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Evolutionary utility of emerging communication systems and Singnal Complexity in Robotics

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Abstract. Communication allows robots to exchange information and coordinate to solve complex tasks. Evolutionary methods are used to emerge communication in groups of robots. However, many variables are involved, and they must be studied to understand their influence on the emergence of communication systems. Thus, a study is presented to try to understand if a standard approach is more effective than using Evolutionary Robotics in order to produce development signals. For this, an environment is adapted to solve the task of discrimination between food and poison areas, which favors the emergence of signals. The experiments are performed in a simulated environment using FARSA and the Marxbot platform. Furthermore, we set three experiments varying the complexity of the emerging communication system in order to measure fitness levels. Finally, we found that a communication system involving more signals significantly increases the task's fitness.

Keywords: Emerging Communication Systems, Artificial Neural Networks, Evolutionary Robotics.

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1 Introduction

From the perspective of Artificial Intelligence (AI), one of the most important components that trigger different levels of intelligence is the communication capacity in certain living species. This component enables these species to exchange personal and environmental information, thereby facilitating cooperation among organisms. In the case of AI, there are various levels for the study of intelligence, one of which is Autonomous Robotics (AR), due to the potential for groups of robots to solve complex tasks in a coordinated manner. Moreover, robots are artificial platforms that allow the development of social, learning, and evolutionary characteristics (Pretorius, Du Plessis, & Gonsalves, 2019), which, under controlled conditions, resemble those developed by living organisms (Das & Jena, 2020).

In this way, robot groups use their communication skills to achieve their goals and make individual and coordinated decisions (Alsamhi, Ma, & Ansari, 2020; Grouchy, D'Eleuterio, Christiansen & Lipson, 2016). This property demonstrates the potential of communication systems in autonomous robot groups. Regarding communication systems, there are various methods to establish them, but two stand out from the rest. The first is programming the production rules and the meaning of the signals. However, this methodology may not be very flexible, and the interaction mechanisms are influenced by the perspective of the programmer. This can result in communication systems that are neither favourable nor useful for robots that must operate in dynamic environments.

The second option is to allow communication systems to arise from the interaction between robots. That is, they emerge as a consequence of the group synchronization. For this, it is necessary to build the appropriate tools for the robots to generate their own communication and synchronization rules. This development approach has the main advantage that the emergence of signals occurs as a consequence of the interaction of the environment and the task. Thus, it is necessary to study the different variables involved in the emergence of communication systems in robots (Alsamhi, Ma, & Ansari, 2019). One of these variables is the complexity of the Emerging Communication Systems (ECS) and their relationship with the complexity of the control systems of autonomous robots. This variable is the one studied during this investigation.

One of the reasons to consider an ECS as complex is given by the number of signals that can be produced and interpreted. Thus, a system based on a pair of signals (binary communication system) is less complex than a system that includes additional signals. For a communication system to emerge and be established, it is necessary that the task and/or the environment be challenging for the robots to require communication skills to solve tasks. Thus, if the environment is complex enough, ECS can emerge and establish themselves. Another factor that seems to dictate the emergence of communication systems in nature is the complexity of organisms. A more complex communication system requires a more developed nervous system to process elaborate signals.

In this way, it can be hypothesized that communication systems with more signals tend to emerge and establish themselves in complex environments, but that they are also more effective if the control system or systems are also complex. Therefore, the present paper seeks to identify if communication systems with an extra number of signals are more useful from the evolutionary and adaptation perspective than a binary one. This article is organized as follows: in the second section, the relationship between a branch of autonomous robotics and emergent communication systems is introduced; in the third section, relevant research for the emergence of communication in robots is shown; the fourth section, presents the details of experimentation and results validation; in the fifth section, results are shown; while in the sixth section, the interpretation of results and discussion is presented. Finally, the last section, addresses our concluding remarks.

2 Evolutionary Methods in Robotics

Natural evolution is the mechanism for the emergence of communication systems in living species. Thus, communication systems are the result of environmental adaptation. The adaptation of the species provides mechanisms for natural selection. Thus, individuals that best adapt to the environment are the ones with the greatest possibilities to preserve their genetic information. Living beings are equipped with different tools in order to develop communication. For example, microorganisms use either chemical (Baeckens, 2019) or electrical signals (Frommen, 2020). Besides, ants (Shamshirband, Babanezhad, Mosavi, Nabipour, Hajnal, Nadai, & Chau, 2020) and bees (George & Brockmann, 2019) use communication to explore near places in search of means of subsistence. It also allows them to identify the location of food and potential hazards. There are other organisms, with more developed and complex nervous systems, such as whales, which use communication systems to locate food areas, danger warnings, and even awareness of emotional states (Pérez, Jensen, Rojano-Doñate & Aguilar De Soto, 2017).
As for humans, communication is more complex (Holler & Levinson, 2019). In this case, evolution has solved complex tasks such as knowledge transmission or reasoning (Gupta, Savarese, Ganguli, & Fei-Fei, 2021), which are performed verbally and nonverbally (Mavridis, 2015). Therefore, facilitating the social and cultural development of species (Mesoudi, 2016). The emergence and development of communication in the human race is also associated with the adaptation of the central nervous system (Bornkessel-Schlesewsky, Schlesewsky, Small & Rauschecker, 2015); initially, communication was based on simple sounds. Currently, the development of this system has helped in the generation of different languages with precise rules for its use.

These examples allow us to confirm that the emergence and establishment of adaptation tools in several species persist as long as it is useful. In other words, communication is a tool that facilitates the development of different daily activities. As a consequence, in nature, the higher the environmental pressures, the greater the challenges organisms must face, which results in the adaptation of the development of the central nervous system. One approach consists of mimicking some of the characteristics that nature has developed to solve problems and apply them to the development of technology (Pertuz, Llanos, & Muñoz, 2021). In other words, the nature's path of emergent communication has inspired us to simulate this on mobile robots. Next, we need to create some artificial conditions to allow the development of control systems that act as some kind of artificial nervous systems (Scutt & Damper, 2019), (Rodrigues, Duarte, Figueiró, Costa, Oliveira & Christensen, 2015). Then, artificial evolution on autonomous robots acts in a similar fashion to its natural counterpart.

The branch of AI that combines these characteristics is Evolutionary Robotics (ER). It studies the evolutionary mechanisms that allow the adaptation of the control elements and morphology of autonomous robots in simulated and physical environments (Pandey, 2022), (Nolfi, Bongard, Husbands & Floreano, 2016). In the case of control systems, optimization tools such as Artificial Neural Networks, Bayesian Networks and Fuzzy Logic Systems are used (Kim & Chon, 2020). The adjustment process of these tools is carried out using an evolutionary computing algorithm such as a Genetic Algorithm (GA). These approaches simulate the process of adapting species to environments, so that the best solutions improve after several iterations. Thus, artificial evolution (computational optimization) is complemented by the environmental pressure that dictates whether a solution is good enough, or not, to solve a given task (Eiben & Smith, 2015).

Based on the above, the ER has three important elements to achieve the emergence of behavior (through the artificial nervous systems): control system, evolutionary process, and the environment itself. Regarding the first component, ANNs are the most important tool used as an information discriminator or control element (Woodford & Du Plessis, 2020), (Bongard & Levin, 2023). This is due to their ability to adapt to the various tasks and dynamic environments, as well as their signal processing capacity (Shah, Powers, Tilton, Kriegman, Bongard & Kramer-Bottiglio, 2021), (Doncieux, Bredeche, Mouret & Eiben, 2015). In addition, it is a bioinspired computational model, in which electrical spikes occur, similarly as in the nervous system.

This model is made up of neurons as basic units, which can change their activation status according to the stimuli presented to them. Activation depends on the influence of the weigthed input simulating synaptic connections. Dense neurons are grouped in layers, so in a feed-forward architecture, information travels from the input layers; typically, with more neurons, to the output layers that have fewer units. This characteristic is important in an ANN because it allows for improved preprocessing on layers: feature detection in the input layer is greater than in the output layer. So, the ANN receives as input sensory information, and in some cases, the information about some of the internal status of the robot. While the output layer is associated with the actuators.

Although both the ANN architecture and the synaptic weights may be coevolved, this complicates the computational search processes carried out by the GA (Kim, Coninx & Doncieux, 2021). This is due to the number of variables that this operation implies (Hiassat, Diabat & Rahwan, 2017). Therefore, on many occasions the evolutionary process only affects the synaptic weights of the ANN. The GA is the most suitable method to adjust the weights of an AAN since the coding of the information for the genotype can take direct values. It is important to point out that evolutionary tools such as a GA produce unsupervised learning. That is, the sequence of actions, or behaviors, emerge under the guidance of a mathematical function called the fitness function. This approach has advantages over other supervised learning algorithms such as backpropagation. This is because the difficulty of creating a database with all the stimuli to which the robot is exposed under different environments. Particularly, if the sensors and actuators are not encoded in a binary format. The second advantage is that the solution of a selected task emerges from the interaction of the robot and the environment, not from the programmer's point of view and its logic of solution of the task.

In the case of artificial environments, the necessary conditions for the emergence of the task should be considered (Gershenson, Trianni, Werfel, & Sayama, 2020), (Trianni & López-Ibáñez, 2015). Among the factors that influence the results are the task to be solved, the involved objects for the task and if the selected task is solved by one or more robots (Cambier, Miletirch, Frémont, Dorigo, Ferrante & Trianni, 2020). In the study of the emergence of communication systems in robots, the design of the environment plays a crucial role (Campos & Froese, 2019). Therefore, if there are no situations or places that should be referenced, the emergence of signals does not occur (Bredeche, & Fontbonne, 2022). Signals are not produced if the communication cycle variables do not exist (sender, receiver, channel, and message). The sender is the one that sends the message, for this it uses a communication channel. The receiver receives and encodes the message, usually to produce a reaction. Because of this, communication systems between individuals that pursue the same goal act as a communication channel (Blumenkamp & Prorok, A, 2021). A signal can emerge in an evolutionary process, as part of the configuration of the search space. This occurs mainly at early stages of the optimization process because this is when exploration often takes more random starting points (Eccles, Bachrach, Lever, Lazaridou & Graepel, 2019). But if the emergent behavior is not enough, the signal must be established using an adequate evolutionary strategy (Simões, Lau & Reis, 2019), (Gigliotta, Bartolomeo & Miglino, 2015). For this, the signal has to be put on a context, which occurs when the receptors react to the perceived signals (Flitch, 2020).

In the case of ER, communication can be effective, and also acts as an additional variable in evolution (Zhu, Neubig & Bisk, 2021). To understand and improve signal emergence, it is important to include all the variables that are involved for communication development (Rashed & Amin, 2016).

3 Related work

One of the experiments on signal emergence in robot groups using ER techniques is presented by Floreano, Mitri, Magnenat & Keller (2007). This work serves as an inspiration for the research presented in this article. The experiment consists of selection between food and poison zones. A group of ten s-bots is set on an arena without walls. Inside the arena are a food and a poisoned zone. These areas were represented by spherical devices that emit a LED red light. Robots start at a random position and must find the food zone. They should also avoid the poisoned area. For this, the s-bots have light communication, by means of a group of LEDs that emit signals that are captured by linear cameras. The color code for a communication signal is blue and it has a binary status (on-off). As for the input layer of the neural networks, it takes values from the location zones (poisonous or

healthy), color components of the color ring (blue or red) divided into four sections that represent a segment within a circular area in a 360-degree field of view. Three neurons were set for the output layer, two encode the robot's motor speed and one to switch on, or off, the blue LED ring.
To adjust the weights of the neural network, a generational genetic algorithm iterates 500 times over a robot colony of 100 groups of 10 individuals. The GA uses selection, crossover, substitution, and mutation operators. Four experimental groups were created, and each was evolved 20 times. The performance of the robots in the last 50 generations of the evolutionary process is measured. This is because the signaling strategy is considered stable at the last stage of optimization. This article proves that communication systems are useful for solving the task of poison avoidance. Communication is often developed when the robot group shares the same genotype. Thus, making a homogenous group that shares the same genetic map that leads to a common resolution strategy. Avoidance occurs when a robot finds a food zone, emits a blue signal, and then makes a circular movement around the food zone. It is reported that if the group of robots shares genes, that is, they are clones given their chromosome map, then the solution is better (Wu, Zhu, Ma, Wang, Bao, Li, & Fan, 2022).

Thus, the strategy involves notifying the rest of the individuals about an area harmful to the colony of robots and moving them away from it. These findings are reported and further expanded on the work of Floreano, Mitri, Pérez-Uribe & Keller (2008). In a heterogeneous colony, fitness levels are low because the produced signals are not relevant. In this case, signals do not generate a response from receivers and communication is not established. The design of the environment and the task to be solved are a good test platform for the study of the emergence of communication in autonomous robots using evolutionary robotics (Bernard, Wischmann, Floreano & Keller, 2023). Although, basic communication occurs with a minimal artificial nervous system. Evolution aids in setting the context for robots to a particular situation that can be signaled by activating the led ring (Santos, Pardo, Ciria, & Lara, 2021). However, an open question remains; if the environment is more complex, will a basic communication system be more effective than one with unnecessary additional context signals (Talamali, Saha, Marshall, & Reina, 2021).

4 Experiment

The objective of this research is to demonstrate that complex communication systems have evolutionary advantages when the environment generates the conditions for signals to emerge and be established. This serves as an effective way to prove that a communication system with more signals represents an evolutionary advantage over basic systems with fewer signals. For this, the task of food selection and poison avoidance is chosen, but with a modified environment. In the original experiment by Floreano et al. (2007) robots tend to point out one of two available zones. This is because they only have one available signal. Our proposal consists of creating an environment that favors signaling under different situations.
In this way, the environment is comprised of a rectangular arena without barriers (see figure 1). The color of the center of the arena is gray (125, 125, 125 in grayscale) and inside of it, robots are initially placed. The central area of the arena is surrounded by walls from left to right. On the left side, the food zone is located, in this case the shape is rectangular from the bottom to the top. The color of this area is white (255, 255, 255 in grayscale).

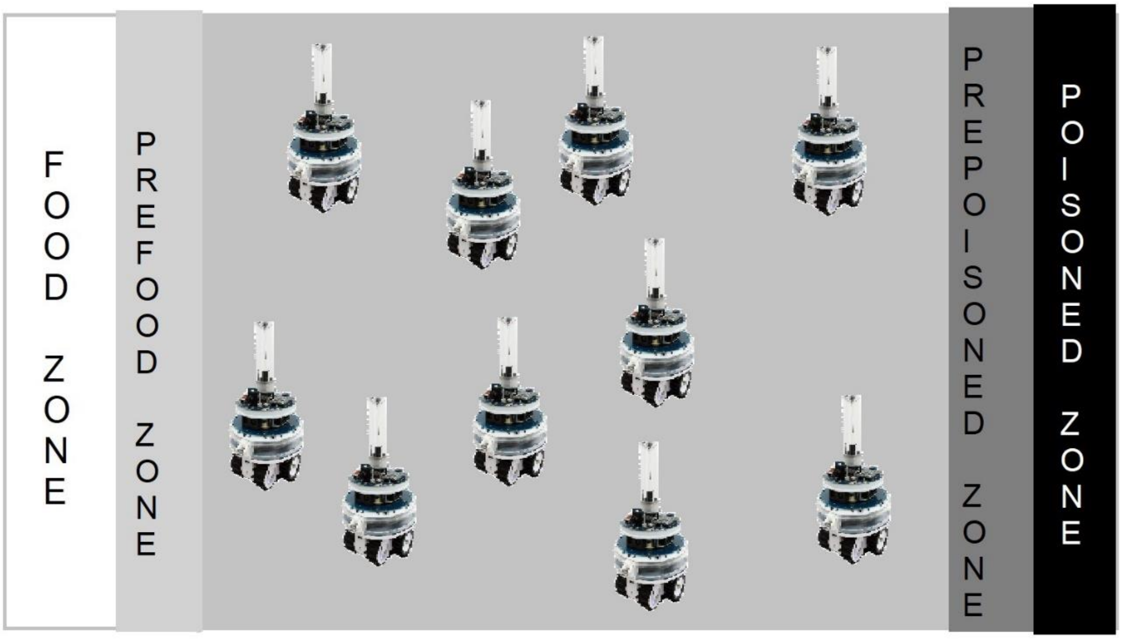

Fig. 1. Environment setting used during the experimental procedure.

An intermediate rectangular area is included between the food zone and the central area of the arena. This area provides some context to indicate to robots the proximity of food. It has the same length as the food zone. This zone is called the prefood zone and is set in a light color (200, 200, 200 in greyscale). The prefood zone replaces the red signal that guides robots in previous experiments (Wishmann, Floreano & Keller, 2012). A similar procedure is performed at the other side of the arena. A rectangular black zone (0.0.0 grayscale) is included to represent the poisoned zone. Opposite the food zone, a pre-poisoned zone is established. A dark color (90, 90, 90 in grayscale) is chosen to differentiate from the rest of the zones. This configuration adds situations that robots can signal, thereby increasing the complexity of the original design. Thus, the robots could potentially signal the food, prefood, poison and pre-poisoned zones food zone, in addition to proximity of walls. Next, 10 Marxbots are scattered around the arena. These robots are built to solve tasks that involve coordination and have sensors and actuators that allow the development of communication. The robot, among other features, has 24 infrared sensors, 12 floor sensors, a linear camera, two pairs of motors that are connected to the treels (a combination of tracks and wheels), a ring of LEDs around its body, among other features.

The experiments are performed in the FARSA simulator (Massera, Ferrauto, Gigliotta & Nofi, 2013). This is an open-source software based on the physical characteristics of real robot models. It is a suitable means for ER experiments because it has several computational robot models, control tools such as ANN, and evolutionary computing algorithms like GA. In the literature, ANNs are used as control systems for colonies of robot groups. The configuration of the ANN is a multilayer feedforward, and the synaptic weights are optimized (see fig 2). The design of the network follows the needs of the environment, the task, and the complexity of the exploration of the solution space. The sensors used for this task are infrared for detecting nearby objects, floor sensors to detect changes in the color of the arena, and a linear camera with its various associated components. Two differential motors, along with an LED ring, are used as actuator elements. The neurons in the middle and output layers of each network include a bias to improve the activation threshold.

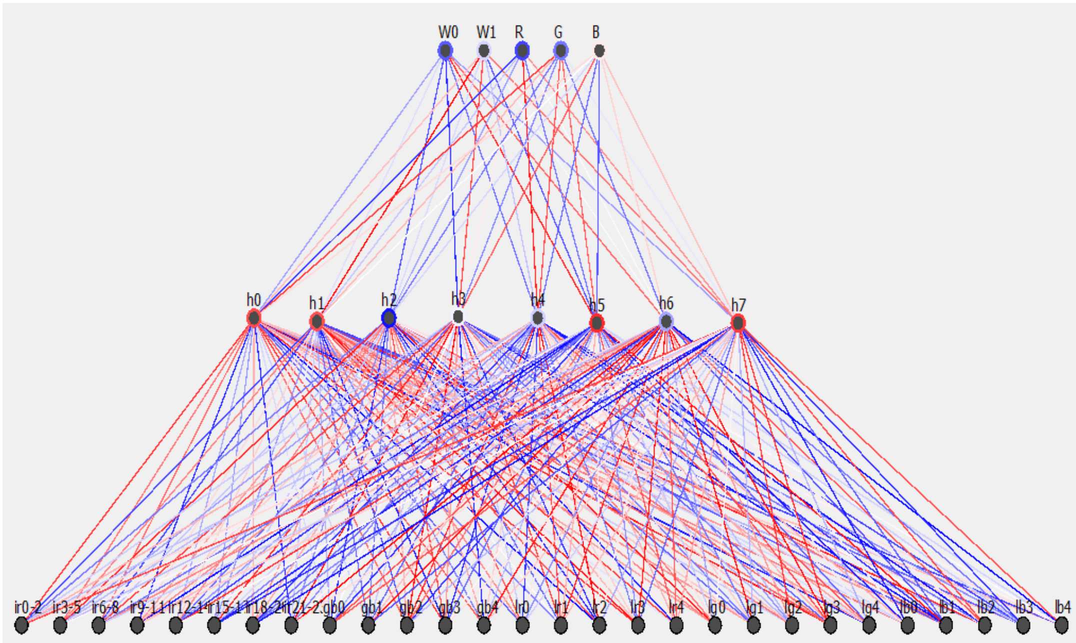

Fig. 2. Configuration of the Artificial Neural Network used to control the robots.

The infrared sensors use binary values, having a value of 0 when there are no nearby objects and 1 when an object is detected. The MarxBot has been equipped with 24 IR sensors, in order to reduce the number of input values we packed in groups of three as a form of sensor fusion. So, it is enough that one of the three sensors of each group activates to detect the presence of an object. Therefore, for the infrared inputs we have 8 neurons (ir0-2 to ir21-23). As for the floor sensors, five grayscale levels are selected: black (0,0,0), dark gray (90,90,90), medium gray (127, 127, 127), light gray (200, 200, 200) and white (255,255,255). Next, the neural network adds information from these five neurons to the input layer (gb0 to gb4). The associated information for these neurons is binary (the presence or absence of a grayscale tone).
For the linear camera, 5 segments representing 72 degrees of a circular area are used. Within these segments, we detect the presence of color in the RGB space (red, green & blue). If one of the components is present within a segment, then the associated neurons send a signal value of 1; otherwise, neurons receive a value of 0. Each ANN has five input neurons to detect the red color (lr0 to lr4) in each segment of the linear camera, and the same for green (lg0 to lg4) and blue components (lb0 to lb4). Hence, making a total of 28 units at the input layer. Next, the middle layer consists of eight neurons (h0 to h7); while the output layer has five neuronal units. Motor speed is coded through the activation level of the two neurons in the output layer (W0 and W1). RGB outputs are used to set the color of signal emitted. In total, the input layer of the ANN is composed of 28 units; and the synaptic weights can take either positive or negative values. The total number of synaptic weights to optimize for each ANN is 305. In comparison with the original experiment, the ANN we used is more complex since it adds a middle layer, and an increase in the number of employed sensors, which results in a more complex search space to explore.
For the evolutionary process, a steady-state GA is used (see table 1), which accelerates the convergence of the search space in comparison to the generational GA. Each evolutionary process consists of 500 generations with 20 individuals or chromosomes each. Then, all chromosomes are tested in the simulated environment 20 times, with each test lasting 500 steps. A final mutation percentage of 2% is used. In each test, the same chromosome is replicated for all ten robots in the colony.

Table 1. Steady State Genetic Algorithm parameters

Characteristic	Value
Generations	500
Individuals	20
Mutation rate	2%
Number of individual trails	10
Number of steps for trial	300
Replication	30

As for the communication system, as previously mentioned, it uses the LED ring as a signal emission element and the linear camera as a detection element. So, the communication system has a visual channel based on signal colors. The fitness function rewards with one unit for each step that each robot remains in the food zone. At the end of each test, the fitness scores of all individuals are summed to calculate the chromosome’s fitness.

$$fitness_{robot} = \sum_{i=0}^{trials} \left(Step_{food-zone}\right) - \sum_{i=0}^{trials} Step_{poisoned-zone} \tag{1}$$

Three experimental groups were created, which were characterized by the number of signals that robots produce. The same ANN configuration is used for all experimental groups as a control condition. The groups are named: 2-signals, 8-signals, and multi-signals. The simplest communication system is binary (2-signals). In this case, the robots either produce signals in red or do not produce signals. This communication system is similar to the original experiment. For the 8-signals communication system, the robots produce r+g+b signals based on the activation of the binary states of red, blue, and green colors. Finally, the multi-signal system is based on the combination of colors produced by the activation of the neurons in the output layer. The difference from the second group is that neurons are not activated in binary form, but in RGB combinations of integer numbers from 0 to 255. This implies a cardinality of 333,375 potential signals. Each treatment is replicated 30 times; then, the average fitness of the last 50 generations of the best individual in each replica is measured. Fitness is used in ER to quantify the adaptation of individuals to their environment. If a robot architecture is favorable in the evolutionary sense, then the benefit will be reflected on the final score. The reason for recording robot performance after several iterations is to have a more realistic fitness level of the robot group when the communication system is more stable. As a consequence, it provides us with insight into the true development of the communication system.

A communication system is considered established when the signaling strategy does not change after several generations (Marocco, Cangelosi & Nolfi, 2003). By manipulating the complexity of the communication system through the artificial nervous system, fitness levels depend on the implemented underlying mechanisms. To compare the performance between treatments, a one-way ANOVA for ranges is used ($p < 0.5$). Since the data did not pass the normality test, this statistical test is complemented with a post-hoc Student-Newman-Keuls. The prediction for this experiment is that the fitness of the most complex communication system will be the highest. This is because robots can take advantage of the context given by different situations that can be signaled.

Finally, signals are produced under four specific situations and arranged in a matrix as: food-zone, poisonous-zone, food-prezone, and poisonous prezone. The prediction in this regard is that more complex communication systems favor the appearance of signals in new conditions.

5 Results

The fitness level of the three procedures (see figure 3) show that the highest fitness score corresponds to the multi-signal communication system, i.e., 8,931.32. This group represented the maximum value of complexity with respect to the number of signals that the robots produce. The lowest fitness level is that of the simplest communication system, which is 8,674.9. The average fitness value, 8,725.88, of the three treatments occurred in the group with 8-signals. The statistical analysis shows significant differences between experimental groups ($p = 0.026$,89 df, $n = 30$). The post-hoc test indicates that the treatment corresponding to the multi-signal communication system is statistically different ($p = 0.008$) from the other two. This procedure also showed that the groups with 2-signals and 8-signals are not significantly different from each other ($p > 0.005$).

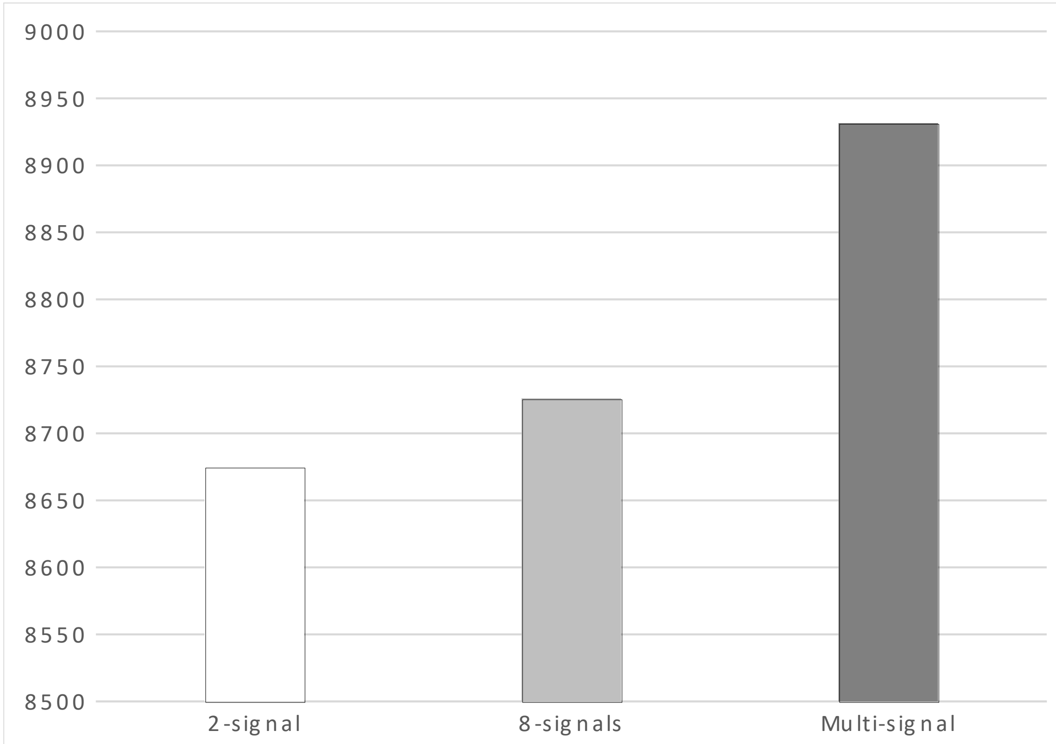

Fig. 3. The fitness comparison of the different communication systems.

Regarding the production of signals (see table 2), in the 2-signal communication system, the robots point to the food zone and the poisonous zone. For the 8-signal system, the production of signals occurs in the food zone, the prefood zone and the poisonous zone. In the case of the multi-signal communication system, all the five zones are signaled.

Table 2. Places marked by the different treatments.

Manipulation	Food zone	Pre-food zone	Central arena	Pre-poisoned zone	Poisoned zone
2-signals	Yes	No	No	No	Yes
8-signals	Yes	Yes	No	No	Yes
Multi-signals	Yes	Yes	Yes	Yes	Yes

6 Results analysis and discussion

This research is focused on the study of emergent communication systems, whose main characteristic is that the participants define the rules for the emission of signals and the produce responses. Hence, we employed the ER approach with the optimization of ANN´s weights using a Genetic Algorithm. This produces environmental pressures on these control tools so that the solution improves generation after generation (Martins & Urbano, 2019). The main objective is to find out if the most complex communication systems, those with more signals, allow improving the solution of a task in a more complex environment. Thus, it has been proven that the complexity of communication systems in autonomous robots is a variable that affects their emergence. For a system with various number of signals to emerge, it is necessary that the environment meets the conditions for this to occur. Therefore, if the environment has more situations to be signaled, then signals emerge and become stable as an adaptable evolutionary strategy. This can be deduced from the results of our experimentation. The comparison between the three levels of complexity of the communication systems shows that those with greater complexity facilitate solving the proposed task. This is due to the design of the environment, which includes five areas where the emission of signals can be established in a straightforward manner.

We noticed from the original work of Mitri, Floreano & Keller, 2011 that robots tend to point out to the food zone. This is due to the collective importance of pointing out that area; as the greater the number of robots in it (Miletitch, Reina, Dorigo & Trianni, 2022), the higher the level of aptitude of the group (Waibel, Keller & Floreano, 2009). If robots emit only one signal, in most of the cases the signals are assigned to the situation that is most favorable (Dorigo, Theraulaz, & Trianni, 2021). At least, in one experiment the signal points out to the poisonous zones (Mitri, Floreano & Keller, 2009). In this case, the evolutionary utility of the signal is to prevent the colony from lowering its fitness score. Similar to the results of the treatment corresponding to the 2-signal communication system, robot colonies solve the task, and the tendency to signal the food zone prevails.

The importance of sending a signal is greater than in the original experiment and is due to the lack of additional light elements that lead the robots to the location of food zones. After the communicative capacity of the robot groups is increased, up to eight signals, fitness also increases. Initially, signals are used to point-out places of interest. Although they theoretically could produce eight different signals, not all emerge and settle after the different repetitions of the experiment. This is associated with the signaling place. Evolution is useful for signaling the food zone, but initially it is not clear what the role of the prefood zone is. After some iterations the prefood zone becomes relevant, because it is used for guiding towards the food zone. Robots signal this area as an initial action that allows the rest of the group to be oriented. This is similar to robots in the first colonies emitting a signal after crossing the prefood zone. Finally, this group also emits a signal in the poison zone, which helps in maintaining the average fitness of the group.

For the third variation of the experiment robots were able to produce up to 333,375 signals, which represents the largest number of all experiments. The signals could be produced in the five different zones (food, pre-food, central, pre-poison, poisonous). This is because signals can be coded in the RGB color space; therefore, in some repetitions of the experiment, robots produce signals in green tones, while others produce signals in yellow, orange, blue, red, pink tones, among others. The signaling of food and the poisonous zone is similar to the original experiment. The signaling strategy of the pre-food zone changed like in the previous group. In this case, robots that are exploring and reach the pre-food zone use this strategy, which allows the rest of the group to find the right direction in a shorter period of time (Hasselmann & Birattari, 2020). This clearly impacts the fitness of the group, leading to a quick resolution of the task.

The utility of the emission of signals in the central zone may be related to the exploration and coordination of the group. By using signals in this zone, robots are coordinated so that exploration is more efficient. These emergent coordination actions are important for solving complex tasks (Borg & Channon, 2020). In the case of signaling the area just before the poisonous zone, it has the evolutionary advantage of preventing the group from losing the overall fitness score. When an individual points out towards the poison zone, it implies that the robot is within an unfavorable zone and its presence represents a decrease in the collective fitness. This action becomes a warning that won't affect the fitness of the group. As initially presented, the complexity of the communication system is related to the complexity of the control system (Fontbonne, Dauchot & Bredehe, 2020). An ANN with more units and more synaptic connections allows more advanced communication systems (Leonard & Du Plessis, 2022). In the case of the experiments presented in this article, the control system is more complex than the AAN presented in the original experiment. The latter is a two-layer network, while the one presented in our work is a multilayer network with extra input units.

As for the experiment of the two signals, the neurons associated with the green and blue components were not necessary for the operation of the network in the coding of the LED ring. However, for the other two versions of the experiment, they are necessary for their operation. Something similar occurs in nature; complex communication systems correspond to the most elaborated nervous systems (Nolfi, 2021). This facilitates the emergence of more sophisticated behavior in the implementation of a multi-signal communication system (Gielis, Shankar & Prorok, 2022). In turn, this leads to the coordination of the robot group when they try to arrive at the pre-food area. Therefore, bio-inspiration is a very important tool for ER (Ponce, Moya-Albor, Martínez-Villaseñor & Bireva, 2020). The use of an approach that resembles natural evolution, where strategies have been developed and incorporated in living species, can be applied to autonomous robots through artificial evolution. This opens the possibility of providing artificial platforms for the study of isolated natural phenomena (Hasselmann & Birattari, 2020); consequently, this method is not invasive for living creatures.

Next, it is important to notice that there are various potential signals in the last group; however not all of them will emerge as signals (Datteri, 2021). This will depend on one hand on their utility (Ecoffet, André & Bredeche, 2020), and on the other hand, on the contextualization process of the colony to complete the basic communication cycle. Evidence from our experiments shows that the selected environment favors the emergence and establishment of communication systems with a greater complexity than those with two signals. The latter, paves the way for the study of the variables that regulate the emergence of communication in autonomous robots. That is one of the recent challenges in ER (Solé & Seoane, 2022). As future work we propose to extend this research by studying the relationship between robot central nervous systems and complex communication system through the use of artificial evolution. This implies adding the topology of the ANN during the evolutionary process. This will lead to a better adaptation to the available environments for the robot colonies to exploit. Our proposal is to use this approach for the implementation of a multi-signal system for labyrinth exploration. Finally, context assignment from the group of robots relating signals to their meaning is a subject that deserves further study.

6 Conclusions

In the presented experiments it has been proven that the emergence and establishment of signals depends on the level of complexity of the communication capacity of the robots. Thus, a communication system with more signals is evolutionarily more useful than a basic one with two signals. This does not imply that a communication system with fewer signals does not serve as a coordination tool to solve a particular task. However, when the environment is highly demanding, a system with more signals will be more adequate. Additionally, complex communication systems often produce the emergence of more elaborate behavior. This is due to the properties of the ANN to make a classification from the available information and the selection of the most urgent action depending on the context set by a particular situation. In turn, this helps evolved robots to improve solutions better than those with simple networks.
As in nature, a set of more developed features is always associated with a nervous system sufficiently developed to control them. Therefore, it shows a relation between the emergence and stabilization of a communication system with several signals and the complexity of the artificial neural network that works as a control element. Finally, the environment design we presented facilitates the contextualization process under different scenarios. Artificial chromosomes may be adapted through evolution, so the reception of different communication signals is related to their emission. A significant pool of signals will be available under various different situations, which in turn will evolve into multi signal communication systems.

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