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The impact of population composition for cooperation emergence in evolutionary robotics

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Abstract. *Communication is an important tool for evolutionary robotics. Some important aspects are the emergence of signals, the environment, and manipulation of social and evolutionary variables. In this paper we focus on social aspects related to exploration in poisoned and food environments. These aspects are as follows: a) intermediate levels of heterogeneity in population of evolutionary robots, and b) cooperation of robots for fitness contribution to regulate the emergence of communication signals. The FARSA simulator and Marxbot robot are used in order to optimize the weights of neural networks using a steady state genetic algorithm. A basic communication system is developed based on color LEDs and linear cameras.*

Keywords: Evolutionary Robotics, Neural Networks, Communication Signals, FARSA, Marxbot.

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1. Introduction

Evolutionary Robotics (ER) was created with the idea of developing morphological and control structures as a result of an artificial evolutionary process. In this field, an algorithm adjusts an artificial intelligent neural structure in order to control a robot. The most common representation for control systems in ER are Artificial Neural Networks (ANNs), and their weights are typically optimized by a Genetic Algorithm (Bongard [3], Montes-Gonzales et. al. [14]).

In nature communication is an important characteristic of individuals and communities. As for robots, communicative skills are used for sharing information such as personal, environmental, social, internal, and external states. Furthermore, communication is an important part of cooperative behavior (Sperati et al [20]).

Several methods allow communication to emerge in evolutionary robotics, through different channels, based on different sensors, e. g. color LEDs, sound, radiofrequency, and movement. The way a communication system is established depends on sensors and actuators with which robots are constituted (Marocco et al [9]).

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In ER populations are evolved in order to solve a common task which can be accomplished using individual or group strategies. Additionally, populations can be either homogenous sharing the same chromosome information, or heterogeneous using information from different chromosomes. Then, in order to score their fitness, the population individuals have to be tested for some iterations in the simulator. Thus, in a homogenous population a population of *n* genetically identical individuals is built based in a single chromosome. In contrast, in a heterogeneous population all their individuals are not genetically identical. However, in this case the fitness function must have a mechanism to combine the score from different chromosomes within the population.

In their work Floreano et al. (2008) show that homogenous populations use communication systems to benefit the overall population. In contrast in heterogeneous populations communication systems emerge as a mechanism to drive away different individuals from food zones. Hence, is very important to understand the mechanisms that allow communication systems to emerge in populations of robots having different configurations (Steels [21]).

Additionally, the emergence of signal communication has an important relation with the conditions of the environment, control systems, and configuration of population (Montes-Gonzalez & Aldana-Franco [13]). Signals are emitted in situations where the possibility exists of collaboratively exploiting a common resource by the individuals of a homogenous population sharing useful information. Thus, signals are highly correlated with behavior, which are prone to build up a basic communicative system. Environmental and social conditions both influence the emergence of signals (Nolfi [15], [16]).

In order to attract individuals when homogenous robot populations are evolved, in both poisoned and safe environments, signals mainly emerge towards the food zones. In the case of heterogeneous populations, signals emerge on non-favorable zones in order to keep away robots from feeding zones. Therefore, signals are associated with a conflict interest level in the population and finally egotistical behavior (Floreano et al. [5]).

In nature, the overall behavior of a community is regulated by those individuals with a high influence over the others (Mengistu, et. al [11]). This could be represented as a social advantage in the evolutionary population (Mitri, et. al [12]). For example, in hierarchical societies like ants (Trianni et. al [22]) and honeybees (Zahadat & Shcmickl [24], Ruiz [18]), individuals who have a greater social value, route the behavior of socially inferior individuals.

Experimental research (Floreano, et. al [6]) shows the importance of kin structure and the level of selection in the evolution to develop a stable cooperative communication. Also, this study demonstrates that cooperative communication and signaling can be evolved in groups of robots with simple artificial neural networks. Besides, the authors show that the evolutionary principles, ruling the evolution of social life, operate in groups of robotic agents mainly shaped by selection. This feature demonstrates that efficient groups of cooperative robots can be designed based on the transfer of knowledge carried out by artificial evolution.

Because communication has rooted social components, its own emergence is related to social factors in ER. Leaders in evolutionary societies must have an evolutionary advantage over the rest of the population. Hence, they are able to regulate the emergence of signals in order to define its meaning and usefulness.

In this paper, we revise the impact of environmental variables in the emergence of cooperation in evolutionary robots. Additionally, we analyze to what extent the inclusion of communication leaders, in the population, affects the emergence of signal communication.

Two experiments were configured in order to prove that intermediate levels of heterogeneity produce intermediate level of conflict of interest, and the inclusion of robots with a high fitness contribution can guide the emergence of alerting signals. The purpose of the first experiment is to show that the level of heterogeneity is an important factor for the emergence of signal communication in robots. As for the second experiment we study how the emergence of signal communication is affected by the presence of those individuals with a large evolutionary contribution over the main population.

This paper is organized as follows. Firstly we introduce the MarXbot and FARSA Simulator. Secondly, in the methodology and materials section we provide the details of our two experiments. Thirdly, the results section shows the outcomes of the experiments. Next, in the discussion we expand the description of our findings. Finally, we draw some conclusions about our work.

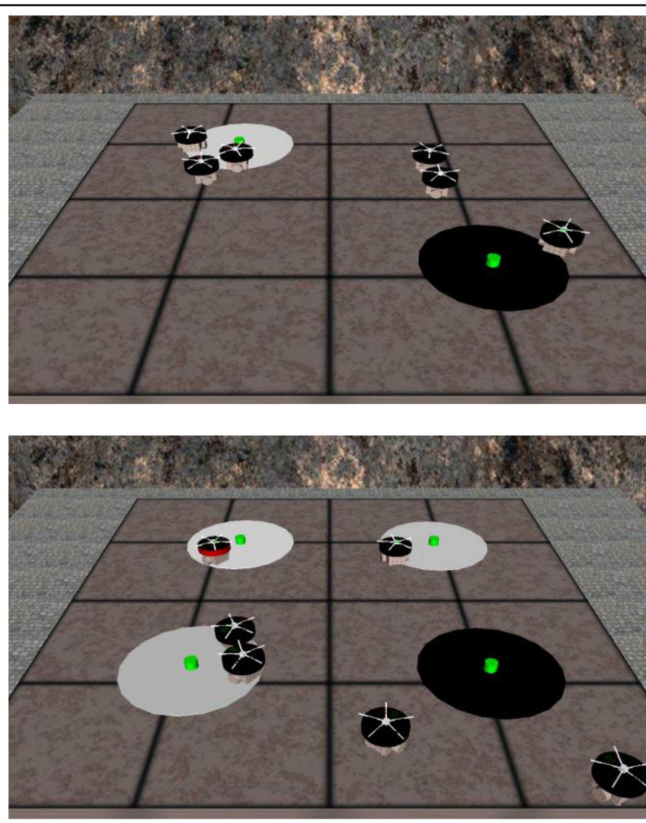

Figure 1. Examples of poisoned and food environments in FARSA

2. The MarXbot and FARSA Simulator

All experiments were conducted in a virtual world based in the FARSA simulator (Figure 1). Neural networks were used in order to control a group of MarXbot robots (Bonani et. al [1]). For evolution the simulator offers two versions of the Genetic Algorithm, the Elementary GA 1-1 (Davis [2]) and the Steady State (Shwehm [19]). In our case for the optimization of the weights on the ANNs we modified the steady state genetic algorithm. Additionally, FARSA is an open-source tool for experimental research on embodied cognitive science and adaptive behavior developed at the Institute of Cognitive Sciences and Technologies (ISTC-CNR) in Rome, Italy (Massera et. al, [10]).

FARSA provides a set of integrated libraries to create several components of embodied models and simulate their interactions with the environment in which they are situated. The graphical interface *Total99* allows the visualization of the experimental components and analysis of the cognitive processes derived from the interactions between the agent and the environment. Also, FARSA has a modular architecture based on three main concepts: 'components', 'configuration file', and 'plugins'.

The components are modules organized hierarchically which represent a process (an evolutionary process) or an object (neural network controller). Next, the configuration file is a text file where all the components, used in a particular project, and their parameter values are specified. This file can be modified through the graphical interface or directly from a text editor. Components facilitate the separation of the code in the main library from new code and provide an easy way to develop new experiments. Plugins can also be edited with the compiled code of existent components and new components developed by the users.

Evolution in FARSA starts with a random population, which is tested in a predefined environment. Next, a population of children is created, which are the result of the application of the mutation operator. Children run in the simulator and their adaptability-scores are compared with those of their parents. A selection of the worst parents is replaced with their best children and a new generation is spanned. In this algorithm the parameters to configure are: percentage of initial mutation, final mutation rate, and decreased rate of mutation. Moreover, the simulator (*worldsim*) is a complete library that allows the development of robots and environments. Thus, FARSA supports several robotic platforms including the marXbot robot (Figure 2).

Figure 2. The MarXbot Robotic Platform

The marXbot robot is a modular miniature mobile robot designed mainly for collective-robotic experiments (Bonani et. al, [1]). The base module has a combination of tracks and wheels (treels) that enables rough-terrain mobility and provides energy through a hot-swappable battery. The robot is equipped with a set of sensors like proximity sensors, 3D accelerometer, and a 3-axis gyroscope. This feature allows computing a rough estimate of the direction and distance of nearby robots. Also, the robot is provided with an attachment module that allows self-assembly with other similar robots. The marXbot is equipped with a distance scanner module and a main computer module provides an onboard linux-based operating system that allows the robot to build a 2D map of its surroundings.

3. Methodology and materials

In relation to the environment, we configured an adaptation of the poison and food experiment by Floreano, et. al [4]. A group of robots was placed in an arena without walls. Robots had to find and spent most of their time in the food zones and avoid poisoned areas. Food zones were represented by a white circular target area and poisoned zones with black circular target areas. A green cylinder was aggregated in the center of each target area as an extra visual reference (see Figure 1).

The steady state genetic algorithm was based on the mutation of initial individuals and the worst parents were replaced by their improved children. For every iteration in FARSA, the mutation rate of each generation was decreased from an initial value of 50% to a minimal value of 1%. The fitness function rewarded with a positive value for each step that a robot spent in a food zone, and punished with negative values when the robot was next to a poisoned area. The complete evolutionary process was composed by 500 generations of 20 teams of six robots with random initial positions. Next, a repetition consists of a run of the complete evolutionary process. The rest of the parameters were as follows: selection of 20 individuals for reproduction; 1% decrease mutation rate; 1 trial of 300 steps; and then 10 trials for a team of six robots with 12 repetitions for each experimental group (6,000 generations in total).

Robots used 24 infrared sensors encoded in 8 average measures of 3 group sensors (FARSA allows grouping and fusing a certain number of infrared sensors). As for the ground sensors, 3 are employed for the detection of gray, black, and white colors. Also, the linear camera detects 5 segments of 72° of red, green, and blue components. As for the actuators, robots controlled 2 motors using only angle information (orientation-based), and the ring of LEDs flashing binary-coded red and blue colors. The neural controller was composed by 26 neurons at the input layer, 15 for the hidden layer, and 4 neurons at the output layer. In total 460 weights were optimized in a feed- forward structure.

As for the signal coding, it was implemented using a binary function that outputs 0 if the value is below 0.5 and 1 otherwise. There are two neurons for coding color signals, respectively representing red and blue colors. However, two more colors can be represented using a combination of the output of these two neurons. Therefore, codification in pairs is as follows, OFF, OFF = BLACK; ON, OFF = RED; OFF, ON = BLUE; ON, ON = PURPLE (Figure 3).

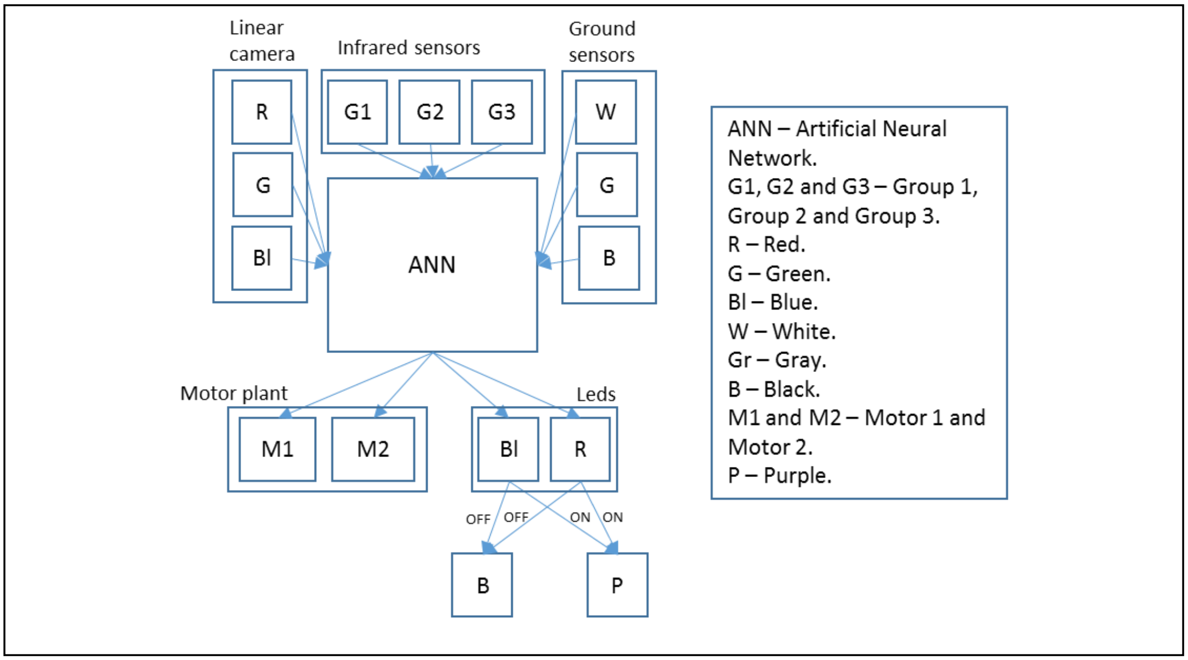

Figure 3. The neural architecture for our experiments

3.1 Experiment 1. Homogenous vs. heterogeneous populations

The aim of this first experiment was to find out to what extent the level of heterogeneity affects the emergence of communication signals in robots. Also to probe that the production of signals is related to the level of heterogeneity. Additionally, we anticipated that intermediate values of heterogeneity produced both intermediate levels of fitness and signal production. In relation to heterogeneity a 'clone' is a concept related to the way the population is integrated. For a homogenous population their individuals share the same chromosome (clones); on the contrary in a heterogeneous population their individual chromosomes are all different.

For the experiment we employed 4 experimental groups that represented different team configurations based on different variations of the heterogeneity level. The groups depending on their heterogeneity level were formed as follows: level 0 with identical chromosomes for each member of the team (control group); level 1 composed by 2 different chromosomes; level 2 composed by 3 different clones; and level 3 composed by a team of 6 different chromosomes.

Two dependent variables were measured: a) the fitness function level and b) the locations where robots emitted signals (food area, poisoned area, another robot presence, or no signals). In our experiments we used the fitness levels because communication emergence brings about additional benefits to robots by sharing food information and increasing their fitness (Marocco et al [9]). The average fitness score of the last two hundred best individuals of each repetition was used as the output variable. This in order to consider that the communication system was stable, evolutionary signals are considered stable when there is no change in signaling strategy after 200 generations of the evolutionary process. The statistical test used for finding differences between groups was a One way ANOVA on ranks (α=0.95) and a post-hoc Student-Newmann-Keuls with fitness level as the dependent variable and heterogeneity level as the independent variable. Signalization was quantified with 4 locations, or situations, where commonly robots emit signals (food, poison, another robot and no signal). Signals were registered for 10 minutes through an instantaneous scan sampling of the best individuals in the last generation of all the repetitions in the experimental groups.

3.2 Experiment 2. The presence of communication leaders affects the emergence of signals

This second experiment was developed to demonstrate that the emergence of signal communication was affected by the presence of individuals with a large evolutionary contribution over populations of genetic clones. The experiment was integrated by 4 groups. Two free variables were used: the fitness contribution associated with the number of signals emitted in 2 levels (2 colors for a pair of individuals with a high fitness contribution and 4 colors of an equal fitness signal contribution); and the number of localized food target areas in 2 channels, i.e. 1 and 3 target areas.

The first group named ‘control-group’ was configured with 20 populations of 6 robots with an equal fitness contribution (+1,-1), 1 target food-area, and 1 poisoned-food area. The second group ‘group-1’ was composed by 6 individuals with the same contribution of fitness (+1,-1), 3 food zones, and 1 poisoned zone. The third ‘group-2’ was formed by 2 individuals with a high fitness contribution (+1,-1), 4 individuals with a low contribution (+0.5,-1), 1 food zone, and 1 poisoned zone. Finally, the fourth ‘group-3’ included 2 individuals with a high fitness contribution (+1,-1), 4 individuals with a low contribution (+0.5,-1), and 3 food zones with 1 poisoned zone.

The fitness function measured the last two hundred best individuals for each repetition, which reflected changes in behavior during evolution under experimental conditions. In order to compare the fitness levels of experimental groups, a two way ANOVA was used as statistical test (α=0.095). Next, it was complemented with a post-hoc of Student-Newmann-Keuls with $p<0.001$ and comparison of two factors: a dependent variable based on statistical tests using the individual fitness level; and an independent variable related to the number of food zones and to the presence or absence of individuals with high fitness contributions. Signals were measured for the last 10 minutes of the best individuals in 4 different places, or positions, where the robots emitted signals (food, poison, another robot, and no signal). A special case is when the robot is under a situation where the LED rapidly flashes one color and changes to another, e.g. the robot finds food, and emits a blue signal, afterwards finds a cylinder and emits a green signal.

4. Results

4.1 Experiment 1

A competitive race between species decreases the performance of individuals, and has an important effect on signal emergence. When the competitiveness level increases, between species, the altruism of individuals decreases (Waibel et al [23]). The One Way ANOVA on Ranks (Figure 4) showed that statistical differences were evident between the four experimental groups ($P=<0.001$, 3df, n=12). Furthermore, the Student-Newmann-Keuls Pos-Hoc test showed differences between all groups ($P<0.05$) related to variations in the fitness level produced by changes in the heterogeneity level.

Firstly, at the highest level of heterogeneity (six different individuals), signalization occurred 42.9% in poisoned zones, 14.2% in food zones, 28.7% in the presence of another robot, and 14.2% of the repetitions did not develop a communication system. Secondly, 25% of the signals for the 3-clones repetitions emerged in poisoned zones, 31.25% for black zones, 31.25% in the presence of another robot, and 12.5% repetitions did not develop any kind of communication. Thirdly, the 2-clones repetitions developed 21.4% of the signals at food zones, 28.5% at black zones, 14.2% in the presence of another robot, and 35.9% no communication system at all. On the other hand, homogeneous population signals were emitted most of the time at beneficial places (80%), and to a lesser extent in poisoned zones (20%).

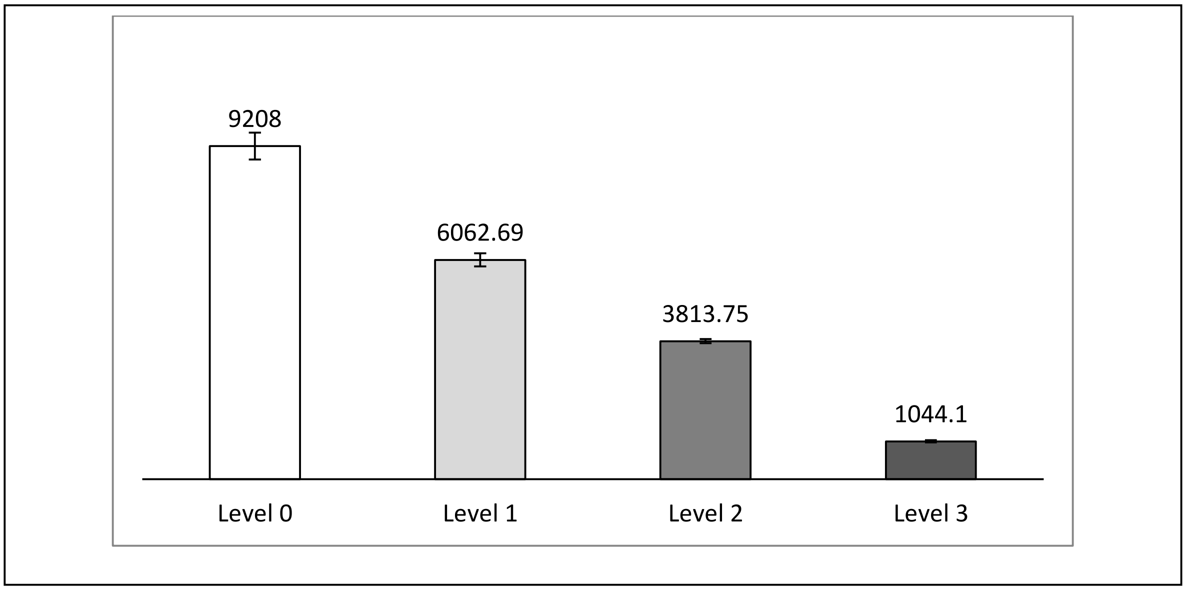

Figure 4. The average fitness and standard error of groups for experiment 1

4.2 Experiment 2

The Two Way ANOVA showed that there were statistical differences between the experimental groups ($P<0.001$, 44df residual, 47df total, a factor of interaction between factors $p=<0.001$ and $n=12$). The Student-Newmann-Keuls Pos-Hoc test showed differences between two factors: the presence of individuals with a high fitness contribution and the number of food zones ($P<0.05$). In consequence the best fitness level was scored by group-1 (see Figure 5).

In relation to the production of signals in the control group, robots produced them 80% of the time in beneficial places, 20% in poisoned zones. For group-1, signals emerged 90% of the time in food zones (25% at food zone 1, 40% at food zone 2, and 25% at food zone 3), 3.3% in poisoned zones, and 7.3% in the presence of another robot. As for group-2, 70% of the time signals emerged in food zones, 15% in poisoned zones, and 10% in the presence of another robot and 5% did not develop a communication system. Finally, in group-3 signals emerged 80% of the time in food zones, 10% in poisoned zones, and 10% in the presence of another robot. Robots in the control group employed an average of 2.2 signals; 3.1 signals in group-1, 1.1 for group-2, and 1.8 signals for group-3.

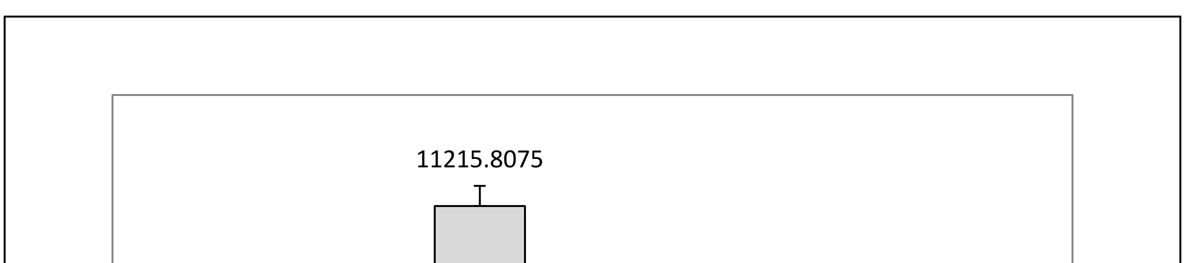

Figure 5. The average fitness and standard error of groups for experiment 2

5. Discussion

In the first experiment, as showed by Mitri et al. [12], the use of one clone facilitated that signals emerged when robots were in safe places like food zones. The results from these authors were confirmed in our experiments for the heterogeneous groups. Hence, when a group of robots was composed by two, three, or six clones; signals were used for attracting robots outside of the safe zones and then attract them to dangerous zones. The statistical tests confirmed that the manipulation of the independent variable (level of heterogeneity) has an effect on the fitness due to the emergence of non-altruistic behavior. In evolution this kind of behavior reduces the level of fitness and affects the emergence of communication signals. Intermediate levels of heterogeneity, confirmed a trend, which in turn results in a decrease of the fitness level.

In the case of groups composed by 2 and 3 clones the tendency of decreasing performance was maintained for intermediate values compared to groups of 1 and 6 clones. We can safely assume that the level of heterogeneity is inversely proportional to the fitness and level of altruism. Overall we found low performance at high levels of heterogeneity in the population. The fitness function level showed differences between groups as a result of different levels of individual contributions over evolution.

In the same experiment, after the total number of generations (6,000), high heterogeneity levels did not develop a stable communication system and this can be due to the complexity of the solution space. In contrast, for a homogenous population where competition between individuals does not exist, all replications produced a stable communication system. This could be related to the value of signals because if individuals did not produce them, a population would not solve the task and reach high levels of fitness. Therefore, evolved communication systems in heterogeneous populations have low levels of altruism amongst identical individuals or species.

Here we observed two strategies, one is the emission of misleading signals and the other is the absence in the production of signals. In the first case, particular specie may produce a communication system to mislead individuals, of other species, from reaching the food zones which can be interpreted as a race competition between species. Eventually a strategy such as this may have better results because it uses one of its members to send competitors away while the rest of his teammates can visit empty food areas. The second strategy is related to the absence in production of signals which in turn facilitates the development of a common color identity of the group. Thus, in this case the failure to establish a communication system may be favorable for the population sharing the same color code and misleading for the others.

As for the second experiment we observed that robots in the control group emitted signals in food zones and before a collision. Furthermore, the availability of more than one food zone causes signals to emerge in a different way. This is the case of group-1 and group-3 where robots used different signals for each located food zone. Our findings demonstrated that signal emergence depends on the utility and the complexity of the environment.

The use of fitness function level as a variable shows that experimental groups that have more than one food zone available showed better performance. Therefore, the availability of various food zones facilitates the emergence of complex communication system producing different signals having a significant associated lexical value. Furthermore, the use of fitness shows that there are statistical differences between experimental groups as a result of the manipulation of the independent variables, i.e. leaders and multiple targets. We found that there is a correlation between these variables due to the level of statistical significance of the test interaction between factors. Also, we observed that experimental groups are susceptible to manipulation of variables. For example, an increase in the number of food zones rises the individual fitness and produces more emergent signals. Additionally, the existence of communication leaders causes fitness decays in the other groups (the control-group and group 1 reach higher fitness levels than groups 2 and 3 that do not have a leader).

Cultural learning in a communication system helps to understand the usefulness in preserving or not a signal with its initial content. Furthermore, after some generations a signal can be developed and its original content be changed or even more can be suppressed. Leaders help to produce initial signals that can be imitated by others, which can be interpreted as a cultural learning that occurs during evolution. In our second experiment we observed that evolution guided from the team leaders helped to establish a stable communication system with an economy in the production of signals. Here, individuals with high fitness contributions produced a social benefit for the rest of the population which in turn tended to imitate signal behavior from the leaders. As many as 4 robots were able to produce blue and red signals in contrast to 2 robots which were able to produce only red signals. Despite the fact that leaders with two signals can be used to code 4 different signals, evolution optimized the selection of leaders that emitted only one color signal. Hence, after the evolutionary processes is finished, all robots emitted red signals in the food zones. We can summarize this behavior as an example of social learning (Heinerman et al [7]).

In relation to the number of available food zones, this has a major impact on the number of robots that are able to identify them. The group that develops stable identification signals related to food areas will have more individuals reaching them and in turn scoring high levels of fitness. However, the presence of leaders regulates the number of emergent signals because signals are mainly developed to point to the food zones and the rest of the population tends to mimic the behavior of the leaders. The population follows the leader even though the population has the possibility to produce additional communication signals.

In summary, in the first experiment we showed the importance of heterogeneity in a population and demonstrated that intermediate levels of heterogeneity produced intermediate levels of altruism. On the other hand in the second experiment we showed that fitness can be increased over evolution by combining social information with fitness information. This was observed in this experiment with group-2 where more fitted individuals acted as leaders even though they were not the strongest in the group. An increase in the availability of food zones makes robots to choose zones accordingly to signal information from the leaders of the group. As a consequence, the rest of robots in the population associated different signals to the remaining the food zones. Also, in the second experiment we demonstrated that is possible to share a common communication signal set, during evolution, by the influence of the communication leaders.

6. Conclusions

For evolutionary robotics the heterogeneity level has an important effect on the emergence of communication systems. Evidence from our results confirms that intermediate levels of heterogeneity produce intermediate fitness values. The availability of reachable places is an important factor for developing communication systems. Furthermore, environmental manipulation favors the production of emergent signals with associated lexical values. Hence, the existence of communication leaders in the group, as a form of manipulation, accelerates the emergence of effective signal communication towards the final steps of evolution.

The utility of leaders for developing a stable communication system can be explained because the social composition of the group is a decisive factor for individual evolutionary development. At an initial stage gene modification is a secondary effect from behavior related to the sensory-motor systems. Later on, a more adapted sensory motor system produces more fitted individuals, which in turn are preserved and their genes are transmitted over the next generations. Hence, our results confirmed that social information has a great influence in gene expression, i.e. epigenetic changes, because sensorial systems induce neural transduction and next they are preserved by adaptation and natural selection (Robinson et al [17]).

Finally, as in nature where individuals with a particular advantage over the others regulate social and cultural processes; in our second experiment we observed that leaders in the groups are capable of producing signals with a clear lexical meaning.

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