Who Is the Leader? Dynamic Role Allocation Through Communication in a Population of Homogeneous Robots

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Abstract. The field of collective robotics has been raising increasing interest in the last few years. In the vast majority of works devoted to collective robotics robots play all the same function, while less attention has been paid to groups of robots with different roles (teams). In this paper we evolve a population of homogeneous robots for dynamically allocating roles through bodily and communicative interactions. Evolved solutions are not only able to efficiently decide who is the leader, but are also robust to changes in team's size, demonstrating the ability of Evolutionary Robotics to find efficient and robust solution to difficult design challenges by relying on self-organizing principles. Our evolved system might be used for improving robots' performance in all the cases in which robots have to accomplish collective tasks for which the presence of a leader might be useful.

Keywords: Dynamic role allocation, communication, collective robotics, robot teams, evolutionary robotics, leaders

1 Introduction

In the recent years the study of collective robotics has been raising increasing interest within the Artificial Life and Adaptive Behavior communities. In particular, Evolutionary Robotics techniques [13], [8] have been successfully used for designing robot controllers able to display *swarm* behaviors, that is behaviors in which a group of robot appears to act as a single unit (see, for example, [5], [3]). Evolutionary Robotics seems to be particularly well suited for designing such kind of robots. One of the main advantages of Evolutionary Robotics is in fact the ability of artificial evolution to find interesting solutions to difficult robotic tasks by exploiting the self-organizing properties of the complex dynamics of the interactions between a robot's control system, its own body, and the environment [12]. When dealing with groups of robots the complexity of the resulting system increases, since the interactions between the robots add up to the interactions between single robots and their environment so to produce an extremely complex and highly unpredictable dynamical system. Such systems are known to be very difficult to engineer by direct design, and this is the reason why Evolutionary Robotics has been raising increasing attention in the field of collective robotics.

Typically, evolved groups of robots constitute swarms, that is groups in which each individual behaves according to the same simple rules, so that the complexity of the behavior of the group emerges from the local interactions between the members. Though extremely interesting, this kind of organization does not permit to develop more complex social behaviors requiring specialization within the group. The reason of this is that typically interesting collective tasks require cooperativeness between the robots and this is typically assured in Evolutionary Robotics experiments by using groups of homogeneous robots. In fact, if interacting agents are non-homogeneous, then the problem of altruism immediately arises, making the emergence of cooperative behaviors extremely difficult (two examples of works devoted to the problem of altruism in groups of communicating agents are [11] and [6]).

It would be extremely useful to exploit Evolutionary Robotics techniques in order to develop *teams* of robots, that is groups of robots in which (1) different individuals make different contributions to the success of the task, (2) roles are interdependent thus requiring cooperation, and (3) organization persists over time (cf. the definition of 'team' provided by [1], in the contest of animal behavior). This poses a difficult but interesting challenge since it is not clear how homogeneous individuals might be able to assume different roles in a persistent manner. A possible solution to this problem might come from endowing robots with communication capabilities, so that role allocation might be negotiated through the exchange of signals. In the recent years several interesting studies have demonstrated the possibility to evolve communication in homogeneous robots so to accomplish some cooperative task (e.g. [4], [14], [9]). If we can evolve groups of homogeneous robots which are able to negotiate their roles through the exchange of signals, then this ability might be later exploited for the evolution of more complex collective behaviors requiring role specialization.

In this paper we describe an experiment in which a group of homogeneous robots is evolved for the ability to negotiate their roles: in particular, one of the robots has to maximize its communicative signal, thus assuming the role of the group's leader, while all the other robots have to minimize their signal. We show that evolved robots are not only able to solve the task, but that evolved solutions are also robust with respect to the number of interacting robots. In the next section we briefly review the two works which are most related to the present one. In section 3 we present the experimental set-up, while in section 4 we show the main results. Finally, section 5 concludes the paper with a brief discussion about the significance of this work and about possible lines of future work.

2 Related Work

To the best of our knowledge, there are only two published works devoted to the study of dynamic role allocation within an Evolutionary Robotics framework: [2] and [15].

Baldassarre and colleagues [2] evolved a group of robots for the ability to aggregate and collectively navigate toward a light target. Apart from infrared and ambient light sensors, robots were equipped with directional microphones, which could detect the sounds emitted by other robots' speakers with a fixed amplitude and a frequency randomly varying within a limited range. While analyzing the various results of different replications of several evolutionary runs, they found that three different kinds of strategies were discovered, which they called 'flock', 'amoeba', and 'rose'. What is most interesting for the purposes of the present paper is that the most efficient solution, the flock one, required different individuals playing different functions, with the individuals which are nearest to the light leading the group straight toward the target at maximum speed and the other individuals following the leaders by trying to maintain the group's cohesion. Since the groups were formed, as usual, by homogeneous individuals, and since robots' controllers were formed by simple perceptrons and hence did not have any internal state, robot's specialization was 'situated', in the sense that it completely depended on the different input patterns that robots received from the environment.

In a similar work, Quinn and colleagues [15] evolved a team of three uniform robots able to dynamically allocating their roles in order to navigate as a group. In this experiment, robots equipment was really minimal: each robot had just four infrared sensors and two motor-driven wheels. Robots were required to move as a group, that is by remaining within each other's sensor range. The analysis of evolved robots' behavior showed that the task was completed by relying on two phases: during the first phase robots organize themselves into a line formation, while in the second phase the robots start to move swinging clockwise and anticlockwise while maintaining their relative positions.

While the behaviors of the robots evolved by Baldassare and colleagues and Quinn and colleagues have several interesting features, the solutions found by evolution are not general, but rather task-specific: the dynamic role allocation performed by those robots can be used only for the specific collective navigation tasks the robots were evolved for, and cannot be exploited for other kind of purposes. Furthermore, that particular solutions do not seem to have the robustness which is typically assured by the use of homogeneous teams. As correctly indicated by Quinn and colleagues, while the predetermination of roles has the clear advantage of not requiring on-line role allocation and of permitting robots' behavioral and morphological specialization, on the other hand the use of homogeneous robots has the potential of being much more robust: since all robots are identical and hence each robot is equally able to play any role, teams of homogeneous robots can potentially be much more able to cope with the loss of individual members with respect to heterogeneous teams. This is clearly true, but this advantage is not demonstrated neither in the work of Baldassarre and colleagues nor in that of Quinn and colleagues. In fact, Baldassarre et al. did not touch the problem of robustness at all, and it is not clear whether the flocking behavior would generalize with respect to the number of robots. On the contrary, the solution found by the robots of Quinn and colleagues did demonstrate *not* to be robust to the lack of an individual: if one of the three robots is removed from the formation the remaining pair maintain the same configuration as when in full formation but ceasing the forward movement. The reason is that the evolution of task-specific role allocation will tend to produce task-specific solution which deeply rely on the specific conditions under which evolution took place.

A possible solution to this problem might consist in directly evolving groups composed by different numbers of robots to perform the same task. In this paper we explore another, much more general, solution: namely, the direct evolution of the ability to dynamically allocating roles between themselves through the use of local communicative signals. Once we have reached a group of robots which are able to negotiate their roles on the fly, we might exploit this ability for solving, with a population of homogeneous robots, any kind of collective robotic tasks requiring role differentiation.

3 Experimental setup

The experimental set-up consists in a group of four identical E-puck robots (Fig. 1 left) placed in a box-shaped arena of 40x40 cm (Fig. 1 right).

Fig. 1. Left: E-puck robot. Right: a group of four epuck robots inside a box shaped arena of 40x40cm

Robots can move in the arena by sending commands to their two wheels and can exchange signals between each others through a dedicated communication channel. Communication is local as each robot perceives only the signal which is emitted by its nearest fellow. Robots' signal are not only used for communication: they also represent the role of the signaling robot. We evolve the robots for the ability to differentiate their roles through the differentiation of their signals: one of the robots must become the 'leader' of the group by maximizing the value of its communicative output, while all other robots, which are non-leaders, must minimize the values of their signals. More concretely, we calculate the fitness of a group of robot in the following way. For each cycle, we consider the average of the differences between the communicative output of the current 'leader' (i.e. the robot with maximal communicative output) and the communicative outputs of all other robots. The fitness is the average of this value for all the cycles of all the trials. Formally, this is how fitness is calculated:

$$F = \frac{\sum_{j}^{C} \sum_{i}^{N} Max_j - O_{ji}}{C(N-1)} \quad \textbf{(1)}$$

where N is the number of robots in the group (i.e. 4), C is the total number of life-cycles of each individual (i.e. 1000 cycles times 40 trials = 40000), MAX_j is the value of the signal of the leader at cycle j and O_{ji} is the value of the signal of robot i at cycle j.

Each robot is controlled by a neural network with a fixed architecture shown in Fig. 2. There are ten sensory neurons: 8 input units encode the state of the 8 infrared sensors, which are disposed around the robot's body; one input unit encodes the signal emitted by the nearest robot, and the last input unit encodes the activation of the same robot's communicative output units during the previous cycle. All the input units send connections to two hidden units, which are leaky integrators with fixed time constants (set to 0.9) and are fully connected between themselves. Finally, the two hidden neurons send connections to both the communicative output unit and to the two motor output units, which are used to command the motors of the two wheels and receive also direct connections from the 8 infrared input units.

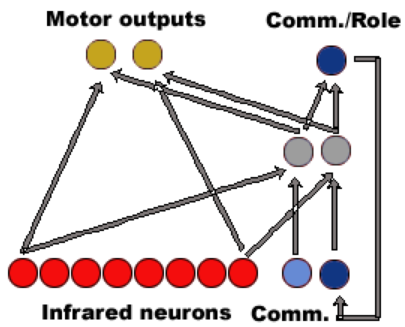

Fig. 2. Neural controller

The free parameters of the robots' neural controllers are evolved as in a standard Evolutionary Robotic set-up [13]. The genome of individuals encode all the network's connection weights and biases. Each parameter is encoded as an 8 bits string, whose value is then uniformly projected in the range [–5.0, +5.0]. The initial population consists of 100 randomly generated genotypes. Each genotype is tested for 40 trials, lasting 1000 cycles each. At the beginning of each trial, four homogeneous robots (i.e. with the same connection weights) are randomly placed into the arena, and they are left free to move and to communicate between each other for all the rest of the trail. After all the trials of all individuals within a generation have been executed, the 20 best genotypes of each generation are allowed to reproduce by generating five copies each, with 2% of their bits replaced with a new randomly selected value. The evolutionary process lasts 150 generations (i.e. the process of testing, selecting and reproducing robots is iterated 150 times). All the experiments were carried out in simulation using the Evorobot simulator [13] adapted so to simulate the e-puck robots.

4 Results

The experiment was replicated 10 times, with different random initial conditions. The average fitness of the best individuals (teams) of all the replications is about 0.82, with the best replication achieving a fitness of about 0.9. By looking at the behaviors exhibited by the best groups of the last generations of all the runs, we could see that in 9 out of 10 replications robots are able, after a short transient during about 100 cycles, to dynamically allocate their role in an efficient and quite stable way. Only in the worst run, which achieved a best fitness of about 0.62, roles never stabilize, with every robot continually changing its communicative behavior in an apparently chaotic way. With respect to the 9 successful replications, we noted that different replications found slightly different solutions, but the behaviors of the best individuals are qualitatively quite similar.

The robots within a group tend to differentiate quite rapidly, with one robot assuming the leader role (signaling with a very high value) and the other three robots setting their communicative output signal at very low values. After differentiation, robots remain in their role for almost the whole life time, although small changes can occur due to the intrinsic dynamical negotiation process. In fact, due to the local communication system, in order to hold a leader role, a robot have to continuously interact with the non-leader robots. This has the interesting consequence that not only the communicative behavior is differentiated, but also the non-communicative one. In other words, although this was not explicitly requested in the fitness function, after role allocation even a robot's non-communicative behavior significantly depends on the role that robot plays within a group. In particular, leaders tend to have a broader explorative behaviour than non-leaders, which “prefer”, instead, to reduce their movements. This is done in order to maximize the number of interactions that a leader can carry out with all other individuals of a group so to maintain its leadership. This kind of group organization is present in all the successful replications, which differ mainly in the kind of behavior exhibited by leaders (in general it is a circular behavior) and in the amount of movement exhibited by non-leaders (which in some cases just circle around themselves without any displacement).

From the point of view of signals, robots tend to produce only two signals: the 'leader' signal L, with very high values (in the best replication this signal assume the value of about 0.96), and the 'non-leader' signal NL, with very low values (in the best replication this signal assume the value of about 0.1). At the beginning of a trial signals are typically produced randomly, while after a few interactions only one robot is able to maintain an L signal since an L produced by a speaker tends to induce the hearer to answer with a NL signal.

How robust is the behavior of the evolved robots? Are these solutions able to generalize to groups of robots composed by a number of individuals which is different from the one the robots have been evolved to cope with? In order to check this we tested the performance of the best individual of the last generation of the best replication of our experiment in five different conditions: in groups of 2, 3, 4, 5, and 6 robots (remember that evolution was run only with groups of 4 robots). For each test, we calculated not only the average fitness (calculated according to the formula 1, which is clearly independent on the number of robots), but also the average number of leaders in the group. In this case, we decided to count as a 'leader' every individual whose communicative output value is above 0.5. We monitor the number of leaders throughout the whole test (i.e. for each cycle of each trial), and we report the percentage of the cycles in which there are different numbers of leaders (from 0 to 6). The results, shown in table 1, clearly demonstrate a remarkable generalization ability of the evolved solution. Evolved robots are in fact able to effectively allocating roles within the groups even in conditions which have never been experienced during evolution. Indeed, instead of decreasing, performance actually increases if the group is composed by a number of robots which is inferior to the one with which evolution took place. In fact, performance seems to be linearly dependent on the number of robots present in the environment: the lower, the better. This is clearly due to the kind of strategy used by evolved robots to solve the task: as this requires a leader to navigate through the environment so to communicate its presence to all other robots, the less crowded is the environment, the easier is for the leader robot to reach all the other robot so to maintain its leadership. On the contrary, as the number of robots increases, the environment gets more crowded, and the easier it is to get to situations in which there are either two leaders or none.

Table 1. Average percentage of leaders during a lifetime of 1000 times 40 trials, in groups of 2, 3, 4, 5, and 6 robots. The last row of the table indicates average fitness, calculated according to formula 1.

N. Leaders	2 Robots	3 Robots	4 Robots	5 Robots	6 Robots
0	0.92	0.95	1.05	6	10.78
1	99.08	95.26	88.62	75.73	71.00
2	0	3.79	10.33	17.34	17.22
3	-	0	0	0.92	0.98
4	-	-	0	0.01	0.02
5	-	-	-	0	0
6	-	-	-	-	0
Average fitness	0.95	0.92	0.90	0.83	0.81

5 Discussion and Conclusion

In this paper we presented evolutionary robotics experiments in which groups of four robots are evolved for their ability to dynamically allocate their roles through their communicative and non-communicative interactions. In particular, evolved robots are able to differentiate both their communicative and non-communicative behaviors so that only one robot assumes the role of the 'leader' of the group, sending high value signals, while all the other robots act as non-leader, almost ceasing their signaling behavior. The task is interesting because the groups of robots are homogeneous (i.e. all the group's members have the same body and control system): as a consequence, robots need to negotiate their roles on the fly. Furthermore, in contrast to most previous works dealing with dynamic role allocation, in which robots can rely on predetermined communication protocols by which robots can share global information (e.g. [10], [16]), in our experiments robots can rely only on the local information provided by their infrared sensors and by a one-to-one communication channel.

The most interesting result of our simulations is related to the generalization abilities of our evolved solutions. In contrast to the two previously published evolutionary robotics works dealing with dynamic role allocation [2], [15], which did not demonstrate any generalization ability, our system proved to be very robust to changes in the number of robots forming a group. While evolved for allocating the role of the leader in groups made up of four individuals, evolved solutions are able to perform reasonably well this kind of dynamic role allocation even in groups of five and six robots, while the efficiency of the evolved strategy is *increased* as the number of robots forming a group decreases (i.e. in groups of 2 and 3 robots). These results clearly demonstrate the feasibility and the potentiality of our Evolutionary Robotics approach to the development of complex collective (social) behaviors in autonomous robots. In fact, the flexibility and robustness demonstrated by our evolved solution has been possible only thanks to our use of groups of homogeneous robots, in which robots' roles are not pre-specified, but must be negotiated thanks to the dynamical interactions between the robots themselves.

We envisage at least three ways for extending the work presented in this paper. The first one, which we are currently exploring, consists in analyzing in more details the strategies of our evolved robots, in order to better understand how roles are dynamically allocated during the transient period at the beginning of each trial and how they are maintained once they have been decided.

A second interesting line for future research is related to the possibility of using our role allocation system as the starting point for developing robots able to accomplish collective tasks which require the presence of a leader. While several swarm-like behaviors might be successfully accomplished by groups of robots without any significant distinction between the behaviors of the members of the group, there are many cases in which the presence of a leader might significantly improve the performance of the group (see [1] for examples in the animal kingdom and [2] and [7] for examples within the artificial life community). In order to develop groups of homogeneous robots able to efficiently accomplish these kind of tasks, we might use our evolved robots, which are already able to rapidly negotiate who is the leader, for seeding the task-specific evolutionary search.

Finally, since the idea of using local communicative interactions between homogeneous groups of robots for dynamic role allocation is not strictly related to the development of a (single) leader, the same idea might be exploited also for developing robots able to dynamically allocate different kinds and numbers of roles.

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