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Original

The improvement of signal communication for a foraging task using evolutionary robotics

F. Aldana-Franco[a] • F. Montes-González[b]* • S. Nolfi[c]

[a]*School of Electrical and Mechanical Engineering. University of Veracruz. Gonzalo Aguirre Beltrán Circuit, ZipCode 91000, Xalapa, Mexico*
[b]*Artificial Intelligence Research Institute. University of Veracruz, South Campus, Zip Code 91097, Xalapa, Mexico*
[c]*Institute of Cognitive Sciences and Technologies. Consiglio Nazionale delle Ricerche, San Martino della Bataglia st, 44, ZipCode 00185, Rome, Italy*

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Abstract: Communication systems represent an evolutionary advantage for a group of robots solving coordinated tasks. In the field of evolutionary robotics, the emergence and establishment of communication are regulated by different variables. These systems can be fine-adjusted by artificial evolution to improve signal communication. Developing communication signals set a multi-objective, multi-purpose frame that imposes restrictions and opportunities for implementing signal communication. In this article we observe that emergent signals appear due to its role as an evolutionarily tool for solving a particular task. Emitters and receivers generate a conceptualization process, which transforms signals into an evolutionary aid. In this way a foraging experiment is implemented in FARSA with the marXbot robot. The experiment consists of a group of robots that feeds in a safe zone while avoiding a poisoned one. Communication is configured with the LED rings and linear cameras of the robots. In general, individuals tend to point to the food zone to attract the rest of the population. Different signals arise after the robots are exposed to the presence of near objects and the poisoned zone. The contextualization of a developing signal depends on relevant scenarios where the emergence and consolidation of the signals depends on the evolutionary importance of the strategies developed by the group.

Keywords: Evolutionary robotics, communication systems, FARSA, artificial neural networks, marXbot

*Corresponding author.
E-mail address: fmontes@uv.mx (F. Montes-González).
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1. Introduction

Communication in robotics is a useful tool that allows the exchange of information on environmental and individual states (Mitri et al., 2011). Robots use their communication skills to interact with robots, humans, also on electronic devices.

A channel, a transmitter, and a receiver are necessary to establish a communication system in robotics. The emitter sends signals through actuators, then the receiver picks up signals using sensors. In this way, if the receiver does not have sensors to acquire signals, communication does not occur. A channel is the communication medium in which signals are transmitted. These three elements are essential for communication, particularly for evolutionary communication systems because optimization methods evaluate different solutions to choose the one that allows the best information exchange channel.

There are many ways in which a group of robots acquire communication skills. One way is to define a set of signals and their meaning from design. Then features are identified and programmed as fixed functions using the distal point of view. Another option is to induce the emergence of communication using an artificial evolution process using the proximal point of view (Nolfi, 2021). In this way, environmental conditions put pressure throughout the artificial evolutionary process to guide emergence and the establishment of signals. In this way, the emergence and establishment of signal communication depends on the robot experience and different variables, some of which have not been completely studied. Therefore, it is important to understand all the mechanisms and variables involved in this emerging process (Steels, 2003).

For a communication system to emerge, it is possible to use the evolutionary robotics (ER) approach (Bredeche et al., 2018). In ER the morphological and / or control structures are the result of the iterative pressure conducted by an artificial evolutionary process (Heinerman et al. 2019; Nolfi, 1998). A common representation of control systems in ER are artificial neural networks (ANN) optimized by evolutionary algorithms (Alattas et al., 2019), such as Genetic Algorithms (GA) (Baldominos et al., 2020). One of the reasons to use evolutionary algorithms is because it is difficult to create a database with all the stimuli that robots face to train the network with a supervised algorithm such as Backpropagation (BP).

Works in the field of ER focus on the evolution of primitive brains that rise under specific environmental conditions (Pretorius et al., 2019). In this way, evolutionary processes are multi-objective optimization methods that traverse search spaces composed of different variables such as sensors, actuators, and control objectives (Egbert et al., 2019). These search spaces are usually complex to explore given their dimensionality. This generates poor results in terms of the control objectives pursued by the robots. If the action of the different variables involved in the optimization process is already known, the complexity of the search space can be reduced (Woodford, & Du Plessis, 2020). For this reason, it is important to understand how artificial environmental characteristics influence evolutionary methods (Bongard, 2013).

This article presents research into the evolutionary importance of signaling strategies and how it affects the emergence of signals. The research started from the premise that when a group of robots establishes a set of signals, a process of contextualization occurs through the generations. This causes the robots to associate the signals with the situations they are confronting. This relates the evolutionary utility of the signal with the contextualization process of an artificial society. This would explain that the signals with less evolutionary advantage can emerge in an evolutionary process but are not well established. From this perspective, it is important to study the evolutionary advantage of communication systems in terms of aptitude and appearance of the signal.

In our work, an experiment was set up to show that the evolutionary advantage of the signals relates to their emergence, which means that restrictions were implemented depending on the environment where robots were placed. The measurement method, which is ample used in ethology, was incorporated to quantify the established signals, and identify the context in which they occurred. Finally, the communication systems were compared in terms of suitability, the number of signals established, and the places where the signals originated.

The document is organized as follows: below we introduce the problem, the justification and the objective of the investigation, in the experiment section the prediction and configuration of the experiment are described; The results section shows all the quantification of the experimentation; the discussion section presents the analysis of experimental results; and, finally, we show some concluding remarks and future work.

2. Related work

In evolutionary robotics, communication systems allow robots to exchange information and the emergency of coordination in groups (Trianni et al., 2004; Martins et al., 2018). For this, communication is based on actuators such as wireless and radio frequency signals, sound, lights, and movements (Hasselmann et al., 2018). The latter is one of the most relevant research fields in the development of ER (Campos & Froese, 2019; Rasheed & Amin, 2016).

Communication skills tend to emerge in robot communities that develop collaborative or competitive tasks as a solution mechanism for the implemented task (Ampatzis et al., 2008). An example is the experiment known as poison and food task for evolutionary robots, which is configured by Floreano et al.

(2007). In this scenario, an evolutionary mechanism is represented for the emergence of communication in robots. In addition, it allows the study of different experimental variables to understand some of the underlying mechanisms for the appearance of communication systems (Palacios-Leyva et al., 2018).

The original experiment consists of a group of robots exploring an environment with food and poisoned areas. The environment is set up with four S-bots in a virtual arena; two devices produce red lights with LEDs. These components represent food and poison zones. The robots find food zones and stay there, they also avoid the poison zones. The robots are controlled by an ANN and the synaptic weights are optimized with GA. The fitness function assigns a point for each step that each robot stays close to the food. The communication is based on LEDs (turn on and turn off) and it is not rewarded in the fitness function. Our main goal presented in this work is to study the usefulness of emergency communication in groups of robots. In experimentation, teams with communication skills are compared to groups without communication skills. The results show that robots that can communicate use this ability to attract the rest of the group with their signals. In this way, when a robot finds the food zone, it begins to surround the food while emitting signals. This task solution strategy is important because the signals are more likely to be seen by other robots than if the robot remains static emitting signals. Thus, it is known that robots with communication skills get to the task in a better way than groups without communication. Communication skills help robots to achieve their evolutionary goal using cooperative strategies. Furthermore, the results show that signals emerge to indicate food to a greater extent than in the poisoned area. This is because the evolutionary advantage of targeting food is greater than poison. Food localization is the goal to achieve during the evolutionary process.

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As for the work of Floreano et al. (2008), they use the same scenario to study the development of signal communication related to group composition. Teams with communication tools are configured in two ways: heterogeneous and homogeneous. Both are classified using a genetic point of view. Robots with identical chromosomes are clones and form homogeneous populations. Groups of robots with different chromosomes are integrated into heterogeneous populations. The evolutionary process consists of 500 generations of computational optimization. The evolutionary process is based on a simulator that reproduces the physical conditions of robot operation. There is no evidence of a particular algorithm is used to adapt simulated ANN to real robots in this study. To evaluate robots at the end of evolutionary processes, teams of robots are selected in four separate ways: homogeneous population, heterogeneous population, the best homogeneous individuals, and the best heterogeneous individuals.

In homogeneous populations, robots mark food areas to attract other individuals. This is not the same as in heterogeneous populations. Thus, as a result, the composition of the equipment is a factor in the appearance of signal communication. This variable improves the strategies for solving the proposed task when the emerged signals are more relevant to the context than in heterogeneous populations. This is due to the evolutionary advantage associated with the exchange of information and composition of populations, which improves their collective aptitude (Mitri et al., 2011).

As for heterogeneous populations, they are unable to maintain reliable communication in the group. A consequence of this is due to the low emergence of altruistic behaviors in heterogeneous populations (Waibel et al., 2009). In other words, the gathering of individuals of the same species to the feeding areas increases the fitness of the team, which is a valid strategy for individuals who share the same evolutionary goals (Scott-Phillips et al., 2012).

This situation was also identified by Lehamn and Keller (2006). They relate to the cost-benefits for the members of a group, as a factor of coordination strategies. In this way, if the cooperation does not imply a negative cost-benefit for the robots; then this type of strategy is evolved. Furthermore, cooperation arises when there is a genetic relationship between individuals. This is the case with the poison and food experiment. Homogeneous teams increase the level of cooperation through communication because clones benefit by sharing evolutionary goals.

This characteristic is shown in nature. Both ant and bee colonies, cooperate to increase their survival capacity (Grueter & Keller, 2016). These societies are hierarchical with already established roles and genetic relationships. Ants have developed a communication system based on a chemical channel and it is used to indicate exploration routes and food (Trible & Ross, 2016). Pheromones are left as a trail by scoutants to point out food sources. A similar behavior is present in bee societies. Movement and humming are used as signals in a complex communication system. In this case, the communication channel is visual. When bees find a food source, they return to the hive and perform a dance to communicate the location of the food source (Van der Steen, 2016). Both cases are a representation of evolutionary development of signal communication in nature and its relationship to the genetic development.

As mentioned above, the emergence of signal-based communication in evolutionary robots is not affected only by population composition. The emergence of communication could also be associated, like any other cooperation strategy, to the cost of the emerging strategy and its relationship with the environment (Steyven et al., 2015). Thus, an evolutionary advantage is a beneficial condition that helps individuals in a population to improve the level of collective fitness in an artificial evolutionary process. Therefore, the emergence and establishment of signals could be the result of the associated value of the strategy of signaling situations that need attention.

In this way, the emergence of signals can be studied from the perspective of the signal and the contextualization that individuals relate environmental conditions and signal emission. An example occurs when robots point to food zones. Initially the signal appears in the evolutionary process as a potential solution, which leads to exploring the search space. This strategy develops during the evolutionary process because the rest of the individuals interpret this as a response of a robot that has found a food-zone. Although a signal emerges and represents a potential reward for the group, is does not fully develop if is not related to an environmental condition. Thus, signals receive a specific value depending on the context of a developing communication system (Solé et al., 2010). After a set of signals has been properly contextualized, communication systems are considered as fully established.

Therefore, senders and receivers develop skills to interpret signals and understand their content. In other words, robots associate the context in which a signal is produced and generate a significant message (Loula et al., 2010). Signals and their context are developed after exposition to adaptive conditions depending on environmental characteristics, which represent a factor that regulates the appearance (Nolfi, 2013) and establishment of robot communication skills (Montes-Gonzalez & Aldana-Franco, 2011).

3. Experiment

The experiment was set up to show that signals emerge and settle down due to an evolutionary advantage in signaling a place or situation. Therefore, it was hypothesized that the signals appear because they offer an evolutionary advantage. In the case of the fitness for the best group using signals; if we reduce its the evolutionary advantage under a particular situation, then new signals emerged under different situations.

Therefore, we implemented a modified version of the original experiment of the poison and food task (Mitri et al., 2009). In the original experiment, homogeneous groups of robots tend to target feeding zones as they move around (Floreano et al., 2007). This experiment setups a framework where signals are useful for evolving robots. Hence, there is an increase in fitness of those groups of individuals that make use of emergent signals.

Next, a lockout condition was designed that sets the motor speed to zero for robots arriving at feeding zones. As soon as a robot reached a food area, it was not allowed to move. So, this action lowered the evolutionary benefit of marking food zones. It is important to mention that the locking condition is not implemented for the poisoned area. The original experiment showed that pointing to this place occurs less frequently and does not sum up to the result.

In this way, an experiment composed of two experimental groups was designed. The first experimental group was called the control-group. In this version, the locking condition was not applied. The second group was named blocked-condition-group. In this experimental group the blocking condition is implemented.

The level of fitness for the second group was expected to be lower than the control group due to the reduction in evolutionary advantages implied by the blocking condition. Furthermore, it was expected that signals emerge under new environmental situations.

The original experiment of Floreano et al. (2007) presents a simulation model without a specific adaptive method to assess the results in real environments. This suggests robustness in the evolved controllers where the reality gap factor does not represent a problem for this experiment (Meier et al., 2021; Mouret & Chatzilygeroudis, 2017). For this reason, experiments were conducted in a virtual world using the marXbot robots and the FARSA simulator (Framework for Autonomous Robotics Simulation and Analysis) (Massera et al., 2013). This is an open-source simulator designed for ER that includes a group of tools and algorithms, neural networks and computational models based on physical characteristics for the Khepera, E-puck, marXbot and iCub robots.

Then, the marXbot robot platform was chosen. It is a modular robot equipped with 24 infrared sensors, 12 ground sensors; and an ultra-extended graphics matrix camera - UXGA. Also, two pairs of Treels that are related to DC motors, associated with a rubber track and an additional wheel; Linux 2.6 Aseba operative system on board; 10 dsPIC33 microcontrollers; and connections to add additional electronic devices.

The environment consisted of a gray rectangular box (see Figure 1). Two circular areas were included inside the arena. The black area represented the poison area, while the food area was colored in white. Each circular region had a green cylinder in the center that added visual information for the location of the zones. This component replaces the red-light setup inside both zones' setup in the original experiment.

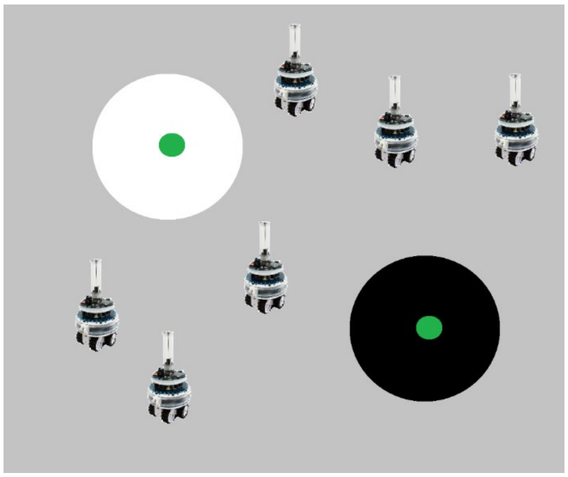

Figure 1. The configuration of the virtual environment, for the poison and food experiment. Six robots started in random positions and searched for the food area while avoiding the poisoned area. The rest of the box is gray. The robots used their cameras and LEDs as a communication system.

The robots were equipped with 24 infrared (IR) sensors that were encoded in eight groups of three sensors using sensor fusion (Ruiz et al., 2019) which reduced the complexity of the search space (Nygaard et al., 2019). The IR sensors detected objects at continuous real values between 0 and 1, with 0 representing the absence of objects. Ground sensors (GS) were used to identify food and poisoned areas. The GS could detect black, white, and gray colors in binary form. In addition, the linear camera was used with the 360 viewing range divided into five 72 ° sections. In this case green (LCG) and blue (LCB) components were used. Sensors detected the presence or absence of color for each color. As for locomotion, two wheels were included; next for the sensory system, the ring of LEDs was used enabling blue color signals.

An ANN was implemented to control robots. The design of the ANN was based on the number of sensors for the input layer, and the number of actuators for the output layer (as in the original experiment). A hidden layer was included to reduce the reactivity of the drivers (Iocchi et al., 2001; Woolley & Peterson, 2009; Lehman et al., 2013). Each control system was based on a Feed-Forward three-layered neural network with 27 neurons and 132 weights (see Figure 2). The input layer was configured with 19 neurons for the input sensors: eight groups of three infrared sensors, one ground sensor for each color in the box, five neurons to detect blue color in each region of the linear camera (signal channel), and five neurons for the green color (proximity of zones). In addition, five biased neurons were used in the hidden layer. Three output neurons with bias were included: two for the motors and one to turn the LED ring on and off. The robots were allowed to use two signals encoded with a binary neuron: one signal for dark tones (0, 0, 0 in RGB) with a binary value of zero, and the other signal for a blue tone (0, 0, 255 in RGB), which corresponds to a binary value of one. Motor movement was directly encoded within the values of the output neurons.

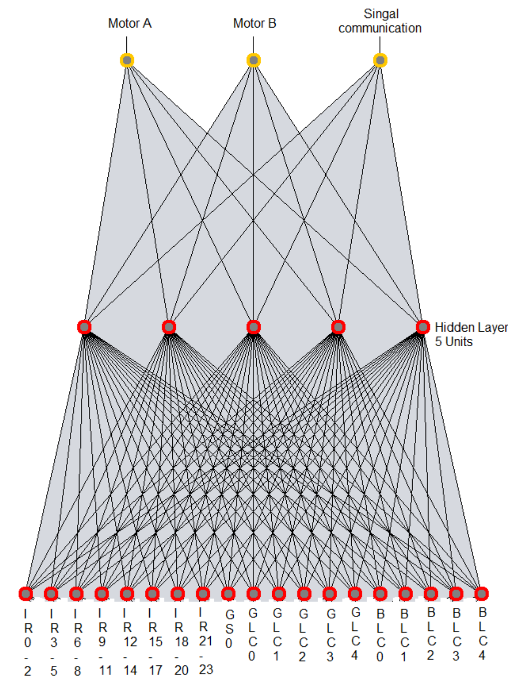

Figure 2. The topology of the ANN used in the experiment. The evolutionary process optimized a feedforward neural network made up of 27 neurons: 19 neurons in the input layer, 5 in the hidden layer and 3 in the output layer

The weights of the artificial neural structures were optimized with artificial evolution. A steady state genetic algorithm (Shwehm, 1996) included in the simulator was used (see Table 1). This algorithm is based on the mutation of an initial population and the substitution of the worst parents for their improved children.

To prove that the results are statistically robust, 30 repetitions were carried for each experimental group. Each repetition represented an evolutionary process with a different initial seed. A complete evolutionary process (see Table 2) consisted of 500 generations. The population of each generation consisted of 20 individuals for reproduction with a mutation rate of 2%. Each chromosome was evaluated in a group of robots, where all individuals had the same controller (clones). Thus, each test group was composed of six robots.

The experimental groups were evaluated 10 times, each of 300 steps. The fitness function rewarded the robots with one point for each step they expend in the food zone and was reduced for each step that the robots stayed in the poison zone.

$$fitness_{robot} = \sum_{i=0}^{trials} (Step_{food_{zone}}) - \sum_{i=0}^{trials} (Step_{poisoned-zone}) \quad (1)$$

Table 1. ANN configuration parameters.

Characteristic	*Value*
Architecture	Feed-forward Neural Net
Layers	3
Number of neurons	27 units: 19 input, 5 hidden layer, 3 output.
Number of weights	132
Transfer function	Sigmoidal
Sensors	19: 8 infrareds for objects, 1 for ground color, 5 for green component of linear camera, 5 for blue component of linear camera.
Actuators	3: 2 for wheels, 1 for color signals

Table 2. Steady state genetic algorithm variable configuration.

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

Two dependent variables were quantified: the fitness function level and the place where robots emitted signals for categories such as food area, poisoned area, the gray floor, and absent signals. Fitness levels related to emerging signals leads robot evolution during the optimization process. In comparison, after the evolutionary advantage of signal communication was reduced, the fitness function was lowered in the control group.

In the literature we have found that for communication experiments is important to ensure that the final behavior results from well-established conditions and not as a fortuitous event during the final laps of the optimization process. In this way, Marocco et al. (2003) consider that a communication system is stable when the robots' signaling strategy remains after 200 elapsed generations. This ensures that the signals settle down as a behavioral strategy, and do not emerge by chance in the last generation of an evolutionary process.

For the experiment, the fitness values start low at initial stages, then as generations elapsed with initial erratic values in the search space, fitness levels increase. When an evolutionary strategy seems promissory, it is maintained and improved over the generations. In these stages of evolutionary stabilization, fitness stops changing strongly, and its value is more stable.

Fitness was averaged for the last 200 generations of all the chromosomes in each evolutionary process. This procedure made it possible to quantify the evolutionary advantage of the appearance of communication under experimental conditions (blocking and non-blocking). The statistical test used to find differences between groups was a Mann-Withney test ($p<0.05$), with fitness as the dependent variable and the blocking condition as the independent variable (presence and absence).

The signaling was quantified under four different conditions or situations in which the robots could emit signals: food zone, poison zone, floor box, and no signal production. For this, the registration focal method, which is commonly used in ethology, was employed to record behavior. This technique consists of registering individual behavior of a general population (Machado et al., 2017). It is possible to measure the frequency, duration, and latency of behaviors in terms of events or states.

Two dependent variables were quantified: the fitness function level and the place where the robots' emitted signals in four categories (food area, poisoned area, rest of the box and no signal production). Fitness levels were used because the appearance of a communication system brings direct benefits to the robots in the optimization process. Thus, when the evolutionary advantage of signal communication was reduced, it was assumed that the fitness function would be reduced compared to the control group.

Behavioral recording was configured as one-zero sampling. The ideal sampling for recording the frequency of behavior consists of assigning one to the frequency value when a behavior of interest is observed. Therefore, if no behavior is observed at the sampling point, the frequency value is zero. The sampling implemented consisted of recording whether a set of behavior appeared in time intervals as a frequency record. For this, it was necessary to identify which set of behavior should be recorded. In this case, the recorded behavior was the production of signals in four different scenarios. In addition, we used a scanning sample because the observation is directed to all the subjects, shifting the attention among them (Davis et al., 2018). This recording method is suitable for groups with few behavioral patterns to be sampled as it was configured in the experiment.

In this way, for the proposed behavioral registration, all chromosomes were evaluated at the end of each evolutionary process. Therefore, each group of robots was recorded for 4 minutes in the FARSA simulator for both experimental groups. A frequency table was created, and the percentage of every recorded behavior was calculated.

4. Results

Results showed changes in the performance of the robots and in the location where the robots emitted signals for the experimental group of the lock-condition. Regarding the data analysis, there were statistical differences between groups ($p \leq 0.001$, $n = 600$, 599 DOF). In terms of aptitude, as indicated by the Mann-Withney test. The highest fitness value corresponded to the control group (see Figure 3).

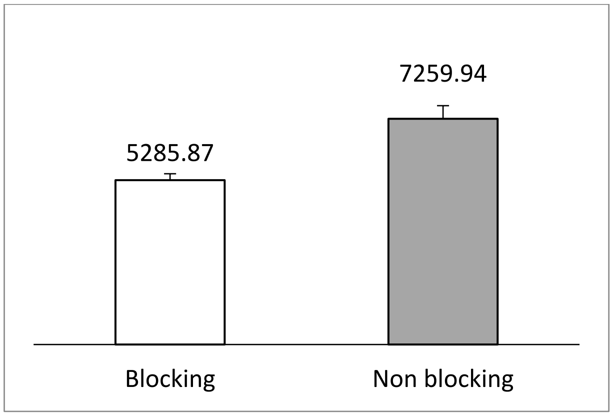

Figure 3. Average fitness and standard error of the groups for the experiment.

The comparison of both groups because of the one-zero scans' registers (see Figure 4) indicated that the signals of the individuals of the control group emerged in food zones in 70% of the evolutionary processes. The rest of the repetitions (30%) did not generate signals. This result coincides with similar studies regarding the emergence of signals for this task.

Figure 4. Signaling strategy in the control group.

On the other hand, within 50% of the repetitions for the group with the blocking condition, the signals emerged in the gray area (see Fig. 5). Venom areas were marked by 20% of the repeats and 30% did not develop signs.

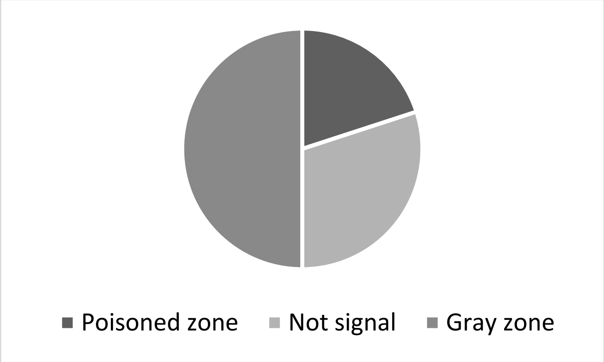

Figure 5. Signaling strategy in the blocking condition group.

5. Discussion

The experimental results indicated that the emergence and establishment of the signals depends on the evolutionary importance of the strategies developed by group of robots. In other words, it is not enough for the robots to produce the signals. For the communication cycle to be complete, it is necessary for the receivers to interpret information coded in the signals. Therefore, the contextualization of the signal depends on the environment where a signal is useful (environmental condition of the signal). This characteristic was observed in the fitness differences and the signal production of the results. The fitness level of the control group was higher than the blocking condition group. The reason was that the blocking condition reduces the usefulness of marking food zones. When the robots reached the food areas, they could not populate this area. This strategy attracted fewer robots because the signal was already seen by robots within the signal's field of view. This was supported by the results of the appearance of the signal in the zero sampling.

In the control group, the results of the appearance of the signal confirm that, in homogeneous populations, food areas are indicated to a greater extent than the rest (Floreano et al., 2007). This agrees with similar scenarios in which favorable areas are indicated (Wischmann et al., 2012). In terms of cooperative emergence, this was a behavior produced by evolutionary pressures that forced groups of robots to cooperate and solve a task (Doncieux et al., 2015). In this way, the fitness function rewarded robots for staying in food areas, and signals were an important part of the solution. For that reason, 70% of the evolutionary process of this experimental group generated a stable strategy of producing signals while the robots surrounded the food area. This strategy was used to attract individuals to the food zone, which increased collective fitness.

Only one communication strategy was recorded for the control group. This is because in some cases the evolutionary process does not produce communication strategies due to random initialization and the complexity of the search space (Duarte et al., 2015). Additionally, robots may produce signals, but if the signals are not useful, they tend to disappear (Cangelosi, 2001).

The importance of targeting feeding zones resides in the exploration that robots present to start looking for potential rewarding places. As soon as a robot finds a food zone, signals are emitted to attract the rest of the group. This strategy also develops in nature (Seeley, 2011) and is related to the cost of evolution (Ratnieks & Shackleton, 2015). A strategy such as this is easier to establish than others such as traveling together, where one robot must assume the role of leader (Cambier et al., 2020; Pugliese et al., 2015).

As predicted, the robots in the control group produced signals under different conditions than robots in the group with the blocking condition. The most popular strategy was to signal potential collisions when the robots were outside the food and poisoned areas. When a robot detected a close object, it started producing a beacon signal. The evolutionary advantage of this strategy is collision-avoidance and is used to reduce search time for food areas. This would indirectly be reflected in the fitness function because the faster the robot gets to the food court, the higher the fitness value for the group.

The strategy of targeting poisonous areas occurred in 20% of the replications. In this case, the evolutionary advantage of the signals was related to sustaining the level of collective fitness. Therefore, the robots were targeting poisoned areas to warn robots that there was a dangerous area that needs to be avoided. This behavior is like bees when they return to the hive and report the presence of food. In the case that a bee has an unpleasant experience at the food site, this kind of information is also shared. The evolutionary importance of this strategy lies in warning the rest of the bees, which implies less risk for the hive (Price & Grüter, 2015). 30% of the repetitions did not produce a stable communication strategy. This was the same level as the control group and is related to the complexity of the search space.

Therefore, the evolutionary advantage of a signal is a variable to adjust when communication systems develop. This is a crucial factor in researching emergent communication systems. In addition, this feature allows us to design which condition or situation is more relevant to consider for the robots group. This characteristic is the basis for aiding robots with the process of contextualizing signals (Wolf et al., 2018). Consequently, this research was an effort to characterize one of the variables that are related to the emergence of communication systems in robots (de Greeff & Nolfi, 2010).

In addition, it is important to highlight that we employed the one-zero scan register that is a common resource in biological research to study the behavior of animals and human beings. This registration method makes it possible to quantify interactions, behavior, and actions (Schell et al., 2018). Then, incorporated into the field of ER, it allows to formalize experimentation in terms of behavior ruling out standard observation procedures.

As future work, it is important to study the specific communication characteristics, their syntax, and semantics. Furthermore, the interaction between the complexity of the environment and the communication system needs to be explored (Shibuya et al., 2018). Finally, it is important to discover additional factors that regulate the emergence of evolutionary communication systems.

6. Conclusions

This research is an effort to study a feature that engages in the emergence of signal communication. It is also a solid attempt to characterize the contextualization process of signals produced by the intentional manipulation of a specific variable to improve a developing communication system. The results demonstrate the importance of the recording method which corelates variables and behavior. This method is commonly used in biology, psychology, and ethology to register the occurrence of behavior. As it was shown, this process can be incorporated in ER to increase the robustness of the experiments and avoid an observation bias; furthermore, to aid in a better interpretation of the experimentation results.

We proved that a signaling strategy is an important feature for leading evolution in the implementation of a communication system. Robots tend to point out the situations that are relevant to the group. In the controlled experiments, individuals circle the food zone to attract the rest of the group and fitness values are increased. However, when robots do not travel towards the food zone (they remain unaware of the feeding area), the evolutionary strategy of pointing towards the food zone is less than effective. In consequence, different signals emerge for dangerous areas, and near objects, to increase the fitness group. Finally, we noticed that for the fixed-variable experimental group, less evolutionary iterations were necessary for the development of a stable communication system. The latter can be explained in terms of the complexity of the task which promotes an environmental opportunity for the development of novel signals in the evolution of a reliable communication system.

Conflict of interest

The authors do not have any type of conflict interest to declare.

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