emotions to the robots in the system, in [7, 8, 9] are specified emotions in multi-robot systems, with the goal of consider the influence of them in the decision making of each robot. On the other hand, the learning and recognition are critical to multi-robot systems [10, 11, 12].

This paper analyses an architecture for heterogeneous robot swarms consisting of three layers [18]: a first layer that is distributed in each robot and supports them, in terms of their processes of performance, perception and communication, as well as managing also their behavior considering reactive, cognitive and social aspects. This layer introduces an affective component, which directly influences the behavior of the individuals; this component is built from an emotional model that considers four basic emotions: joy, sadness, anger and rejection. The second layer supports the collective processes that emerge in the system, based on the concept of emergent coordination; this layer allows the implantation of swarm intelligence algorithms. The third layer manages the processes of learning, both individually and collectively. The architecture facilitates the emergence and self-organization in the system, so it is necessary to verify the emergence of such concepts.

In this paper, we study the emerging behaviors in this multi-robot system. For this, a series of verification methods are used to analyze the collective intelligence of the swarm and the situations they could solve. Additionally, in this paper, we use the AR2P model (it is a model for recognition of patterns [22, 23, 26, 27]) to equip the robots with the ability to recognize situations. The capability of the robot to recognize situations allows it to make better decisions, in order to facilitate emerging processes. For example, if a robot needs to recruit other robots to transport an object, it will optimize the recruiting task by sending messages to individuals that it recognizes that are willing to collaborate.

The rest of the paper is organized as follows. Section II describes the multi-robot architecture. In the section III is described the case study and the instantiation of the architecture, and finally, the section IV presents an analysis about the emergent behavior in the Multi-Robot System. The section V describes the conclusions.

II. ARCHITECTURE FOR MULTI-ROBOT SYSTEMS WITH EMERGENT BEHAVIOR

In [18, 19], the authors present an architecture for multi-robot systems with emergent behavior, called AMEB, which is structured in three levels: one individual, one collective and another for the knowledge and learning management (see Fig. 1).

AMEB aims to manage the processes that occur in a multi-robot system, in particular, with the goal of facilitating the emergence in the system. It is a distributed architecture, with decision-making processes at the local level; it has learning mechanisms and shared memory spaces, aspects that are specific to emergent systems. An architecture of emotion management is included in the individuals that make up the system, this in order to influence the behavior of each individual, so that the behavior of each individual depends on its emotional state.

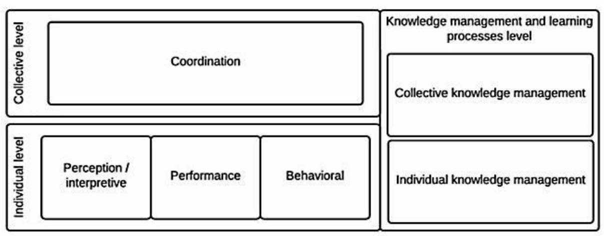

Fig. 1. AMEB Architecture

The individual level of AMEB is responsible for managing the processes inherent to the functioning of the individual, controls its mechanisms of perception, action and behavior, it is a source of information for the other levels. Its perception module sends to the coordination level the necessary information about the environment of the robot and its interactions with it. Also, at the individual level of AMEB, a behavioral module is implemented [19], which aims to manage the behavior of the robot. The behavioral module describes a series of internal components of each robot, which through their interactions generate the behavior itself. These components are:

- Reactive component: This component interacts directly with the components of perception and actuation of the robot, and it is responsible for generating reactive behaviors in the robot. This component manages survival behaviors of the individual, and has priority over any other behavior that can be generated.
- Cognitive component: This component generates deliberative behaviors in the robot, based on its local knowledge. Here, it generates complex behaviors, built from primitive behaviors, which allows running specific and more complex actions.
- Social component: It explodes the collective knowledge in decision-making processes of the robot. It interacts closely with the other two levels (collective and knowledge management), for the planning, coordination and/or cooperation processes in the system, in order to generate behaviors that allow the robot to interact with.
- Affective component: based on [17], it is proposed an affective model, which considers a set of positive or negative emotions involved in generating behavior of robots, which affects the level of self-organization and emergence of the system. These emotions directly affect the individual and collective behavior of the robots. In the behavioral model proposed in this paper, the affective component inhibits or activates the behaviors generated by the cognitive and social components.

The affective component is based on an emotional model (see Fig. 2), which considers the set of next emotions ε = {anger, rejection, neutral, sadness, joy} [20, 21], where the *X* axis represents the satisfaction or dissatisfaction state of the robot in the interval [-1,1] (see Fig. 2), and the emotional spectrum ranges from highly negative emotions like anger, to highly positive emotions like joy.

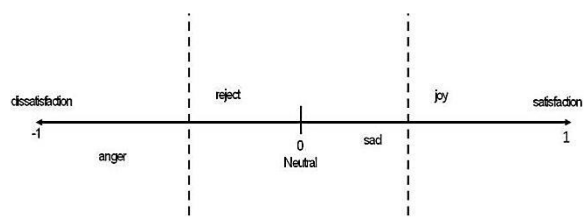

Fig. 2. Emotional model

The coordination level allows the collaboration and cooperation between the individuals, and the level of learning builds the knowledge of the system. This level manages the individual and collective knowledge. For more details about these levels, see [18, 19]. In this paper, we are interested in the affective component, for its influence in the emergent behavior of the multi-robot system.

A. *Formalization of the Affective Component*

An emotion (Em) evaluates the degree to which a process or phenomenon meets the needs of the individual. The value of Em is given by the following equation, which determine the current emotional state of the agent in a given time interval, which depend on a series of factors that define the internal state of the robot, and that are related to the operation of the robot and its performance in the environment [19]:

$$\mathrm{Em}=\frac{1}{n}\sum_{t=1}^{n}\frac{BS_t+OS_t+SS_t+IS_t}{4} \qquad (1)$$

Where: t=0 is the initial time and n the final time of the time interval. The state variables BS, OS, SS and IS are normalized in the interval [0, 1]. The description of the state variables that affect the emotional state of the robot is:

- *Battery State (BS):* it represents the energy level of the battery of the robot (battery percentage). The charge level affects the performance of the robot.
- *Operation State (OS):* It represents the level of performance of the robot, which is in relation to its active duration in the system. For example, if a robot is active for a high percentage of time, then it is assumed that it contribute to maintaining its state of mind high.
- *Security State (SS):* it is defined by the collisions average (due to competitions or obstacles) and faults per minute. If the robot presents few faults and collisions, then it has a good performance; it is assumed that this affects positively its internal state.
- *Interaction State (IS):* it is defined by the social capability (or interaction) of the robot, measured by the number of messages (sent, received) per minute exchanged. The number of messages exchanged helps establish the level of sociability in the robot. For this work, more interactions positively affect the robot.

Below is a scale of the range of values that allow us to discern the type of emotion according to the result of the equation (1).

TABLE I. RANGE OF VALUES FOR THE EMOTIONS

Emotion (Em)	anger	reject	neutral	sadness	joy
Range	[-1, -0,5]	[-0.4, -0.1]	[0,0]	[0.1, 0,5]	[0.6,1.0]

The calculation of the emotions can be done by two fuzzy methods: the first method integrates the fuzzy state variables into the eq (1). The second method uses fuzzy rules, one for each emotion. In the following, some examples of how to calculate the emotions by the first method, in the time interval of 1 to 3 seconds. Suppose:

TABLE II. EXAMPLE OF VALUES OF THE STATE VARIABLES

t	BS	OS	SS	IS
1	0.3	0.5	0.5	0.4
2	0.4	0.5	0.5	0.3
3	0.3	0.5	0.5	0.3

Using the eq(1), Em= 0.4166. According to Table I, this value represents an emotional state of sadness. This method is proposed to evaluate the quality of recognition of emotion recognized by diffuse rules. The rule is applied, read reading of the values of the state variables, the quality metric is calculated by equation 1 and the results are compared. When there is mapping the quality and recognition is accurate otherwise it is inconsistent. For the values of the example in question, the output is consistent with rule 1 and is inconsistent for rule 2.

In the case of fuzzy rules, BS, OS, SS and IS are defined as fuzzy variables composed of the fuzzy sets: low, normal and high. Some examples of emotions using fuzzy rules are:

- If <*BS is low*> and <*OS is normal* > and <*SS is normal* > and <IS *is low*> then emotion is sadness
- If <*BS is high or BS is normal*> and <*OS is high or OS is normal* > and <*SS is high or SS is normal* > and <*IS is high*> then emotion is joy

B. How the system works

The robot perceives stimuli that influence in its state. This activates the emotional process of the robot, which generates a satisfaction index (SI) that defines the current emotion in the robot and the type of behavior associated (see Fig. 3). In [20, 21] are considered three types of behavior: imitative, cognitive and reactive, which are related to a specific emotional state. They are based on the three sub-intervals defined in the Fig. 2, an interval related to reactive behaviors, one related to cognitive behaviors, and the last interval related to imitative behaviors. In our proposal, the same assumptions are made.

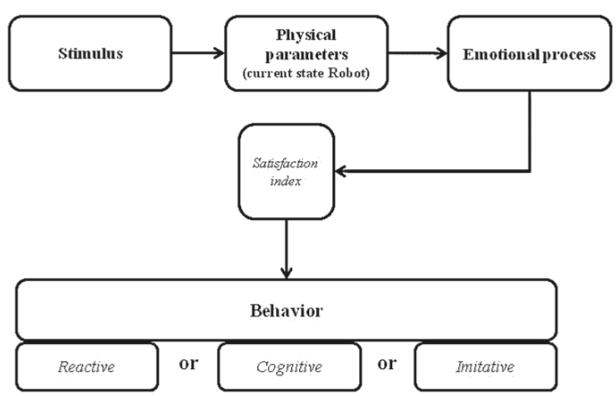

Fig. 3. Emotional process

In general, highly positive emotions predispose the individual to imitate the behavior of other team members, while the slightly positive lead to a process where the cognitive aspect predominates over the imitative aspect. Also, slightly negative emotions lead the individual to a process of internal reflection for decision making, and finally, a highly negative emotion leads to behaviors that are clearly reactive, where the individual seeks to achieve their survival by reacting to the stimuli of the environment without previous reasoning.

The inclusion of emotions in the multi-robot system seeks to improve its adaptability to the dynamics of the environment, as well as facilitate the emergence in the system, by modifying the way of performing the behaviors that each individual is able to execute. The conjunction of individual behaviors, builds the overall behavior of the system, which by its nature cannot be predicted a priori [25]. For example, in an instant t the robot can be happy. In this mental state, it can "*explore and find".*

So, the affective component determines the current robot's emotion, which is affected by the environment stimuli and the current robot's state. According to the architecture proposed in [18, 19], each robot shares its internal state with the other robots in the system, in order to recognize its emotion, using the following format:

<file_robot_n>
<body> sub_state_1= value</body>
<body> sub_state _2= value </body>
<body> sub_state _3= value </body>
<body> sub_state _4= value </body>
<file_robot_n/>

Based on these sub_states, which represent the *BS*, *OS*, *SS* and *IS* variables with three possible values: normal, high and low; can be calculated the emotion of the robot, which represents the robot's satisfaction index-*Si*. *Si* will affect its actuation and perception parameters, leading to a specific behavior (see Fig. 3).

The emotional state of a robot must be determined at runtime, because can fluctuate its intensity according to the stimuli received and the changes in its current state. In this way, it is required a recognition algorithm, in order to recognize the emotions of the robots in a given moment. In this paper is used the AR2P algorithm, for more details about this approach see [22, 26, 27].

III. EXPERIMENTAL CONTEXT

In this section, we present the set of tests carried out through simulations without using physical robots.

A. Test platform

We suppose a test environment composed of walls, obstacles, marks on the ground that represent areas of battery charge, as well as marks that simulate objects to move, and whose function is to attract robots (see Fig. 4).

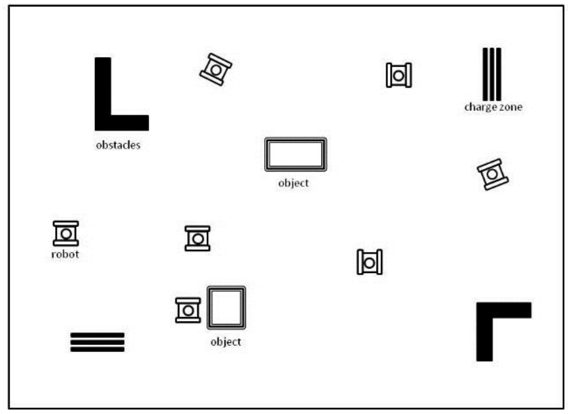

Fig. 4. Test platform

Additionally, the multi-robot system is composed of general purpose robots [24], which are managed by our architecture [18]. The architecture presents the following characteristics: i) It is a fully distributed architecture; ii) Decisions are made locally by each robot; iii) There is a collective memory.

Additionally, the robots invoke the AR2P algorithm to recognize the emotions of the other robots. Information about the internal state of the robots is shared across the collective memory.

B. Case study

The purpose of the case study is to show the emergent behavior in the multi-robot system, for example, for recruitment, decision making, among others. To carry out the tests, the next scenario is considered.

Cooperative hunting is a phenomenon that occurs in nature where a group of individuals have as their common goal to catch a moving prey and then feed. In some species the individuals are coordinated without the presence of a leader, the coordination of the group emerges naturally. In a general way, we can identify the following sub-tasks during the hunting process [25]:

- Detection: an individual of the group detects the prey and alerts to the other individuals.
- Persecution: it begins, where variables such as the speed and direction of the hunters are regulated according to the response of the prey.
- Corner: some species corner the prey with the aim of attacking collectively.
- Feed: depending on the species, individuals feed on the prey as a group.

In this case, individuals go through different states of their behaviors, from the excitement of the moment of the persecution, until the calm and satiety after feeding.

The robot's emotional state is determined by the model presented in section II, which is affected by the values of the sub-states described in that section.

IV. Emergence Analysis in the multi-robot system

Now, we are going to test the capability of the multi-robot system to generate emergent behavior using different points of views.

A. Emergent behavior analysis using the MASOES model

In [20, 21] has been proposed a verification method of the emergence in a system, using a set of concepts related to emerging properties, which are:

- Density (D): It measures the degree of compactness in the robotic equipment.
- Diversity (DI): It measures the degree of homogeneity of the group of robots on the system.
- Synthesis (S): It measures the quality of the aggregation mechanism.
- Independence (IN): It measures the degree of autonomy of the robots, in terms of their capabilities for decision making without relying on other robots.
- Emotivity (E): It measures the degree of emotionality of the system, according to the emotional model implemented.
- Self-organization (SO): It is measured from three aspects: degree of satisfaction of the system, its anticipation and robustness.
- Emergence (EM): Measures the degree of evolution of the system through the emergence of some emerging properties, such as patterns at temporal and spatial level, collective norms, etc.

It also defines a series of concepts associated with the architecture itself:

- Number of robots (NR): It refers to the number of robots acting at a given moment in the system.
- Type of behavior (TB): It refers to the different types of behavior that robots may have.
- Direct interaction (DI): It refers to the number of direct interactions between robots.
- Indirect interaction (II): It refers to the number of interactions of robots through the environment.
- Aggregation Mechanism (AM): It refers to how the information handled by the individual can be useful to the collective.
- Reactive Component (RC): It refers to the reactive behaviors of the individual.
- Cognitive component (CC): It refers to cognitive behaviors through processes of reasoning and learning.
- Emotional component (EC): It refers to the robot's emotions.
- Social component (SC): It refers to how the agent interacts with the other individuals in the system.
- Type of emotion (ET): It refers to the type of emotions present in the system.

In the verification method proposed in [21], is defined a Fuzzy Cognitive Map (FCM) [32, 33] with these concepts, which has been implemented in the FCM Designer Tool [34]. The FCM verifies the emergent behavior of a system, according to the characteristics of the concepts in the system [21].

Table III presents the results according to the verification method, for our scenario. The values of the concepts can be low, medium or high, according to their contribution in the system. In the hunting scenario, the initial value of *emotiveness* is high (0.95) because the robots can change of emotion by the different states that occur in the hunting action, the emotion types are high (0.9) and the behavior component is high (0.95) because our system has a behavior component based on an affective model (see Fig. 2). Also, the individuals of the group present a high degree of density (0.9). The other concepts associated with emerging properties are initialized to 0 in order to observe their behavior during verification.

For this scenario, according to Table III, the emergence can be verified (final state of this concept is 0.99), where the emotiveness, social component and reactive component contribute significantly to the emergence in the system. The number of robots remains in the medium state, the direct interaction goes up to a high value, and the indirect interaction even though its value decreases is still high, which indicates that the messages transmitted directly contribute more to the appearance of the emergency in the system.

TABLE III. ARCHITECTURAL CONCEPTS

Concept	Initial State	Final State
Emotion type	0.9	0.5
Social component	0.95	0.88
Aggregation mechanism	0.5	0.90
Reactive component	1	0.85
Cognitive component	0.10	0.72
Behavior component	0.9	0.81
Number of robots	0.4	0.6
Behaviour type	0.8	0.97
Direct interaction	0.10	0.86
Indirect interaction	0.95	0.76
Density	0.9	0.87
Diversity	0	0.88
Synthesis	0	0.80
Independence	0	0.86
Emotiveness	0.95	0.85
Self-organization	0	0.99
Emergence	0	0.99

B. *Emergent behavior analysis using simulations*

In order to test the emergence, in this section we have used a scenario composed of 5 robots, where the initial states of the factors that influence their emotional states are established in a random way. At the end of the simulation is used the FCM to evaluate the emergence in the system with the data obtained from the simulation.

Table IV presents the number of times an emotion appeared in the system, and the associated behavior types that were generated during the simulation. It is observed that in this case, the behaviors are concentrated around negative or slightly negative emotions, such that reactive and cognitive behavior predominates; according to what is expected in the proposed scenario, where the reactive behavior of the individuals contributes to the achievement of the objective, due to the emotional model proposed in [19].

Figure 5 shows the evolution of the emotional state of the robots during the simulation. At first, the robots go through an emotional instability, then the emotional state begins to present changes, but within the same emotional spectrum. As the simulation goes on and the robots are running out of battery, then their emotions begin to have a negative tendency.

TABLE IV. NUMBER OF EMOTIONS AND BEHAVIOR TYPES

Emotion	Reject	Angry	Sad	Joy
	81	0	92	12
Behavior types	**Reactive**	**Cognitive**		**Imitative**
	81	92		12

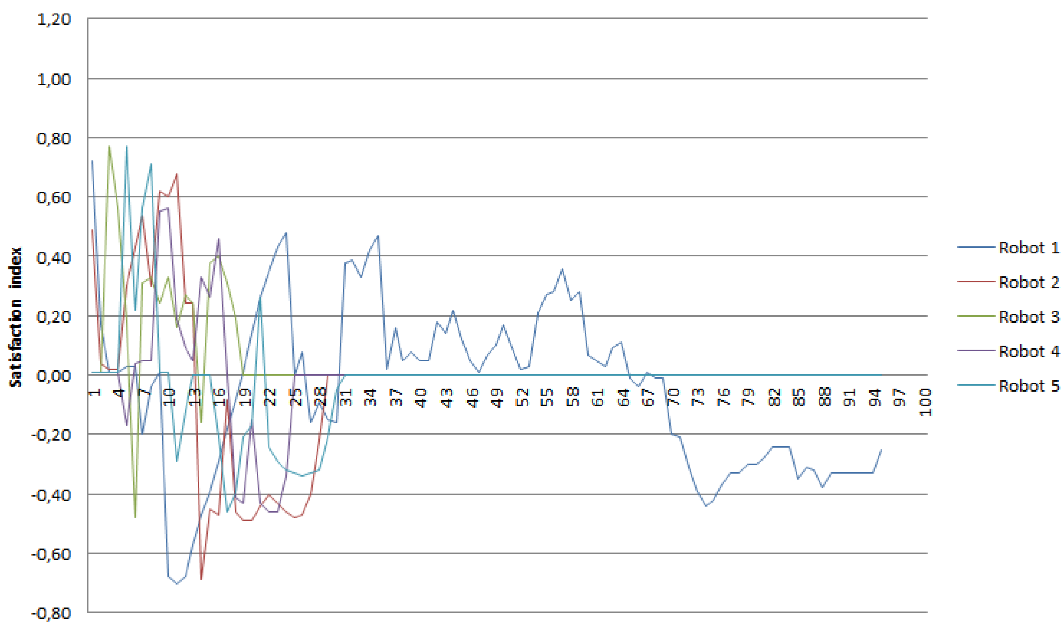

Fig. 5. Evolution of the emotional state of the robots

From this test case are obtained the values of the architectural concepts used to verify the emergence in the system, using MASOES. In Table V, the values obtained in the simulation (initial values) and the final values after executing the FCM, are presented.

TABLE V. ARCHITECTURAL CONCEPTS

Concept	Initial State (based on the simulation)	Final State
Emotion type	0,7	0.5
Social component	0,60	0.88
Aggregation mechanism	0,5	0.90
Reactive component	0,99	0.85
Cognitive component	0,99	0.72
Behavior component	0.9	0.81
Number of robots	0,5	0.66
Behaviour type	0.65	0.97
Direct interaction	0.5	0.86
Indirect interaction	0,5	0.76
Density	0	0.87
Diversity	0	0.88
Synthesis	0	0.88
Independence	0	0.86
Emotiveness	0	0.85
Self-organization	0	0.99
Emergence	0	1

It is observed that the concept of emergence reaches a high value, similar to the self-organization concept. The reactive component maintains its value high and the social component increases its value, which is consistent with the data obtained. Figure 6 shows a comparison between the initial and final values of the architectural concepts, after executing the FCM. The concept of emergence has had a high variation.

Collectively, the robot group has a slightly negative emotional state, which makes that the behaviors in the system are reactive and cognitive. We remark that in the test case based on hunting such behaviors occur. For example, sudden changes steering movements to avoid collisions with other hunters, sudden speed changes to follow the prey, etc.

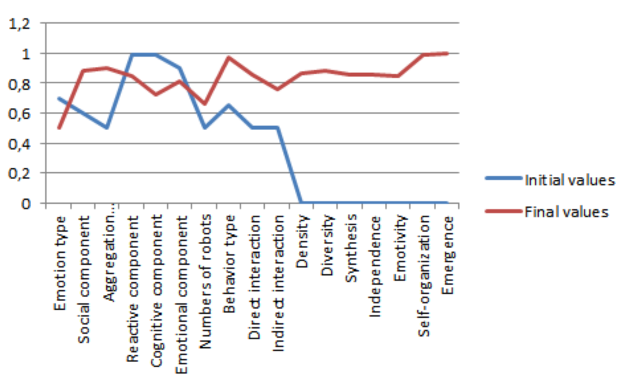

Fig. 6. Architectural concepts variation

V. CONCLUSIONS

The proposed architecture (AMEB) facilitates the emergence in multi-robot systems, through its three layers. The architecture allows the local decision-making in each robot, and supports the interactions of the robot with the environment and with other robots.

The behavioral component of the robots allows different behaviors and intentions towards the execution of a task. This component is based on an emotional model, which allows the recognition of the emotions in order to generate emergent behaviors. This gives a large flexibility to the system to execute different tasks. For example, the method for the collective decisions in the multi-robot system is based on the emotions.

The emerging properties of AMEB were proved in one task that occur in nature, in some animal species, where they carry out collective hunting of moving prey. The results obtained in the experimentation show that the architecture is capable of managing tasks of this type, based on an emergent behavior.

The emergence of behaviors since emotional states is not mentioned explicitly in previous works about emergence in multi-robot systems [3, 4, 5, 6] or emotions in robots [13, 14, 15, 16, 28, 29, 30, 31]. In our work, the inclusion of emotions facilitates the emergence, since the individual can respond in different ways to the situations presented to it. In our proposal, the inclusion of the emotions allows emergent and self-organized processes [18, 19, 24].

Next works will be dedicated to extend this model considering more emotions, more situations (scenarios), among other things, in order to test the scalability of our approach. Also, more experiments will be carried out with real robots with the ability to recognize emotions in other robots, so that the recognition influences the decision making and the actions they carry out.

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