On the Modelling of Bio-Inspired Collective Experiments with Real Robots

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Abstract

This paper describes the implementation and modelling of a biologically-inspired collective behaviour. The experiments are concerned with the gathering and clustering of randomly distributed small cylinders. Each experiment has been repeated five times and carried out in a simulated environment (parametric simulation) and with a group of ten Khepera miniature mobile robots. The simulated and experimental results are compared, quantified and discussed showing the main points of interest and the weaknesses of both approaches. Moreover, the paper points out similarities and differences with the results previously published in [10].

1 Introduction

Recently, we have observed a growing interest for the bio-inspired approach in the field of collective robotics (see for instance [5]). *Bio-inspired collective robotics* favours decentralised solutions, i.e. solutions where coordination is *not* taken over by a special unit using private information sources, or concentrating and redistributing most of the information gathered by the individual robots. Inspired by the so-called collective intelligence demonstrated by social insects [2], bio-inspired collective robotics studies robot-robot and robot-environment interactions leading to robust, goal-oriented, and perhaps emergent group behaviours. The bio-inspired approach in collective robotics seems to be a promising way to solve problems which are hard to tackle using classical control methods.

Unfortunately, because it is difficult to build an adequate and reliable set-up for experiments with real robots, many researchers in autonomous robotics are still forced to carry out investigations with simulated robots in simulated environments. This is especially true in the context of collective robotics. This paper argues for the necessity of both approaches, the simulation and the experiments with real robots, in order to understand the mechanisms which are involved in the collective behaviour, such as interference among robots, stigmergic communication or behaviour emergence.

Let us now address the state of the research in a particular well-suited experiment in bio-inspired collective robotics: the gathering and clustering of randomly distributed objects. First, we consider the biological inspiration for this experiment. In some species, ant colonies are able to collect objects (such as food or dead ants) and place them in particular places. All ants of a given colony place the food at the same place and the carcasses in another place. In this way they can collect and store food or carry dead ants to a "cemetery": if a large number of ant corpses or food particles are scattered outside of a nest, they will pick them up, carry them for a while, and drop them. Within a short time we can observe that the corpses are being arranged into small clusters and, over time, the number of clusters decreases and their size increases until eventually all the corpses will be in one or two large clusters. The emergence of these clusters has been studied with social insects by Deneubourg [6], who showed that a simple mechanism involving the modulation of the probability of dropping corpses as a function of the local density, was sufficient to generate the observed sequence of the clustering of corpses.

Gaussier and Zrehen [7] carried out an experiment with a group of Khepera robots implementing similar mechanisms with the same property: the probability of dropping corpses was a function of the local density. They mounted a hook behind the robot, which, given an appropriate sequence of movements, enabled the robot to grasp and shift small cylindrical objects. Precise rules for the basic behaviours were defined: the perception of the objects and obstacles (Winner-Takes-All neuronal net) as well as dragging and placing objects were preprogrammed in such a way that the global probability of building a cluster was greater than that of destroying it. Therefore, after a few minutes, the first clusters began to appear on the arena. However, no quantitative analysis of the experiments was reported by the authors.

Beckers and collaborators [1] did the same experiment with robots of approximatively 25 cm in diameter. The collective behaviour was analysed on the basis of the stigmergy principle. Essentially, it consists in the production of a certain behaviour in agents as a consequence of the effects produced in the environment by previous actions. The experiment was carried out using 1 to 5 robots in an arena where many pucks of 4 cm in diameter were scattered. The robots were equipped with a frontal surface to push the pucks. A microswitch was installed behind the surface to control the maximal number of pucks which can be pushed at the same time. The robot was able to shift two pucks, but when three pucks were detected by the microswitch, the robot stopped pushing and changed direction. Three replications were carried out for each experiment and the collective performance was evaluated measuring the time needed by the robot group to gather all the pucks in a single cluster (between 100 and 350 minutes). The results indicated that the optimal density of robots on the arena surface, in order to accomplish the given collective task in a minimal time lapse (relative to the number of robots), was three (superlinear team performance). According to the authors, the reasons for the presence of this optimum were attributed to the geometry of the clusters and to the constructive and destructive interferences among the agents.

In [8] similar experiments were carried out with a very simple robot architecture based exclusively on a Braitenberg vehicle [3]. The authors used 1 to 5 robots of about 23 cm in length, an arena of 230×260 cm and cubic objects. The experiments were reproduced three times and lasted 20 minutes. The effect of factors such as the number of the objects to be gathered and the number of robots working together were also studied. A precise statistical analysis was carried out but no modelling of the experiment was presented.

In [10] we also presented a similar experiment, which was conducted with a group of 1 to 5 Khepera robots equipped with the gripper module and 20 scattered small cylindrical objects (which will be referred to as “seeds” from now on) in an arena of 80×80 cm. Each experiment was repeated 3 times. The measured performance was the average size of the cluster created during about 30 minutes. However, due to the difficulty that the recognition algorithm had to distinguish between a seed and another robot, often a robot dropped a seed in front of another robot and the latter grasped the seed (seed exchange) or a seed was dropped in an isolated position in the middle of the arena or close to one of its walls. For the same reason, the robots tried to grasp each other and they often became entangled for a few seconds. As a consequence, it was possible to analyse quantitatively the data, but the high rate of destructive interferences and of experimenter interventions prevented the creation of a parametric model in simulation which could have generated similar results.

The experiments presented in this paper are carried out with a more reliable distinguishing algorithm. We aim to show that the improvements in the control architecture and a systematic measuring procedure of the team performances will allow us to compare the experimental results with those obtained in simulation with a probabilistic finite state machine. It is worthwhile to mention that the purpose of the simulated parametric model is not to deliver data which fit as close as possible to the experimental data. The simulations aim to outline the parameters of the real set-up which play a crucial role in the evolution of the collective performances. A better comprehension of collective mechanisms, such as interference among the robots or stigmergic communication, will help to evaluate the expected collective performances of a given number of robots, a given amount of work, a given work area and a pre-established control architecture. We are convinced that questions like how to program a single robot to get a desired emergent behaviour or how to obtain superlinear team performances (which means that n robots work more efficiently than one robot n times longer) are still open.

2 Materials and Methods

2.1 Experiments with Real Robots

2.1.1 Experimental Set-Up

Khepera is a miniature mobile robot developed to perform ”desktop” experiments [11]. Its distinguishing characteristic is a diameter of 55 mm. Other basic features are: a substantial processing power (32 bits processor at 16 MHz), energy autonomy of almost half an hour, precise odometry, light and proximity sensors. In its basic configuration Khepera is equipped with 8 infrared (IR) sensors, 6 on the front and 2 behind its cylindrical structure. On the front these sensors are distributed with a gap of about 14 mm. The wheels are controlled by two DC motors with an incremental encoder (12 pulses per mm of advancement of the robot), and can rotate in both directions. The simple geometrical shape and the motor layout allow Khepera to negotiate any kind of obstacle or corner. Each robot can be extended with a gripper module, which can grasp and carry objects with a maximum diameter of 50 mm. Due to its size, Khepera is a convenient platform for single-robot experiments, even more so in collective robotics experiments: 20 Kheperas can easily work on a $2\,\mathrm{m}^2$ surface, this being equivalent to a workspace of 10×20 m for robots with a 50 cm diameter. The experiments are carried out with a group of 1 to 10 Kheperas and 10 to 40 seeds (see fig. 1 as an example). The seeds have a cylindrical form, with a diameter of 16 mm and a height of 25 mm. We use two square arenas with different sizes, the largest having double the surface of the smallest (80×80 cm and 113×113 cm). The initial scattering of the seeds and the

a) b)

Figure 1: a) Seed scattering at beginning of the experiment and b) after about 2 hours, at the end of the longer experiment.

starting position of the robots are arbitrarily predefined and differ from replication to replication. Several experiments which differ in the number of scattered seeds, the number of robots, and the working surface are performed and the team performances are measured and compared. As performance measurement we chose the same as in [10], that is the mean cluster size expressed in number of seeds at a given time. Measuring the team fitness in such a way is easy and coherent with the probabilistic modelling of the simulation. Furthermore, it allows us to compare the present results with the previous ones. The experiments terminate when a pre-established time lapse is over, in our case approximatively 20 minutes, and are repeated 5 times. A further experiment, which lasted about 2 hours and was replicated 3 times, is also presented as reference.

It is worth emphasising that in both experiments the robots operate completely autonomously and independently; all sensors, motors and controls are on-board, and there is no explicit communication (IR or radio link) with other robots or with the experimenters. The only possible interactions among robots are the reciprocal avoidance of collisions and an indirect form of messages, which arise from the modifications of the environment (i.e., for instance the cluster geometry).

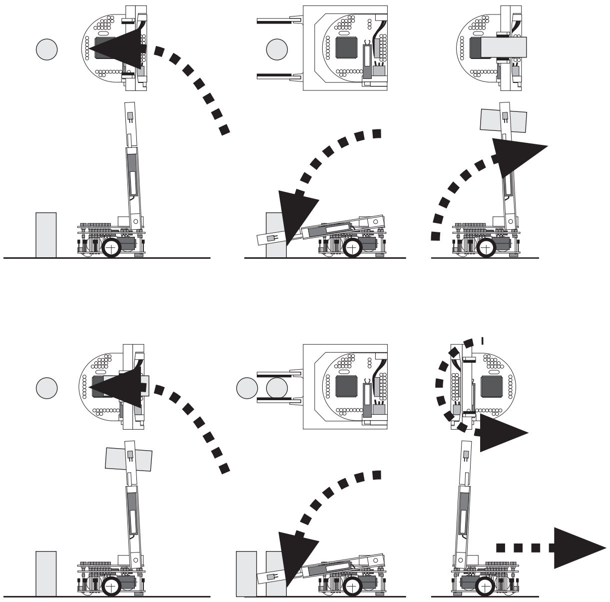


Figure 2: Behaviour of the robot in front of a seed.

2.1.2 *Control Algorithm*

The control architecture is basically a subsumption architecture [4] with two layer levels (layer 0 and layer 1) and a more complex function to switch among the behaviours of the first layer.

There are seven basic behaviours: avoiding deadlock, searching, discriminating, obstacle avoidance, moving back, picking up the seed, and dropping the seed. The only behaviour which can suppress the others is the avoiding deadlock behaviour (layer 0): the robot reads the proximity sensors and the odometry error and it moves back or rotates in order to overcome the deadlock. This is very useful when the robots are entangled

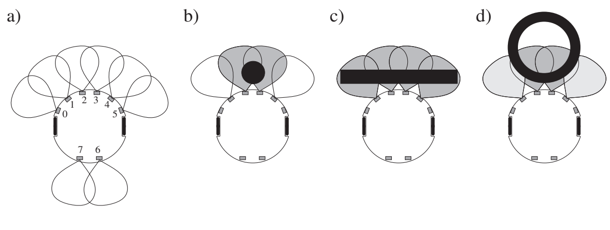


Figure 3: The detection lobes of the proximity sensors of the Khepera. A dark lobe means that the sensor is saturated, a light lobe means a low or zero activity.

Cluster Size [seed]	0	1	2	3	4	5	6	7	8	9	10
Construction Probability	0	0	0.51	0.44	0.38	0.34	0.30	0.27	0.25	0.23	0.21

Table 1: Construction probabilities as a function of the cluster size once the cluster is found.

Cluster Size [seed]	0	1	2	3	4	5	6	7	8	9	10
Destruction probability	0	1	0.37	0.31	0.27	0.24	0.22	0.20	0.18	0.17	0.15

Table 2: Destruction probabilities as a function of the cluster size once the cluster is found.

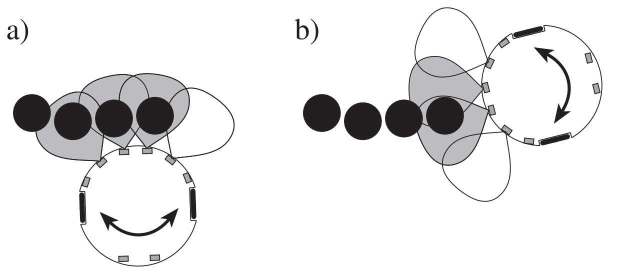


Figure 4: The robot discriminating behaviour is based on a "wobble" movement, sampling continuously its proximity sensors in front of the found object. The picture shows this behaviour in front of a cluster of seeds: in case a) the robots discriminates the cluster as an obstacle, in case b) as a single seed.

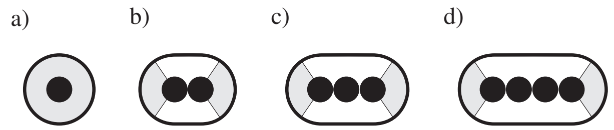


Figure 5: Geometrical representation of the result of the discriminating algorithm when a cluster is found. The ratio between the detection perimeter and the total perimeter of the cluster represents the probability to increment the cluster size of one seed.

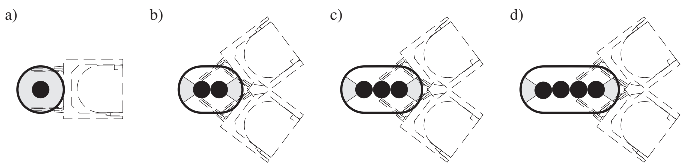


Figure 6: Geometrical representation of the destruction probability of a cluster: the robot, in order to decrement the size of the cluster of 1 seed has first to detect the cluster as in figure 5 and then grasp a seed. Due to the geometrical constraints of the gripper, the access perimeter for seed grasping is more limited than the detection perimeter. The resulting probability is therefore represented by the minimum of the two mentioned perimeters.

or when, after a timeout, the robots cannot discriminate correctly the object noticed by its proximity sensors.

Let us briefly describe the switching among the basic behaviours of layer 1. The searching behaviour consists in moving straight forward until an object is noticed by one of the 6 front proximity sensors. The obstacle avoidance behaviour is obtained using a neural network with a structure inspired from the Braitenberg vehicle 3c [3]. The last three behaviours, moving back, picking up and dropping the seed, are illustrated in fig. 2. We can summarise the resulting robot behaviour with the following simple rules: the robot moves on the arena looking for seeds. When its sensors are activated by an object, the robot begins the discriminating procedure. Two cases can occur: if the robot is in front of a large obstacle (a wall, another robot or an array of seeds), the object is considered as an obstacle and the robot must avoid it. In the second case, the object is discriminated as a seed. If the robot is not already carrying a seed, it moves slightly backwards and grasps the seed with the gripper; if the robot is carrying a seed, it moves further backwards and drops the seed it is carrying close to the one it has found; then, in both cases, it turns about 180 degrees and begins searching again. It should be noted that when the robot moves backwards it continuously checks its back proximity sensors to be sure that there is no obstacle behind it. This continuous test allows to grasp or drop the seed at the right distance.

The discriminating behaviour is the most complex one. The previous algorithm took advantage of the different saturation of the four front proximity sensors: if the activity of the two central sensors exceeds a given activity threshold, the robot also checks the activity of the two lateral ones. If they are also very active, this indicates to the robot that there is an obstacle ahead; if the two lateral sensors are not saturated, it indicates to the robot that there is a seed in front of it. Basically, the actual algorithm is similar to the previous one: the improvement is based on an increased number of spatial and temporal samples. Furthermore, in order to improve the discriminating ability, each robot is equipped with an IR reflecting band (whose reflecting power is about one thousand

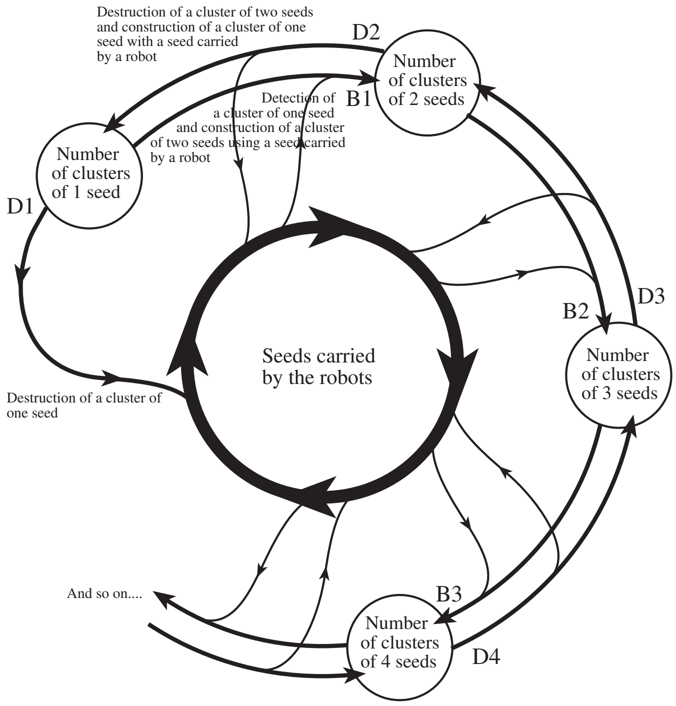


Figure 7: The dynamics of the clustering experiment represented as a probabilistic finite state machine.

times greater than white paper): the size of the robots indicated by the proximity sensors is therefore increased and at a distance of 4-5 cm a robot is already recognised as an obstacle by the other robots. A test of reliability reported in [13] has shown that this algorithm correctly discriminates objects with a probability of 0.89.

Figure 3 and 4 illustrate the activity of the proximity sensors of Khepera in front of different objects. With the control algorithm mentioned above, the typical form of a cluster will be more or less an array of objects.

Figure 5 and Figure 6 illustrate the geometrical situations considered in the calculations of the construction and destruction probabilities of a cluster of a given size when the robot has found it. The numerical results of these considerations are reported in table 1 and table 2.

2.2 Simulation with a Probabilistic Finite State Machine

In this section we describe a simple parametric model of the clustering experiment. We take into account only the building and destruction probabilities of a cluster and its probability to be found by a robot (proportional to its detection surface). The robot is represented by a point. Its coordinates are randomly assigned at the beginning of each program iteration (see the first random process depicted in fig. 8a). There are four fundamental simplifications in our simulation:

- the robot has no physical dimensions; as a consequence, there is no interference among the simulated robots;
- the robot discrimination never fails when the robot detects an object;
- the robot is not moving in the environment: the simulation calculates the global probability of finding a cluster based on the total detection area and the arena surface;
- in order to convert the number of iterations into time, we assume that the clusters are scattered homogeneously on the arena and that we can calculate the minimal mean distance between two of them (see fig. 8a); using the mean distance and the experimental mean velocity of the robots (in these experiments 80 mm/s), we can compute the minimal time to move from one cluster to another, which is set equal to two simulation iterations (a simulated robot needs at least two iterations to pick up a seed from a cluster and to drop it in the same or in another one);
- the arena boundary effects are not considered, which means that the building-destruction probability for a cluster is determined only by its size and not by its location in the environment.

We define a Probabilistic Finite State Machine (PFSM) as a finite state machine in which the transitions from state to state are probabilistically determined (see fig. 7). The machine has as many states as possible clusters with different sizes, which actually corresponds to the number of seeds scattered on the arena. The transition probabilities from state to state are calculated as a function of the total construction and destruction area represented by all the clusters with the same size. As a consequence, the rules to calculate the transition probabilities are pre-established by the geometrical constraints of the set-up but their values are updated every time that the number of clusters of a given size changes. Notice that, for a cluster of size n, if there is no cluster of size n-1, its building probability is zero.

Every robot can increment or decrement the size of a cluster by one seed. The building and destruction probabilities (Bi and Di of fig. 7, with i between 1 and the number of scattered seeds) are conditioned by two stochastic processes which are explained in fig. 8. First, a random position in the environment is assigned to the robot. If this position is inside the detection area of a cluster, the second random process is started. According to the state of the robot (carrying or not carrying a seed) the size of the found cluster is incremented or decremented by one seed if the number delivered by the random process is within the construction or destruction region (calculated with the values of tab. 1 and tab. 2). Both random processes are repeated for each robot independently before the next iteration of the program is started. Notice

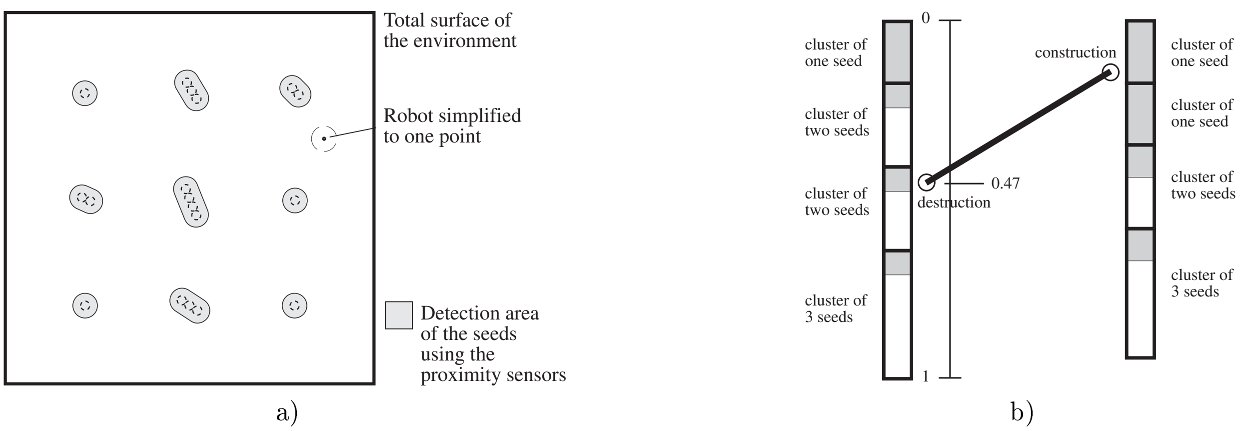


Figure 8: a) The first random process: the clusters are represented with their detection area scaled with the total surface of the environment; the probability that a robot encounters a cluster is proportional to the detection area of the cluster. b) The second random process: the robot can modify the size of the cluster, incrementing or decrementing it by 1 seed, only if the robot runs into the cluster from the positions described in fig. 5 or fig. 6. The two bars represent the whole set of clusters scattered at a given moment on the arena: if the random cursor (set on the left bar at 0.47) fails on a grey zone, the selected cluster will be decremented (left bar) or incremented (right bar) by 1 seed.

that both random processes always consider the whole actual set of clusters and are very lightly coupled: the former delivers only a boolean value "true" if a cluster is found but neither its size nor its position in the arena. As a consequence, the second process, if enabled by the first one, also takes into account the whole actual set of clusters, which is scalar represented by the building and destruction probabilities of each cluster.

3 Results and Discussion

As mentioned in the previous section, we use the mean size of the clusters as collective performance measurement of the group of robots. Most of the following plots are ordered with the team fitness of the real robots on the left side and the team fitness of the simulated robots on the right side. In all of the other figures, only the average fitness of the 5 replications is plotted (3 replications for the longer experiment, see fig. 13).

In order to estimate the repeatability of the experiments and the reliability of the model we have calculated the relative error on the basis of the data variance of each experiment for all the time frames: the experimental results were affected by a relative error always smaller than 25% (35% with only 3 replications in the longer experiment) and the simulated results by one smaller than 20%. Although the number of simulations for each experiment can be very easily increased, it does not make sense to do that because of the repeatability of the experimental results. The experimental relative error could be decreased by a more extended set of replications for a given experiment. However, this could drastically increase the time spent for experimenting, if the same team fitness is measured.

Figure 9 shows the team fitness for a group of 1 to 5 robots. Although the team fitness of the real group of robots is slightly greater than that of the simulated ones, the two plots shown are quite similar. The main difference is that the performances of the groups of 4 and 5 real robots is more rapidly saturated than those of the smaller groups, which is not the case in the simulations. This can be explained by considering the interference among real robots, which is not taken into account in the simulation. As time goes on, the cluster stability is greater because of their size. As a consequence, the amount of work to be done (destroying or constructing) is less than at the beginning. Therefore, there are proportionally more robots moving around the arena looking for seeds: they interfere as mobile obstacles with the robots which are engaged in constructing or destroying operations. Do not forget that, as described above, the control algorithm during picking up and dropping seeds checks if there is any obstacle behind the robot. If there is an obstacle (for instance another robot), the cluster is missed and a new search begins. On the other hand, the team fitness of the group of 3 real robots is substantially greater than the corresponding simulated one. The robot-to-robot interactions could also lead to a better territorial division, which can effectively increase the team efficiency (time saving).

The interference among real robots arises even more clearly in fig. 10: with ten seeds the fitness increases rapidly but after about 300 s it becomes saturated and there are too many robots for too few seeds. Considering only the parameters of the model (which means the

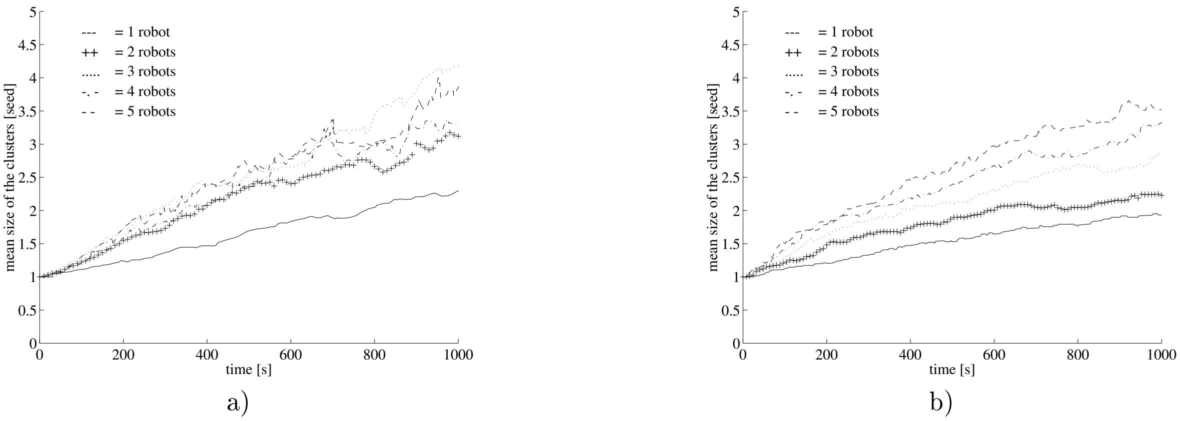


Figure 9: Fitness of the group with increasing number of robots (1 to 5) on the arena of 80x80 cm and 20 seeds to be gathered. (a) Results of the experiments with real robots. (b) Results of the simulations.

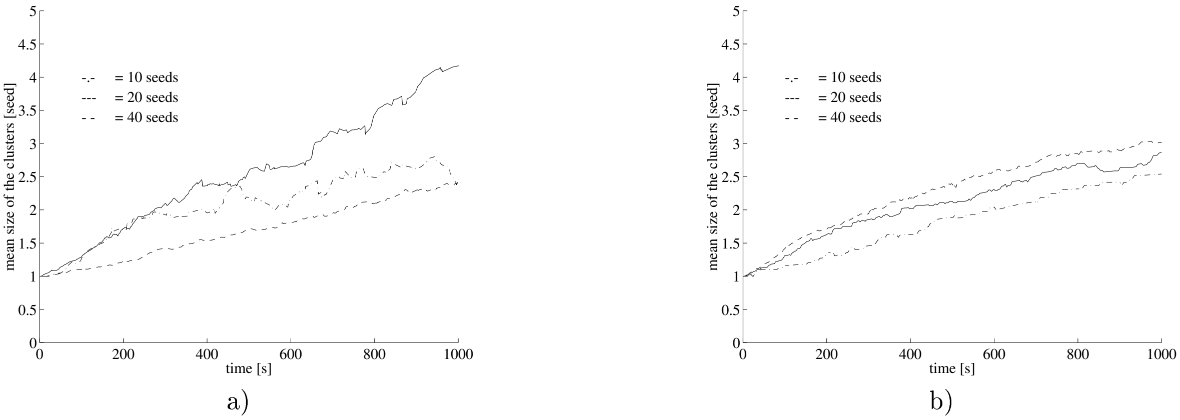


Figure 10: Fitness of the group with 3 robots and an increasing number of seeds (10, 20 and 40) on the arena of 80x80 cm. (a) Results of the experiment with the real robots. (b) Results of the simulations.

construction and destruction probabilities), the number of seeds does not play a crucial role. If the number of scattered seeds is higher, it is easier to find a seed; on the other hand, the mean size of the cluster increases more slowly because of the large number of seeds to be gathered. The former mechanism compensates the latter and the result is that in the simulation there is only a slight difference in the slope of the team fitness changing the total number of seeds scattered on the arena. A further difference between simulation and real robots is noticed in the team fitness with 40 seeds: the limited efficiency of the distinguish algorithm in the real robots decreases the slope of the team fitness even if the probability to find a seed is greater than in the other cases. As mentioned before, this factor is not considered in the simulation.

Fig. 11 compares the team performances where the number of robots, the surface, and the number of seeds to gather is doubled. The purpose here is to demonstrate that robot- and seed-density (meant as amount of work to do) are two key parameters of the experiments and that we can obtain the same results in the team fitness with the same density of robots and seeds (this is very important because of the rare availability of a greater number of robots). If we compare fig. 11a with fig. 11c we can conclude that, considering the repeatability of the experiments, the differences between the two pictures are negligible. This tendency is confirmed by the simulations (compare fig. 11b with fig. 11d).

Fig. 12 shows that in both simulation and experiments with real robots there is no superlinearity in the team performances. On the contrary, in the experimental results with 4 and 5 robots there is a sublinearity because of the destructive interferences.

Finally, fig. 13a shows the experimental results obtained using a special tool developed at our laboratory to extend the autonomy of the Khepera robots [9]. Al-

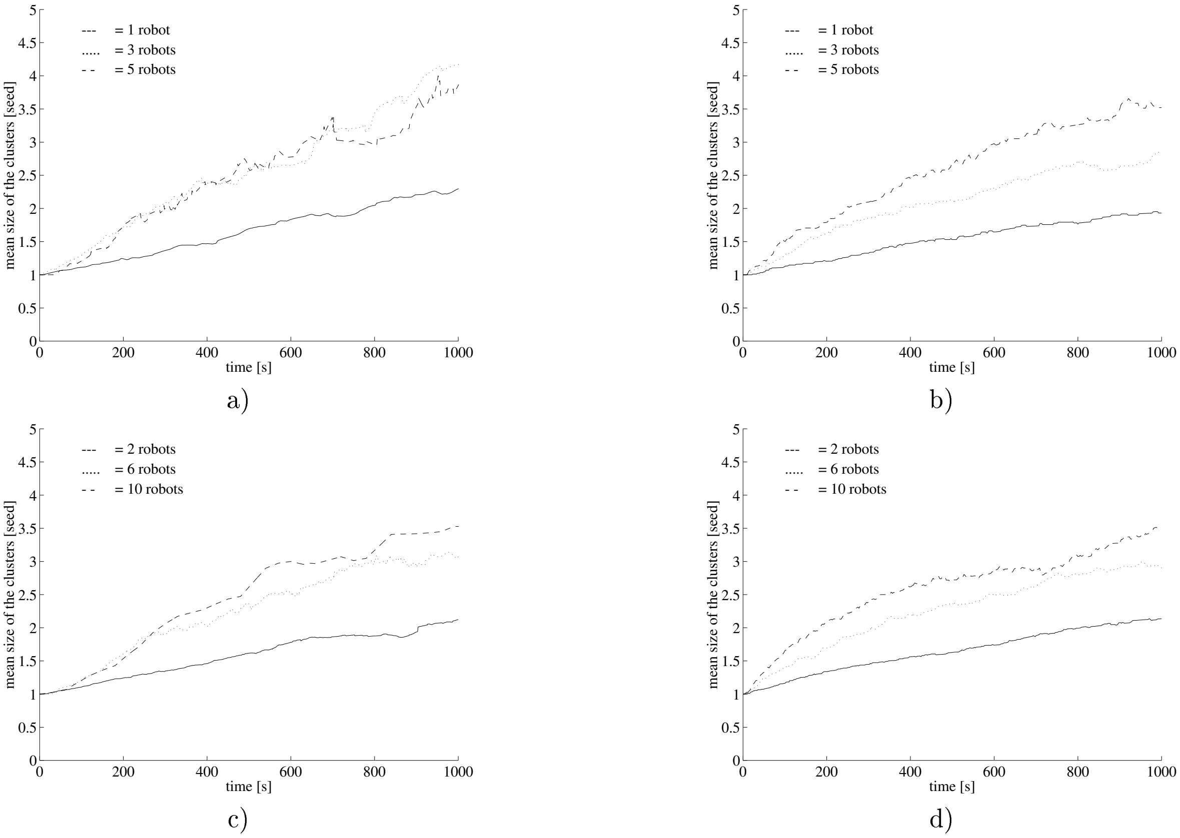


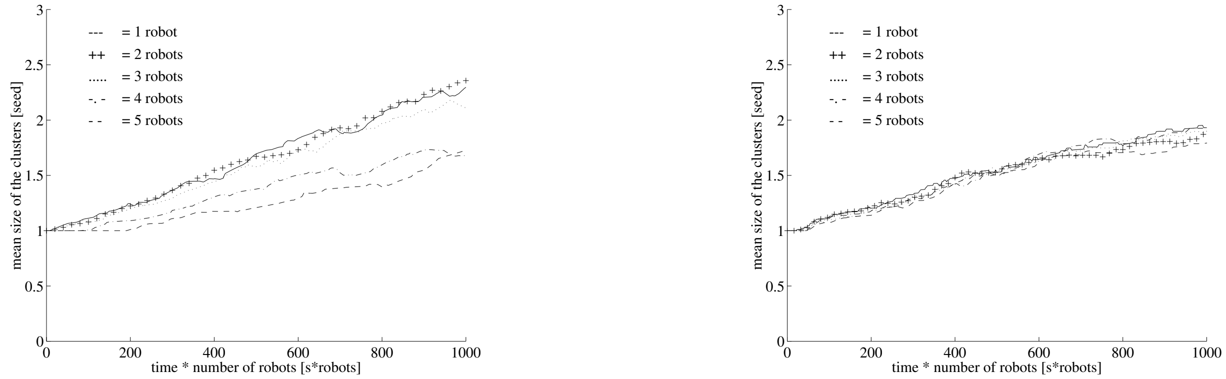
Figure 11: Fitness of the group with increasing number of robots (1,3 and 5) on the arena of 80x80 cm and 20 seeds to gather in a) and fitness of the group with the double of teammates (2,6 and 10), the double of seeds (40) and an arena two times bigger (113x113 cm) in c). The corresponding simulated fitnesses are depicted in figure b) and d).

though a single experiment replicated only three times can not be representative, the figure shows that after 3000 seconds the team fitness becomes saturated due to interferences. In comparison, we have performed the same experiment but longer in simulation. The simulation results are shown in fig. 13b. Since the probability to build a cluster is consistently greater than that to destroy it, the seeds can be gathered in a single cluster if enough time is available. We guess that it is not possible to obtain this result with real robots and the set-up described in this paper due to the crucial role played by interferences. Remember also that the resulting building probability (building probability minus destroying probability) is ever smaller. As a consequence, before all the seeds can be gathered together, the average of the cluster size could reach a saturation zone where interference and building gradient contributions are in equilibrium. As a final remark, it has to be pointed out that the improvement of the discriminating algorithm has also changed the building probability for single-seed clusters. Due to the weak reliability of the previous algorithm, another robot could be discriminated as a seed and, consequently, single-seed clusters were often created in the middle of the arena or beside the wall. Adding a probability for building one seed clusters in the PFSM parametric model has led to a radical change in the fitness tendency: after about 40 minutes the team fitness did not increase and the mean cluster size remained about 3.

4 Conclusion

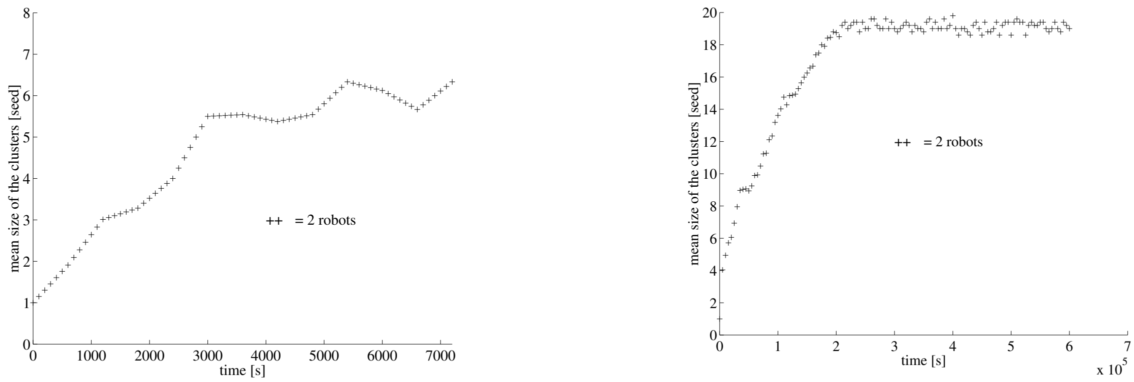
The results of this paper have shown that it is helpful, in collective robotics, to compare simulation results with real robot experiments in order to better understand mechanisms such as interference or stigmergic communications. The previous section has shown that the parameters chosen for the simulation (number of robots, number of seed, geometry of the environment and of the interaction seed-robot) play a crucial role in the evolution of the team fitness. The influence of these key parameters has also been verified in the experiments with real robots, changing one parameter at a time.

Furthermore, this paper has pointed out that in order to compare the results of the two approaches, it is



a) b)

Figure 12: Mean fitness of the single teammate within a group composed by an increasing number of robots (1 to 5) on the arena of 80x80 cm and 20 seeds to gather. (a) Results of the experiments with the robots. (b) Results of the simulations.



a) b)

Figure 13: The evolution of cluster mean size during a) 2 hours with real robots and b) about 7 days in simulation (the time needed for this simulation is about 5 minutes on a SUN Sparc Station 20).

necessary to choose a team fitness function which can be easily quantified. In our opinion, the noise present in the real world makes it necessary to repeat each experiment at least five times to have an acceptable relative error, whose upper limit was set in these experiments to 25%. The new discriminating algorithm has considerably improved the reliability of the experimental fitness measurement so that a comparison between the simulated and the real world performance data is more significant.

Both approaches, simulation and experimentation, have also shown their limitations in view of obtaining interesting collective behaviour running on real robots. It is very difficult to simulate robots considering all the mechanisms and the noise of the real world: the optimal key parameters found in simulation could be quite different from those of the real environment. Therefore, we advocate a parametric simulation of the robots, which will not suppress the need to experiment with real robots but will help to understand the mechanisms found in the real world. On the other hand, the limited energy autonomy of the Khepera robot as well as the whole procedure needed for preparing the set-up represent a great handicap to perform many replications of the same experiment. Not only do the robots have to be charged between two successive experiments, but the battery discharging process during the experiment may considerably change the performances of the algorithm (we notice some difference in the discriminating algorithm, which is quite sensitive, between the beginning and the end of the experiment; we intentionally cut the last 3 minutes from the processed data shown in the previous plots).

The results show that in this kind of experiments with no explicit communication among robots and with no adaptivity in the robot control, a greater number of robots does not necessarily help to increase the fitness. If we compare the performances of each teammate with that of the single robot, we see that the robot working alone always achieves the best performance (linearity or sublinearity of the fitness).

The introduction of adaptivity could, for instance, allow the single robots to switch from an active phase to an inactive one when the ratio between the amount of work (in our case the seed finding rate) and the interference (in our case the encounter rate with other teammates) decreases under a given threshold. Similar mechanisms are supposed to play a crucial role in ant colonies [12]. These are intriguing examples of adaptive collective behaviour which can be an important source of inspiration for collective robotics, when the collective behaviour is generated by a completely decentralised system.

The communication ability, although not needed to solve non-cooperative collective tasks, could be a further feature to improve the team fitness. In an experiment similar to that described in this paper, explicit communication would help to decrease the interference rate if the robots could communicate their actual activity (destroying, building a cluster or looking for seeds) to their fellows. In most cases, local communication would be more efficient than global communication, because of the greater available bandwidth (parallel communication channels).

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