Cooperative Object Transport Using Evolutionary Swarm Robotics Methods

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Abstract

This paper describes a set of simulations in which autonomous robots are required to coordinate their actions in order to transport a cuboid object that is too heavy to be moved by a single robot. Robots’ controllers are synthesised using artificial evolution and dynamic neural networks. We compare two different types of robots: in the NT-condition, the robots are equipped with a camera and proximity sensors. In the T-condition, the robots have additional torque sensors. The results show that best evolved groups of the T-condition outperform those of the NT-condition. Moreover, we show that the best evolved groups can adapt to variability in size and weight of the object as well as to the small variability in the cardinality of the group. We also show that simple forms of recruitment behaviour emerge without being selected for during evolution. This work unveils interesting relationships between design choices and characteristics of the evolved solutions, and it contributes to develop design guidelines for engineering robust and successful swarm robotic systems.

Introduction

In multi-robot systems, group transport refers to the coordinated action of a group of robots in order to collect and retrieve objects that are too heavy to be transported by a single robot. In swarm robotics, group transport is a particularly challenging task because the coordinated response of the group should be achieved without centralised control, global information, and non-stigmergic forms of communication (see Dorigo and Şahin, 2004). Under these conditions, natural swarms, and in particular ants manage to transport large food items, by overcoming problems such as the distributions of porters around the burden, and the coordination of the forces in order to avoid to work against each other (Sudd, 1965).

Swarm roboticists aim to mimic the behaviour of natural swarm by looking for the individual rules that generate such robust group-level response. For example, in (Berman et al., 2011), the authors observed a particular species of ants (Aphaenogaster cockerelli) in order to extract and reproduce in a simulated swarm robotic system those rules that govern the individual action during group transport. Other studies have looked at different aspects that can bear upon the efficiency of the group during transport. In (Dorigo and et al., 2013), the authors investigated the effects of the degree of relatedness of the individuals by proposing a swarm robotic system in which the group transport is accomplished by multiple groups of robots, in which each group is homogeneous (i.e., all the robots are the same), but robots of different groups have different structural and functional characteristics. In (Wang et al., 2004), the authors look at the effects produced by the introduction of hierarchies in the group (e.g., leader and followers). In (Kube and Bonabeau, 2000), the authors extend a work originally developed in (Kube and Zhang, 1993) to look at the efficiency of group transport strategies by varying the shape of the object as well as the cardinality of the group (i.e., the number of robots in the group). The results of this study indicate that group transport strategy becomes progressively less efficient when the ratio between number of robots and length of surface on which to exert forces increases.

Sensitivity to size and shape of the object, in addition to undesired negative effects during test on scalability with respect to group cardinality seem to be the major obstacles to the design of efficient group transport strategies in swarm robotics systems (see Groß and Dorigo, 2009). To overcome these limitations, roboticists have been exploring alternative solutions. For example, in (Mataric et al., 1995) the authors look at the effects of direct communication. Their study shows that a two-robot group capable of coordinating the action through a dedicated communication protocol outperforms a two-robot group that can not use direct communication. The aim of communication was to help the robots to complement each other partial sensory view of the object. Communication in group transport scenarios seems to be an effective tool to boost the group performances. However, the use of dedicated communication protocol bears upon the robustness and scalability of the system (see Brambilla et al., 2013). With the aim to improve the efficiency of group transport, a series of studies investigated the use of more sophisticated forms of transport, such as assembly that requires the robots to physically grasp either the object or other group.
mates which are either directly or indirectly connected to the object. The authors in (Groß and Dorigo, 2004, 2008) showed that group transport strategies based on assembly are robust and scalable with respect to various characteristics of the object as well as to the cardinality of the group.

The work on assembly above mentioned is one of the few among those dedicated to group transport, in which the authors opted for Evolutionary Swarm Robotic (ESR) methods. ESR is a design method based on the use of artificial evolution to find set of parameters for artificial neuronal networks that guide the robots to the accomplishment of their task. ESR can be used to synthesise individual mechanisms underpinning complex group responses such as those required in group transport. Our long term objective is to show that ESR can help to overcome some of those limitations currently observed in swarm robotic systems engaged in group transport scenarios, through the design of self-organised and adaptive transport strategies. Recent studies have emphasised the need to engineer self-organisation through investigations focused on the effects of design choices offered by the evolutionary approach on the quality of the solutions (Doncieux and Mouret, 2014; Trianni, 2014). This study aims to contribute to the development of a principled methodological approach to the design of group transport strategies using ESR. In particular, we investigate the effects produced by the characteristics of the robot sensory apparatus on the design of group transport strategies in simple swarm robotic systems that can only push objects.

Our experimental design is made of two conditions: in the T-condition the simulated robots are equipped with a camera for colour perception, proximity sensors, and torque sensors; in the NT-condition the robots can only use the camera and proximity sensors. The results of the study show that artificial evolution exploits the additional torque sensors by developing more robust and more effective group transport strategies which are robust to variations in size and mass of the object as well as with respect to the cardinality of the group. Moreover, the perceptual apparatus of those robots equipped with torque sensors generate adaptive responses that have not been selected during evolution. In particular, the robots are capable of using behavioural responses, originally evolved to avoid deadlocks during coordination, to develop recruitment behaviour.

We are aware that one of the criticism moved to the evolutionary approach concerns the loss of performance during transfer of the evolved solutions on real hardware (see Francesca and et al., 2014). Although our work is in simulation, our robot model and the physics of the robot-world interactions have been carefully developed in order to facilitate the transfer to real hardware. We are currently testing and comparing performances of the system in simulation and on real robots. At the time of writing, this comparative analysis has not been completed yet. However, as shown in http://users.aber.ac.uk/elt7/ECAL2015_suppMat/, the results of initial tests demonstrate that the best evolved solutions can be successfully ported on real robots. Thus, we believe that ESR approach can be an effective design method to provide swarm robotic systems the mechanisms required to mimic the group transport behaviour observed in natural swarms. This work unveils interesting relationships between design choices and characteristics of the evolved solutions, and it contributes to develop design guidelines for engineering robust and successful swarm robotic systems.

The Task and the Simulation Model

This study focuses on an object-transport task in which a group of two robots is required to push an elongate cuboid object which is too heavy to be moved by a single robot. The robots are initially positioned in a boundless flat arena at 50cm from the object (see Fig. 1). From their initial positions, the robots can perceive the object with their camera, and when sufficiently close to it, they can sense it with their infra-red sensors. The task requires the robots to independently search for the object and move towards it. Once in the proximity of the object, the robots have to coordinate their actions in order to push the object by exerting the forces required to transport it as far as possible from its initial position.

To take into account the dynamic aspects of this group transport scenario (e.g., forces, torque, friction, etc.), the agents and their environment have been simulated using Buller physics engine. The object has a cuboid shape (30cm length, 6cm width, 6cm height) with a mass of 280g. Our simulation models an e-puck robot (see Mondada and et al., 2009). The robot model consists of three rigid bodies, a cylindrical chassis (3.55cm radius, 6.2cm height 200g mass), and two motorised cylindrical wheels (2.05cm radius, 0.2cm height, 20g mass) connected to the chassis with hinge joints. Both wheels can rotate forwards and backwards at a...
Figure 2: The robot’s controller for the T-condition. Continuous line arrows indicate the efferent connections for only one neuron of each layer. Hidden neurons receive an afferent connection from each input neuron and from each hidden neuron, including a self-connection. Output neuron receive an afferent connection from each hidden neuron. Sensors to sensor neurons correspondence is indicated underneath the input layer.

maximum speed of 8cm/s.

Each robot is provided with eight infra-red sensors (IR\(^i\) with \(i = \{0, \ldots, 7\}\)), which give the robot a noisy and non-linear indication of the proximity of an obstacle (e.g., the object or another robot). The IR sensor values are computed using a non-linear regression model of the sensor readings collected from the real e-puck (see Michel, 2004, for details). Each robot is also equipped with a camera that can perceive coloured items (i.e., the object which is green, or robots which are all red). The camera has a receptive field of 30\(^\circ\), divided in three equal sectors \(C_i\), with \(i = \{1, 2, 3\}\), each of which can return one of four possible values: 0 if no item falls within the sector’s field of view; 0.4 if one or more red items are perceived; 0.7 if a green item is perceived; 1.0 if red and green items are perceived. The camera can detect coloured objects up to a distance of 50cm.

This study is made of two experimental conditions: the T-condition and the NT-condition. In T-condition, the robots are equipped with additional torque sensors, placed on the robot left and right wheel (\(Q_R\) and \(Q_L\)). In NT-condition the robots do not have torque sensors. A high level of random noise applies to all sensors and motors to guarantee that the controllers transfer to the real robot with no loss of performance (see also Jakobi et al., 1995).

The Controller and the Evolutionary Algorithm

The robot controller is composed of a continuous time recurrent neural network (CTRNN) of \(N = 13\) sensor neurons for controllers of the T-condition, and \(N = 11\) for controllers of the NT-condition. All controllers have 6 internal neurons, and 4 motor neurons (see Beer and Gallagher, 1992, and also Fig. 2, which illustrates the structure of the network). The states of the motor neurons are used to control the speed of the left and right wheels as explained later. The values of sensory, internal, and motor neurons are updated using equations 1, 2, and 3.

\[
y_i = gI_i; \quad i \in \{1, \ldots, N\}; \quad (1)
\]

\[
\tau_i \dot{y}_i = -y_i + \sum_{j=1}^{N+6} \omega_{ji} \sigma(y_i + \beta_j); \quad i \in \{N+1, \ldots, N+6\}; \quad (2)
\]

\[
y_i = \sum_{j=N+6}^{j=N+10} \omega_{ji} \sigma(y_j + \beta_j); \quad i \in \{N+7, \ldots, N+10\}; \quad (3)
\]

with \(\sigma(x) = (1 + e^{-x})^{-1}\) . In these equations, using terms derived from an analogy with real neurons, \(y_i\) represents the cell potential, \(\tau_i\) the decay constant, \(g\) is a gain factor, \(I_i\) with \(i = 1, \ldots, N\) is the activation of the ith sensor neuron (see Fig. 2 for the correspondence between robots sensors and sensor neurons), \(\omega_{ji}\) the strength of the synaptic connection from neuron \(j\) to neuron \(i\), \(\beta_j\) the bias term, \(\sigma(y_j + \beta_j)\) the firing rate \(f_j\). All sensory neurons share the same bias (\(\beta_j\)), and the same holds for all motor neurons (\(\beta_O\)). \(\tau_i\) and \(\beta_i\) of the internal neurons, \(\beta_T\), \(\beta_O\), all the network connection weights \(\omega_{ij}\), and \(g\) are genetically specified networks’ parameters. At each time step, the output of the left motor is \(M_L = f_{N+7} - f_{N+8}\), and the right motor is \(M_R = f_{N+9} - f_{N+10}\), with \(M_L, M_R \in [-1, 1]\). Cell potentials are set to 0 when the network is initialised or reset, and equation 2 is integrated using the forward Euler method with an integration time step \(T = 0.1\).

A simple evolutionary algorithm using roulette wheel selection is employed to set the parameters of the networks (Goldberg, 1989). The population contains 100 genotypes. Generations following the first one are produced by a combination of selection with elitism, recombination, and mutation. For each new generation, the five highest scoring individuals (the elite) from the previous generation are retained unchanged. The remainder of the new population is generated by fitness proportional selection from the 60 best individuals of the old population. Each genotype is a vector comprising real values coding for the network’s connection weights, decay constants, bias terms and gain factor. Initially, a random population of vectors is generated by initialising each component of each genotype to values chosen uniformly random from the range \([0, 1]\). New genotypes, except the elite, are produced by applying recombination and mutation. Each new genotype has a 0.3 probability of being created by combining the genetic material of two parents. During recombination, one crossover point is selected. Genes from the beginning of the genotype to the crossover point is copied from one parent, the other genes are copied from the second parent. Mutation entails that a random Gaussian offset is applied to each real-valued vector.

component encoded in the genotype, with a probability of 0.04. The mean of the Gaussian is 0, and its standard deviation is 0.1. During evolution, all vector component values are constrained to remain within the range [0, 1].

The Fitness Function

During evolution each group undergoes a set of $E = 8$ evaluations or trials. A trial lasts 60s (i.e., 600 simulation steps with 1 stimulation step corresponding to 0.1s). At the beginning of each trial the controllers are reset, and the robots are positioned in the arena. Each trial differs from the others in the initialisation of the random number generator, which influences all the randomly defined features of the environment, the noise added to sensors, and the robots initial position and orientation. The robots initial relative position with respect to the object is an important aspect which bears upon the complexity of this task. This is because the robots initial position contributes to determine the orientation with which the robots approach the object and consequently the nature of the manoeuvres required by the agents to coordinate and synchronise their actions. During evolution, the robots starting positions correspond to randomly chosen points on a circle’s circumference of 50cm radius that has the object in it’s centre. First, one point is randomly chosen and one robot is positioned in the arena. For the second robot, we proceed in the following: in half of the trials, the second robot is positioned at 180° with respect to the first one; in the other half of the trials, the second robot is randomly positioned either on the right or on the left of the first one, at an angular distance randomly chosen in [30°, 40°]. Each robot is randomly oriented in a way that the object can be within an angular distance of ±60° from its facing direction. These criteria should generate the required variability to develop solutions that are not sensitive to the robots initial positions.

In each trial ($e$), an evaluation function $F_e$ rewards groups in which the robots remain closer to the object, and transport the object as far as possible from its initial position. $F_e$ is computed in the following:

$$F_e = \sum_{t=0}^{T} \left( f_1^t + f_2^t \right) + f_3^t; \text{ with } T = 600; \tag{4}$$

$$f_1^t = \sum_{r=1}^{R} IR_1^r + IR_2^r + \left( 1 - d_r \right); \text{ with } R = 2; \tag{5}$$

$$f_2^t = O_{velocity}; \tag{6}$$

$$f_3^t = \Delta O_{position}; \tag{7}$$

$t$ is the current time-step; $d_r$ is the Euclidean distance between the centroid of robot $r$ and the centroid of the object. $d_r$ is set to zero if the robot gets closer than 20cm to the object. $IR_1^r$ and $IR_2^r$ are the readings of the front infra-red sensors of robot $r$. $O_{velocity}$ is the linear velocity of the object. $\Delta O_{position}$ is the Euclidean distance between the position of the object’s centroid at the beginning and the end of the trial. $f_1^t$ rewards groups in which the robots approach and collide with the object. $f_2^t$ rewards groups that transport the object at maximum speed regardless of the object’s trajectory. $f_3^t$ rewards groups that transport the object. The aim of $f_2^t$ is to favour those transport strategies that, being $\Delta O_{position}$ equal, generate longer trajectories. The fitness of a genotype ($F$) is the average team evaluation score after it has been assessed $E = 8$ times: $F = \frac{1}{E} \sum_{e=1}^{E} F_e$.

Results

For each of the two experimental conditions, 26 differently seeded evolutionary simulations have been run for 4000 generations. At the end of the evolutionary phase, for each experimental condition, we have re-evaluated the best groups of each generation of the last 3000 generations of each run. This post-evaluation test aims to evaluate the effectiveness of the group transport strategies in a set of operating conditions larger than the one experienced during evolution, in which the object length, the object mass, the group cardinality (i.e., the number of robots in a group), and the robots initial relative positions are varied. During post-evaluation, homogeneous groups of 2, 3, and 4 robots are required to transport objects of length 20cm, 30cm, and 40cm, and of 3 different masses, each of them sufficiently heavy to require a combined effort of all the agents of the group to transport the object. For each operating condition (i.e., for each combination of object mass, object length, group cardinality), the evaluation is repeated 21 times (trials), by varying the robots initial relative positions according to the 7 different patterns shown in Fig. 3. Each pattern is repeated 3 times changing the robots initial orientation. Each post-evaluation trial lasts 60s (i.e., 600 simulation cycles).

Fig. 4 shows the performances of the best group of each

![Figure 3: Starting positions during post-evaluation test. Black circles indicate starting positions of two-robot groups. For thee-robot and four-robot groups, the starting positions can be obtained by including the grey and the white circles, respectively. Thick lines represent the object.](image)

run in each experimental condition. The runs are ranked in descending order of performance, with group of run n. 1 being the one with the highest median. As expected the groups that can use torque sensors (see Fig. 4, grey boxes) have a better performance than the groups that do not use torque sensors (see Fig. 4, white boxes). By visually inspecting the groups’ behaviour we noticed that this performance difference can be explained with reference to how the groups of the T-condition use the additional sensory information provided by the torque sensors.

The robots without torque sensors move towards the object and keep on pushing it at maximum speed. These robots do not have any means to distinguish between those circumstances in which the forces exerted on the object move it from those that don’t. Thus, they “blindly” keep on pushing the object even when the forces do not produce any significant object movement. This may generate deadlocks (e.g., robots working against each other) from which the robots may not be able to recover. Alternatively, the combination of the direction of pushing and minimal rotational movements of the object help the robots to recover and eventually to coordinate their effort to transport the object. The robots are more likely to incur in deadlock situations when they start from the opposite sides of the object (e.g., starting position n. 1 in Fig. 3). However, in these more difficult starting conditions, robots of the most successful groups, can avoid deadlocks by getting closer to each other before reaching the object. This happens occasionally when they see each other while they are approaching the object.

The robots with torque sensors can use the additional sensory information as a valuable feedback to perceive when the forces exerted on the object do not produce any movement. If torque sensors indicate that the robot’s action do not produce any benefit, then the robot stops pushing the object, moves first few centimeters away from it, and then towards the object again but in a slightly different position. This manoeuvre is repeated until either both robots place themselves in a position relative to the object from which they can effectively transport the object, or until one robot sees one of its group mates. In this case, the robot moves closer to the group mate/s. When all robots get closer to each other on the same side of the object they initiate the transport. The group transport can be achieved either with all robots pushing the object side by side, or with one or two robots pushing the object and the others pushing those in contact with the object. In summary, the torque sensors help robots to avoid deadlocks and improve the group performance.

On the Robustness of the Best Groups of the T-condition

The results illustrated in previous Section indicate that artificial evolution can generate successful homogeneous groups of robots by designing neural mechanisms that exploit the potentialities of the robot sensory apparatus to develop effective group transport strategies. In this Section, we show further data which illustrate how effective the best evolved group of the T-condition is in dealing with conditions never encountered during evolution.

Graphs in Fig. 5 summarise the results of the best evolved controllers of T-condition during the previously illustrated post-evaluation test. Graphs in Fig. 5a, 5b, and 5c refer to results with objects of 20cm, 30cm, and 40cm length, respectively. Recall that the evolutionary conditions concerned two-robot groups required to transport a 30cm object of 280g. Thus, in Fig. 5b the second box represents the performance of the system when re-evaluated in evolutionary conditions. This box can be used as a term of comparison to estimate the robustness of the robotic system in all the other test conditions.

For each group cardinality, and for each object length, there is a common trend which indicates that heavier the objects, shorter the distances the object has been transported. The other important aspect that emerges from these graphs is the drop in performance when four-robot groups are required to push 20cm length objects. The object dimension compared to the group cardinality reduces the number of possible transport strategies to only those in which some of the robots push other robots which in turn push the ob-

Figure 4: Graph showing the distance (in meters) the objects have been transported by each of the best evolved groups of each evolutionary run of each experimental condition, during 567 trials (7 different robots initial positions, 3 object lengths, 3 object masses, 3 group cardinality, and 3 initial robot orientation). White boxes refer to groups of condition NT-condition; grey boxes refer to groups of condition T-condition. Each point in the box refers to the group performance in a single trial. Boxes represent the inter-quartile range of the data, while dashed horizontal bars inside the boxes mark the median value. The whiskers extend to the most extreme data points within 1.5 times the inter-quartile range from the box. Empty circles mark the outliers.
The effect of length can be observed in all the robots of a group. Thus, heavier objects can only produce a loss of performance. The effect of length can be expected since even the lower the group performances (see Fig. 6). The effect of the length and the ratio between mass and length of the object. The bigger the ratio, the lower are those produced by the length and the ratio between mass and length of the object. The lighter length objects the object longer the object length the object length, with crosses for 40cm length objects, triangles for 30cm length objects, and circles for 20cm length objects.

Since the robots usually need more time to arrange themselves in this transport formation, the performances in this test condition tend to be lower. There is also a slight loss of performance for all the four-robot groups, which is caused by a combination of factors. The most relevant is the effect of robot-robot collisions which are more likely to happen in larger groups. If during a collision the robots occlude each other camera, they have no means to distinguish whether they are in touch with another robot or with the object. Therefore, there are robot-robot collisions that trigger pushing behaviour that penalises the group. These are temporary deadlocks that tend to disappear after few seconds. However, these are events that increase the time for coordination and shorten the time for pushing. Moreover, in larger groups, for any starting positions, the robots generally need more time to arrange themselves in a way to exert the forces required to transport the object.

We have also run a statistical analysis on the performances of the best group of the T-condition, using linear mixed models, taking into account random effects of the starting positions. This analysis has shown that we can not reject the null hypothesis that there is not differences between two, three, and four-robot groups. In other words, group cardinality has no effects on performance. Statistically significant effects are those produced by the length and the ratio between mass and length of the object. The bigger the ratio, the lower the group performances and the longer the object length the lower the group performances (see Fig. 6). The effect of mass/length ratio on performances is expected since even the lighter object is heavy enough to require the effort of all the robots of a group. Thus, heavier objects can only produce a loss of performance. The effect of length can be

Figure 5: Graphs showing the performance of the best evolved groups of the T-condition during post-evaluation. Each graph shows the performance of homogeneous groups of 2, 3, and 4 robots while transporting object of different masses, as indicated on the x-axes. The performance is measured in term of distance the object has been transported in 60s trials. The object length is: (a) 20cm; (b) 30cm; and (c) 40cm. Each point in the boxes refer to the performance in a single trial.

Figure 6: Graph showing the relationship between the different factors (i.e., length and ratio between mass and length of the object) and group performances (i.e., the distance the object has been moved in 60s trials) using linear mixed model. The graphs shows data points and fixed effect for different object length, with crosses for 40cm length objects, triangles for 30cm length objects, and circles for 20cm length objects.
explained by taking into account the particular behaviour of robots of this group. Each robot, once in the proximity of the object, moves along the object perimeter by applying forces in different positions until an effective distribution of forces is found. This means that longer the object length, longer the time it takes to find an effective distribution of forces. Therefore, the loss of performance is a consequence of less time left for transport.

In Fig. 7, we show how the performance of the best evolved solution of T-condition varies with respect to the different robot initial positions. Starting position n. 3 is the one with the worst performance. Visual inspection of the robots behaviour have shown that this starting position penalises four-robot groups, since it generates a higher number of robot-robot collisions, some of which triggered the “maladaptive” pushing behaviour mentioned above. However, the graph shows that the groups manage to efficiently cope with the effects produced by the variability in starting positions.

Recruitment Behaviour

In this Section, we show results of a further post-evaluation test, called recruitment-test, which shows that the majority of the best evolved solutions can show a simple form of recruitment behaviour which is serendipitous, since it is not part of the behavioural repertoire selected for during evolution. We have post-evaluated each best solution of each run of the T-condition with a test in which two-robot groups have to transport a 20cm, 280g object. Each solution has been tested 21 times (i.e., 3 times the 7 starting positions illustrated in Fig. 3). In order to test the group for recruitment, we modified the operating conditions in the following. For each trial, the starting position of robot A is moved up to a distance of 80cm from the object. From its starting position robot A can not perceive the object. Moreover, robot A is initially “frozen”. It can not move. Robot B starts the trials as shown in Fig. 3, at 50cm from the object. The camera view of robot B is extended to 100cm. Robot A is free to move if robot B gets closer than 10cm to it after having touched the object.

Recruitment happens if robot B finds out first that the object can not be move by pushing it. Then, it has to move towards robot A. Once robot B gets sufficiently close to robot A, the latter is free to move. However, robot A needs to be guided towards the object by robot B, since only robot B perceives the object from a distance longer than 50cm. In each trial, we infer whether or not recruitment took place simply by looking at the distance the object has been transported after 120s. If the object has not been moved at all, we assume that something went wrong with the recruitment. Otherwise, we assume that the recruitment has been successful.

The graph in Fig. 8 shows that the distance the object has been transported during the recruitment-test. The graph shows that 10 out of the 26 groups manage to transport the object more than 1 meter away from its initial positions in more than half of the trials (see Fig. 8, median values). Considering that both robots are required to transport the object, this result indicates that robots of these groups have developed an effective recruitment behaviour. This social behaviour is generated by the robots instinct to approach the group-mate after having found out that the object required more robots to be transported.
Conclusions

In this study, we have illustrated the results of a set of experiments in which a swarm of robots are required to transport an object by coordinated pushing actions. We have shown that, robots equipped with torque sensors can generate transport strategies that are fairly robust to variability in length and mass of the object, as well as to the cardinality of the group. The behaviour of the best evolved groups looks analogous to the one observed in some species of ants, where the coordination is accomplished through a set of individual responses including realignment, repositioning and reaction to stigmergic communication.

We observed that, in best evolved groups of the T-condition, the torque sensors is primarily used by the robots to generate feedback to distinguish between actions that results in a successful object movement from those that don’t. This feedback helps the robots to recover from deadlocks and to coordinate the forces in order to avoid to work against each other. This is a clear example of how small changes into the sensory-motor configuration of the robot can help evolution to find successful evolutionary paths that lead to robust and adaptive solutions. We have also shown that our robots are capable of developing recruitment responses even if recruitment has not been considered (i.e., selected for) during evolution. Recruitment behaviour stems from a robot’s tendency to approach the closest group mates. In normal conditions, this behaviour has the function to bring the robots on the same side of the object to avoid to work against each other during transport. However, if for any reason a robot is left alone pushing a too heavy object, the tendency to approach a group mate can take the robot away from the object closer to a distant robot, mimicking a simple form of recruitment. This suggests that ESR methods offer a way to generate feedback to distinguish between actions that result in a successful object movement from those that don’t.

To validate the results of our study, ongoing work focuses on test with real robots. In the future, we aim to test the effectiveness of ESR design methods in generating solutions that are required to adapt to objects of irregular shapes. We also aim to expand the behavioural repertoire of the swarms, by integrating more complex form of recruitment and object retrieval responses that require the object to be transported to specific locations.

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References


