A Probabilistic Model for Understanding and Comparing Collective Aggregation Mechanisms

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Abstract. This paper presents a flexible probabilistic model for the description of aggregation processes in autonomous collective robotics. Two different experiments are considered: one carried out by the authors, the other by Beckers et al. [1] with teams of reactive autonomous robots which differ from a morphological as well as from a control point of view. Rather than simulating robots moving within an environment, the probabilistic model represents the clustering activity as a sequence of probabilistic events during which cluster sizes can be modified depending on simple geometrical considerations and robot control parameters. It is shown that, for both considered robotic platforms, the evolution of the cluster sizes is perfectly described, both qualitatively and quantitatively, by the probabilistic model. By comparing the results at the model level, a better understanding is gained of the influence of the interaction geometry and of the robot control parameters on the collective aggregation dynamics.

1 Introduction

Biologically inspired collective robotics favours distributed 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.

Often, fully distributed control is combined with minimal robotic skills: robots are not able to communicate to each other, to plan their activity or to adapt their behaviour continuously. With such simple controllers, a gathering task becomes essentially a geometrical problem with a probabilistic nature which is well adapted to be described by simple probabilistic models.

The motivations for such a modelling are two-fold. *Firstly*, because of its minimalist essence, it enables the investigation and the determination of which characteristics of the experiment are most influential on the clustering process.

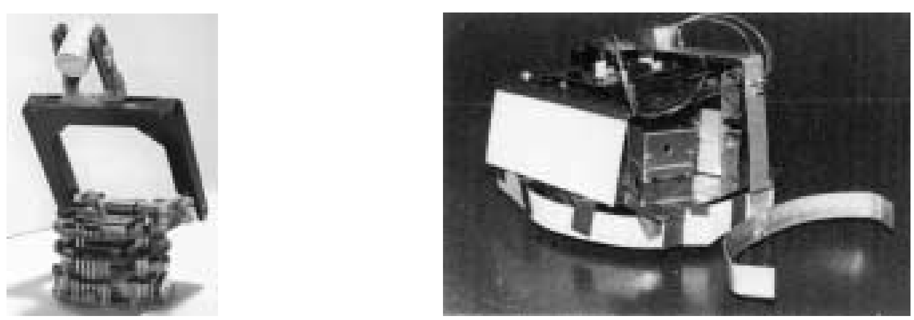
Secondly, working with probabilistic simulations means time saving. In particular, it would be interesting to dispose of a tool which allows the evaluation of critical characteristics of an experiment before the robot's final design is accomplished or before a much more complicated sensor-based simulator is developed.

Collective distributed clustering of spread objects is inspired by studies of aggregation processes with social insects, such as ants for instance [3]. In [1, 5, 7], similar experiments were carried out with real robots and reactive control architectures. In the former two papers, a precise statistical analysis was carried out but neither a modelling of the experiment nor a comparison with simulation results were presented. In [7] we presented a probabilistic model and we compared its predictions with data delivered by Webots, a 3D simulator of Khepera robots [8].

This paper firstly presents new results with real robots over long experiments which match perfectly with the predictions reported in [7] and, secondly, it shows how the probabilistic model can describe an experiment with a completely different robotic platform such as the one used in Beckers et al.'s experiments [1].

2 Materials and Methods

This section presents the two experiments at the experimental and at the modelling level. We focus on the experiment with the Khepera robots and we use the experimental data of Beckers et al. to demonstrate that our model is valid for a completely different set-up. The relevant differences between both set-ups are shown in Tab. 1.



a) b)

Fig. 1. a) Khepera equiped with gripper. b) Robots used by Beckers et al. (photo courtesy of Prof. J.-L. Deneubourg)

2.1 Experimental Set-Up

Experiments with Khepera. All Khepera robots [9] used in the experiments are extended with a gripper module (see Fig. 1a) and equipped with an IR

a) b)

Fig. 2. a) Seed scattering at beginning of the experiment and b) at the end of one of the longest experiments (after about 2:05 h)

a) b)

Fig. 3. a) Example of aggregation process with 3 robots in Webots. Seed scattering at beginning of the experiment and b) after about 4:15 h of simulated time

enhanced reflecting band (not shown in Fig. 1a). This band avoids that moving robots can be recognized as objects to grasp and increases the robot-robot avoidance distance (see Tab. 1). The same robot configuration can be obtained using the Webots simulator [8]. Webots is based on the "as realistic as possible" reproduction of the sensor capabilities as well as of the robot-robot and robot-environment interaction kinematics. As term of comparison, the mean acceleration ratio for this experiment between Webots and real time is about 15 on a workstation Ultra Sun 1 with five robots.

We can summarize the robot's behaviour with the following simple rules. The robot moves on the arena in a straight line looking for seeds. When its sensors are activated by an object, the robot starts a discriminating procedure. Two

Table 1. Comparison between Khepera's and Beckers et al.'s set-ups. All geometrical dimensions are given in [cm]. Beckers et al.'s robots are equipped with a 17 cm wide C-shaped gripper (*), see Fig. 1b

Set-up	Arena	Seeds			Robots		Detection range			Initial scattering
		∅	h	nb	dim	nb	seeds	walls	robots	
Khepera	80x80	1.7	2.5	20	5.5∅	1–10	1.7	1.7	6.5	arbitrarily irregular
Beckers et al.	250x250	4	2.5	81	17x21	1–5	8.5*	20	20	regular grid

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 avoids it. In the second case, the small obstacle is considered as a seed. If the robot is not carrying a seed, it grasps the seed with the gripper; if the robot is already carrying a seed, it drops the seed it is carrying close to the one it has found; then, in both cases, it resumes looking for seeds. Note that, because only the two extreme seeds of a cluster can be identified as seeds (in opposition to obstacles) by the robots, clusters are build in lines (see Fig. 2 as an example).

Beckers et al.'s Experiments. In [1], each robot is equiped with IR sensors for obstacle avoidance and a C-shaped gripper. The gripper is provided with a micro-switch which is activated when a certain number of pucks are pushed.

We can summarize the robot's behaviour with the following simple rules. The robot moves on the arena in a straight line looking for pucks and avoiding obstacles (wall or teammates). If the pucks pushed by the gripper are three or more, the micro-switch triggers a puck-dropping behavior: the robot leaves the pucks on place and resumes the searching behaviour. Notice that, because of the sensorial orthogonality in the distinction between pucks and obstacles, cluster are recognized and accessible from any angle. The resulting cluster form is therefore approximatively circular.

2.2 Probabilistic Model

The central idea of the probabilistic model is that instead of simulating robots moving within an environment, their activity is represented as a sequence of probabilistic events. Robots could therefore be seen as dice being thrown into the arena at each iteration, with their random location as well as their current state (i.e. carrying zero, one or two objects), determining their next state and the next state of the environment (i.e. the state of the clusters). The model takes into account physical sizes (arena, robots, and objects), the geometry of robot-robot and robot-environment interactions, the time needed to manage them,and the sensor range for detecting objects, walls or teammates. An interesting feature of this method is that the probabilistic model is easy to implement because it is closely related to the flowchart of the robot controllers.

In the considered aggregation process, the transition probabilities among the different states of each robot controller are conditioned by three (four for Khepera experiments) stochastic processes. The *first* stochastic process assigns a random position to the robot. If this position is inside the detection area of a cluster, the *second* random process is started. According to the robot state, the size of the found cluster is incremented or decremented by one or two objects if the number delivered by the second random process is within the incrementing or decrementing region (calculated with the values of Fig. 4c and Fig. 5c). Notice that Khepera and Beckers et al.'s robots differ not only from a morphological but also from a sensorial and therefore behavioural point of view. On one hand, when Khepera notice an object, it always rotates on place till the object is in

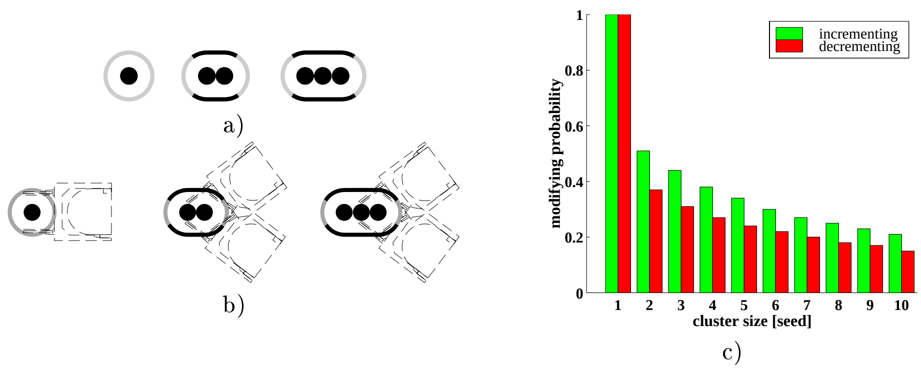


Fig. 4. Khepera (scale 1:10). a) Geometrical representation of the cluster incrementing probability. The ratio between the identification perimeter (*light grey arc*) and the total detection perimeter of the cluster represents the probability to increment the cluster size by one seed. b) Geometrical representation of the cluster decrementing probability. The robot, in order to decrement the size of the cluster by 1 seed, first has to detect the seed on the cluster tip as in Fig. 4a and then grasp it (the angle from which a seed can successfully be grasped from a cluster is slightly smaller than its detection angle, see dark grey arc in Fig. 4b). c) The above mentioned geometrical considerations are translated in probabilities of incrementing or decrementing the cluster size given the state of the robot (carrying or not a seed), once the cluster has been found

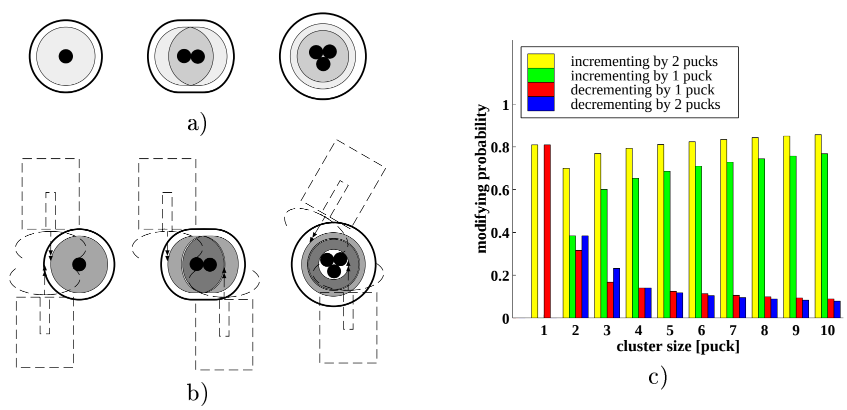


Fig. 5. Beckers et al. (scale 1:20). a) Geometrical representation of the cluster incrementing probability. The ratio between the grey areas and the whole detection area of the cluster represents the probability to increment the cluster size by two pucks (*very light grey*) or one puck (*light grey*). b) Geometrical representation of the cluster decrementing probability. The ratio between the grey areas and the whole detection area of the cluster represents the probability to decrement the cluster size by one puck (*dark grey*) or two pucks (*very dark grey*). c) The above mentioned geometrical considerations are translated in probabilities of incrementing or decrementing the cluster size given the state of the robot (pushing one puck, pushing two pucks or unloaded), once the cluster has been found

front of it. It is able to accomplish this behavior because it is equiped with a belt of IR sensors. As a consequence, the modifying probabilities are calculated from perimeters of clusters. On the other hand, this behavior is not accomplished by Beckers et al.'s robots because the gripper is only able to measure the pressure exerted by the pucks but not the contact point. As a consequence, these robots access the clusters from any point and any angle and we have to consider surfaces rather than perimeters for calculating the modifying probabilities. The *third* stochastic process, the interference with other teammates, can can occur during the search as well as during object pick up or drop activity. If the random position assigned to the robot is inside the detection area of one of the teammates, the robot's activity is frozen for a given number of iterations corresponding to the real time lapse needed for avoiding the teammate. The *fourth* stochastic process, implemented only in the Khepera experiments' modelling, takes into account the object distinguishing efficiency (0.89) of the implemented controller. Each random process is carried out for each robot independently before the next iteration of the program is started.

In order to convert the number of iterations into time, we consider the time needed by a robot to sweep the detection area of a single seed (equivalent to an iteration) and calculate a fixed conversion factor (F) as follows (see [7] for further details). $A_{\mathrm{detobject}}$ = detection surface of a single object, W_{robot} = robot width, $\bar{v}_{\mathrm{robot}}$ = mean forward velocity of the robots.

$$F = \frac{A_{\mathrm{detobject}}}{\bar{v}_{\mathrm{robot}} W_{\mathrm{robot}}} [\mathrm{s/iterations}] \qquad (1)$$

As term of reference, the mean acceleration ratio between the probabilistic simulation and real time is about 4000 on a Ultra Sun 1 with five robots.

Probabilistic Modelling of Experiments with Khepera. The cluster modifying probabilities for Khepera are depicted in Fig. 4. Every robot can increment or decrement the size of a cluster by one seed at a time. With the used numerical values ($A_{\mathrm{detseed}} = 20.4\ cm^2$, $\bar{v}_{\mathrm{robot}} = 8.0$ cm/s, $W_{\mathrm{robot}} = 5.5$ cm) the resulting conversion factor is F = 0.46 [s/iterations]). The conversion factor is also used for taking in account the duration of the actions of the robots. For instance, with the implemented discriminating behavior, it takes 3 s for avoiding obstacles and 10 s for modifying the size of a cluster. The algorithm translates these time lapses into number of iterations during which the searching behavior is frozen.

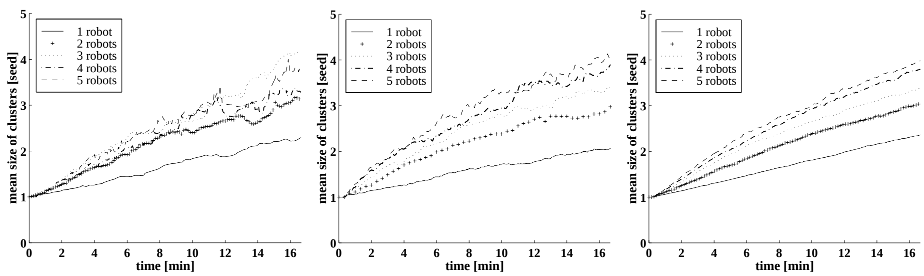
Probabilistic Modelling of Beckers et al.'s Experiments. The cluster modifying probabilities for Beckers et al.'s robots are depicted in Fig. 5. Every robot can increment or decrement the size of a cluster by one or two pucks at a time. With the used numerical values ($A_{\mathrm{detpucks}} = 12.6\ cm^2$, $\bar{v}_{\mathrm{robot}} = 27$ cm/s, $W_{\mathrm{robot}} = 17$ cm) the resulting conversion factor is F = 0.027 [s/iterations]). The robot takes about 0.5 s to avoid an obstacle and about 1.6 s to modify the size of a cluster.

3 Results

We have carried out several sets of experiments with different number of robots and durations (see Table 2). The plots show the mean over all the runs and error bars represent the standard deviation around the mean.

3.1 Experiments with Khepera

All experiments are carried in the three different implementations (real robots, Webots simulator and probabilistic model) and different group sizes, except for the longest experiments which have been realized only with a group of three real robots. It is worth to notice that the about 18 hours needed for all the runs of the long experiments with real robots have been performed without any recharging break thanks a special tool [6, 7] which allows the robots to be supplied from the floor (see Fig. 2).



a) b) c)

Fig. 6. Aggregation evolution with increasing number of robots (one to five). a) Results of the experiments with real robots. b) Results of the Webots simulator. c) Results of the probabilistic modelling

In order to check whether or not there is a significant difference between data collected from the simulations and the real experiment, we performed a Mann-Whitney test [4] on the distributions of mean cluster size at the end of the shorter

Table 2. Characteristics of the experiments carried out. *mcs* = mean size of the clusters, *bcs* = size of the biggest cluster, *nc* = number of clusters

Set-up	Robots	Duration	Nb of repetitions			Measurement	Figures
			real	Webots	prob. model		
Khepera	1–5	16 min	5	10	100	msc	6
Khepera	3	600 min	5	10	100	msc, bcs, nc	7
Khepera	1–10	till single cluster	5	10	100	nc	8a
Beckers et al.	1–5	till single cluster	3	–	100	nc	8b

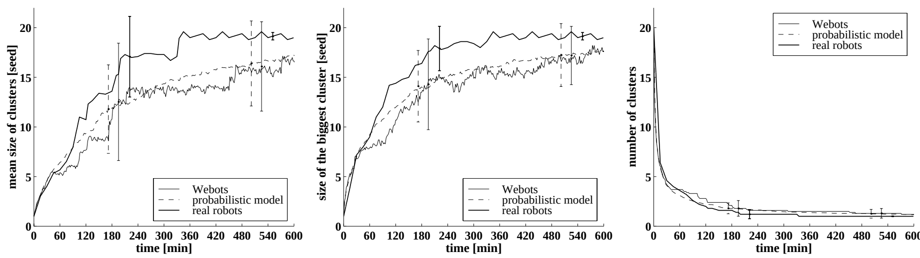


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Fig. 7. Evolution of aggregation process during ten hours. The results of real robots, Webots simulator and probabilistic modelling are overlapped in the same plot. Notice that the resulting plots are the average of a different number of runs with different sample times (15 minutes for real robots, 2 min for Webots and probabilistic modelling). In order to obtain a plot with real robots extended over a pre-established, wide time window, we recorded the aggregation noise during two hours after a single cluster arose. This allowed us to stop a given run once all seeds were gathered in a single cluster and to extend the run data with the recorded noise

experiments and on the time needed to gather all seeds in the longer experiments. With the help of this non-parametric test, we compared the distributions of pairs of data sets. The results show that there is no statistically significant difference ($p<0.05$) over 27 data sets except in three cases (Fig. 6, one robot, Webots vs. prob. model and three robots, real robots vs. prob. model; Fig. 8a, nine robots, Webots vs. prob. model).

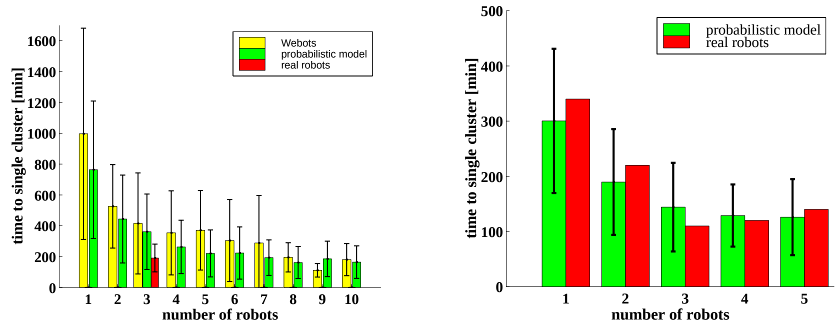
Fig. 6 shows the initial clustering evolution for a group of one to five robots. Although the results of both simulations, Webots and probabilistic model, are slightly smoother than those of the real ones (they are namely the average of a larger number of experimental replications), the three plots present a good agreement.

Fig. 7 illustrates longer experiments with a group of three robots. Once again, both the sensor-based simulation and the probabilistic model are in good agreement. Real robots data show a slightly faster evolution of the aggregation process but this is mainly due to the reduced number of runs in comparison to simulation. The mean real robot data are in any case within the mean value extended with the standard deviation of simulation data.

Fig. 8a shows a comparison of Webots simulator and probabilistic model based on mean and variance of the time needed by the robots to gather all the seeds in a single cluster.

3.2 Beckers et al.'s Experiments

The comparison between the results of our probabilistic model and the ones reported in [1] is shown in Fig. 8b. There is a good agreement between both results based on mean and variance of the time needed by the robots to gather



a) b)

Fig. 8. Comparison between the results of simulations and real robots on the time needed to gather all the objects in a single cluster. a) Khepera experiments. b) Beckers et al.'s experiments

all the pucks in a single cluster. However, we were not able to perform any statistical test because single run data were no more available.

4 Discussion and Conclusion

This paper presented a simple and flexible probabilistic model which has been applied to two completely different robotics platforms. The good agreement of the clustering dynamics described by the probabilistic model with data collected with real robots or more sophisticated simulators such as Webots shows that the proposed minimalist model incorporates the essential characteristics of the clustering problem. These characteristics have been identified to be probabilities of modifying the size of clusters and probabilities of having interferences with other robots. These probabilities are essentially based on geometrical considerations and can be derived from the sensory capacity of single robots. Once these probabilities are established and interaction time lapses measured, the probabilistic model has the interesting feature of being a prediction tool of the same quality as a detailed sensor-based simulation, while being significantly simpler and faster.

Another interesting feature of the model is that the identification of the primary characteristics of this particular clustering problem is a step forward towards the understanding of collective mechanisms underlying clustering in general. For instance with the Khepera set-up, the model has predicted, before the long experiments were carried out, that it was possible to gather all the seeds in a single cluster, if enough time is available. In fact, since clusters of isolated seeds are in an irreversible way eliminated during the aggregation process and since aggregation is enhanced by a positive building gradient (the incrementing probability is consistently greater than the decrementing probability, see Fig. 4), these predictions have been confirmed experimentally. This resulting building gradient is even more enhanced in the experiments of Beckers et al.: the greater the cluster size, the more stable the cluster is. This mechanism, simply depending on the robot-environment interaction, speeds up the team performances (Beckers et al.'s robots are able to cluster 4 times more pucks in half the time needed by a Khepera team of the same size).

Finally, the results show that in this kind of experiments, where the coordination between robots is essentially probabilistic, the data obtained present a high variance. One possible solution to reduce variance and increase coordination while keeping the team control fully distributed, would be to introduce a form of explicit local communication (signalling or symbolic communication).

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