

Efficiency and Task Allocation in Prey Retrieval

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Abstract. Prey retrieval, also known as foraging, is a widely used test application in *collective robotics*. The task consists in searching for objects spread in the environment and in bringing them to a specific place called *nest*. Scientific issues usually concern efficient exploration, mapping, communication among agents, task coordination and allocation, and conflict resolution. In particular, interferences among robots reduce the efficiency of the group in performing the task. Several works in the literature investigate how the control system of each robot or some form of middle/long range communication can reduce the interferences. In this work, we show that a simple adaptation mechanism, inspired by ants' behaviour and based only on information locally available to each robot, is effective in increasing the group efficiency. The same adaptation mechanism is also responsible for self-organised task allocation in the group.

1 Introduction

Scientific interest in collective robotic systems, in which several independent robots work together to achieve a given goal, can have both an engineering and a biological origin. From an engineering perspective, systems made of several agents are appealing because they represent a way of improving efficiency in the solution of tasks that are intrinsically parallel, such as the delivery of items in a factory or the exploration of unknown environments. From a biological perspective, many robots working together (or in competition) are interesting because they are a good test-bed for theories about self-organisation [8].

Recently, researchers interested in the design of the control programs for groups of robots have taken inspiration from biological systems, where swarms of animals are able to solve apparently complex problems. Some of the solutions that animals adopt rely on the exploitation of the dynamics brought forth by the interactions among agents and between agents and the environment.¹ A control program that emulates these solutions exploits some features of the environment

¹ A well known example is that of ants that lay and follow pheromone trails while foraging. The interplay between the pheromone laid by each ant and its evaporation makes the shortest path to the food source become the preferred one [6, p. 26–31].

and does not rely on direct means of communication. The robotic field that studies this approach is referred to as *swarm robotics*.

We present here a preliminary study of a system that uses swarm-robotic techniques. We consider a retrieval task for a group of robots. Taking inspiration from prey retrieval in ants, we analyse the effects that a simple form of adaptation has on the behaviour of the group. After having introduced the concept of group efficiency in retrieval, we show that adaptation is a valid means to improve the efficiency and that a self-organised task-allocation phenomenon takes place.

This work was carried out within the framework of the SWARM-BOTS project, a Future and Emerging Technologies project founded by the CEC, whose aim is to design new artifacts able to self-assemble and that co-operate using swarm-intelligent algorithms.

This section continues describing the field of swarm robotics and the SWARM-BOTS project. Section 2 describes the problem of prey retrieval in robots and ants. Section 3 defines the concept of efficiency of retrieval and explains our approach to its improvement. Section 4 describes the hardware and the software used to run the experiments. Section 5 reports and discusses the results we obtained. Section 6 describes related work. Finally, Section 7 draws some conclusions and lists possible future directions of research.

1.1 Swarm Robotics

Some collective behaviours observed in Nature, such as in ant colonies or other animal societies, can be explained without the assumption of direct communication among individuals, but only by exploitation of the environment. This is a form of indirect communication called *stigmergy* [12,14]. “In situations where many individuals contribute to a collective effort, such as a colony of termites building a nest, stimuli provided by the emerging structure itself can be a rich source of information for the individual” [8, p. 23]. “In stigmergic labor, it is the product of work previously accomplished, rather than direct communication among nest-mates, that induces the insects to perform additional labor” [24, p. 229].

Controllers that use stigmergic communication are usually simple. They are often made of reactive behaviours which exploit the dynamics and the complexity of the environment itself. The same controller can be used on a huge amount of robots of the same kind, that is, in a swarm. The design of such controllers is the object of study in the field of *swarm robotics*, which is part of the field of *swarm intelligence* [6].

An important issue in swarm robotics regards the understanding of the relationship between local and global behaviours in the swarm. The dynamics and the factors that play an important role in the group are not easy to identify, to model and to control. In this context, a good analysis and understanding of the dynamics of the system plays a crucial role.

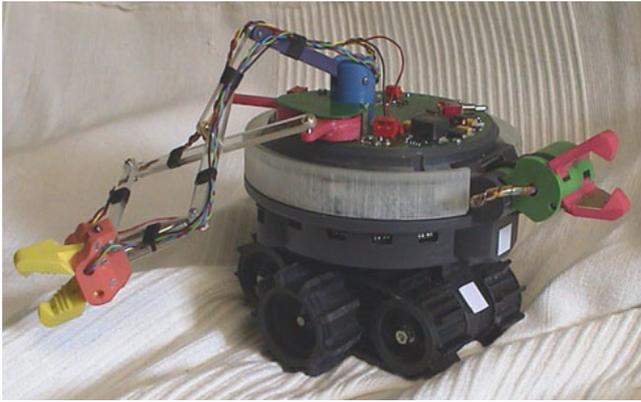


Fig. 1. Picture of the prototype of an *s-bot*.

1.2 The SWARM-BOTS Project

The aim of the SWARM-BOTS project² is to develop a new robotic system, a *swarm-bot*, composed of several independent and small modules, called *s-bots* (Fig. 1). Each module is self contained, capable of independent movement and of connecting with other modules to form a *swarm-bot*. This process is intended to be self-organised in order to adapt to dynamic environments or difficult tasks. Examples of difficult tasks are the pulling of heavy objects or exploration on rough terrain. Collaboration is achieved by means of stigmergic communication. The control program of each *s-bot* uses techniques derived from swarm intelligence and inspired from similar phenomena observed in biology [3,8].

The project lies between the fields of *collective robotics*, where robots are autonomous but do not connect to each other, and of *metamorphic robotics*, where robots need to be always connected and therefore are not fully autonomous. Some works in collective robotics are described in Sec. 6. Examples of metamorphic robots are described in [17,19,20].

2 Problem Description

The typical environment used in the literature for prey retrieval experiments is given by (Fig. 2):

- a group of robots, which we also call *colony* or *swarm*;
- objects spread in the environment (they may have different size and shape, they may be fixed or move, they may appear or disappear with some probability distribution, etc.), which are called *prey*;
- a special area called *home*, *nest*, or *target*.

² For more information on the project see www.swarm-bots.org

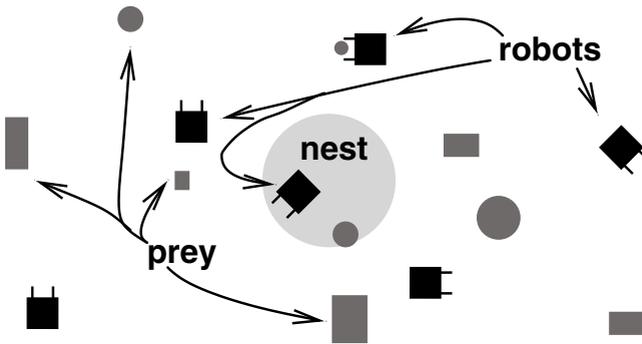


Fig. 2. Schema of a prey retrieval task. A group of robots has to collect objects in the environment (the prey) and to bring them to an area called nest.

The task the robots have to solve is to find the prey and bring them to the nest. To distinguish the robots that actually carry the prey from the others, the former are called *foragers*.

Prey retrieval, also known as *foraging*, is among the different tasks that Cao et al. [9] consider the canonical domains for collective robotics. It is often used as a model for other real-world applications, such as toxic-waste cleanup, search and rescue, demining or exploration and collection of terrain samples in unknown environments. The main scientific interest concerns the question whether there is an actual performance gain in using more than one robot, since the task can be accomplished by a single one [9]. Other works in literature [4,13] identify in the interferences among robots the factor that makes the performance grow sub-linearly with the number of robots.

There are many similarities with foraging in ants. In particular, ants' foraging is a collective behaviour exactly as in robotics, therefore it comes natural to look into it for some inspiration. Many aspects are still under study, but the main features of ants' foraging can be summarised as follows (Fig. 3) [11,16]:

1. ants explore randomly the environment till one finds a prey;
2. if the prey is not too heavy, an ant tries to pull it to the nest; otherwise, it tries to cut it or to use short or long range recruitment;
3. the prey is pulled straight to the nest (pushing is never observed), both in case of individual or collective retrieval;
4. after the retrieval, the ant returns directly where it found the prey.

The foraging behaviour of a single ant may be influenced by several factors, like age, genetic differences or learning. The role of the latter was studied by Deneubourg et al. [10] from a theoretical and numerical point of view. We explain more in details their model in the next section.

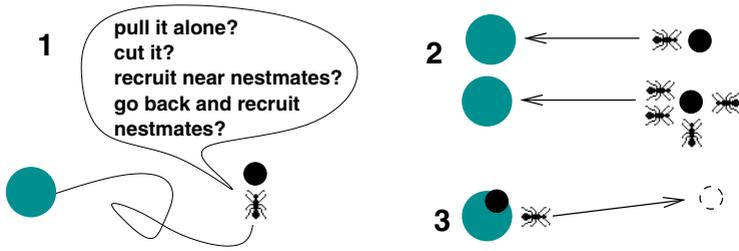


Fig. 3. Prey retrieval in ants. 1) A forager randomly explore the environment. When it found a prey it selects which action to take. 2) Both if the prey is retrieved alone and collectively, ants pull (never push) it straight to the nest. 3) After the prey is retrieved, the ant that found the prey returns straight on the place where it was discovered.

3 Efficiency in Prey Retrieval

In order to continue the presentation of our work, we need to give a precise definition of the term “efficiency” and to explain its role in the collective task of prey retrieval. The definition we give comes from the observations of ants.

Prey retrieval in ants has two components that must be taken into account. On the one hand, ants need prey to obtain energy to survive. This is the *income* of the colony. On the other hand, searching also has drawbacks, that can come from dangers in the environment, from the interferences among nest-mates (such as blocking the way to other ants, or collisions that slow down their speed), or from the fact that ants spend energy to move. All these are the *costs* of the colony.

Income and costs depend on the number of foragers X . They both increase with X , but not in the same way. The income saturates when X is too big (ants can not retrieve more prey than their actual number in the environment, even if the number of forager X is doubled), but costs potentially increase without limit. There is a point in which costs are higher than the income. If we define *efficiency* of the group as

$$\eta = \frac{\text{income}}{\text{costs}}, \quad (1)$$

there is a value \hat{X} than maximises it. That is, if \hat{X} foragers are used, the cost of retrieval per prey is minimal.

We indicate as “*performance* of the colony” the number of retrieved prey, that is, the income. Note that the words “performance” and “efficiency” have been used with different meanings in the robotics literature. For instance, “performance” refers to the time it takes to retrieve all the prey in the environment in some works, or the number of retrieved prey in others. We claim that these definitions depend on the particular application the researchers have in mind for their group of robots. For instance, time is an important factor in case of search and rescue applications, but the number of collected items is more interesting

in the case of spatial exploration. We are more interested in the latter application, that is, something that resemble more ants' foraging. Since ants never stop looking for food, a concept of performance based on time is useless in our context.

Ants suggest some ways to improve the efficiency of a swarm of robots in a prey retrieval task, but most of them are hard to implement. For instance, they use recruitment and stigmergic communication, which unfortunately rely on chemical substances whose effect can not be easily emulated with robots. Evolution surely played an important role in tuning the behaviours of ants for optimal foraging in particular environments, but a solution based on *evolutionary robotics* [18] requires too much time on real robots and, when it is used on-line, is too slow in case of sudden changes in the environment.

Deneubourg et al. [10] suggest that ants use life-time adaptation. The authors model each ant with an agent that has a probability to leave the nest P_1 , which is modulated according to previous successes or failures. If an ant retrieves a prey, its P_1 increases. If it spends too much time without success, its P_1 decreases. They show that this hypothesis can explain some of the patterns in ants' foraging behaviour.

We expect, if we use a similar algorithm for our swarm of robots, to observe the following effects:

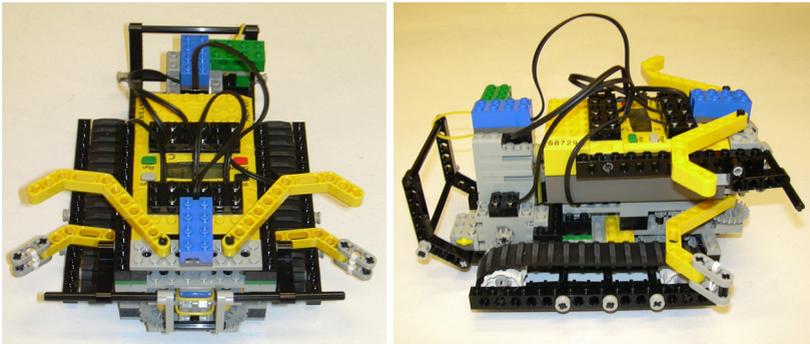
Efficiency increase: if there were many more robots than prey, many robots would not be successful in retrieval. They would decrease their P_1 and spend more time in the nest, leaving more room for the others to work. If there were far fewer robots than prey, some robots would eventually exit the nest and be successful in retrieval, increase their P_1 and spend more time in foraging. The efficiency of the group would improve in both cases without external intervention: that is, the improvement is *self-organised*.

Task allocation: some robots would retrieve by chance more prey than the others, and therefore their P_1 would increase; therefore, they would spend more time in foraging. But, the more the time spent, the more prey they would retrieve and the higher their P_1 would become. This is an amplification phenomenon typical of many biological systems [8]. The opposite would hold true for those robots that were less successful. After a while, two classes of robots would appear in the environment, allocated to two tasks: *foragers*, with high P_1 and that retrieve prey to the nest, and *loafers*, with low P_1 and that prefer to stay in the nest. The allocation is, again, self-organised.

The robots described in the next section and the experiments of Sec. 5 are meant to test these two hypotheses. Our robots do not use direct communication and interactions among them are only indirect. For instance, a successful robot decreases the density of prey and therefore the behaviour of its nest-mates.

4 Hardware and Software

We used real robots instead of simulation. The latter offers many advantages, such as speed and reliability, but it is based on a model of the environment in



(a) Front view.

(b) Side view.

Fig. 4. Picture of a *MindS-bot*.

which important aspects might be missing or badly approximated. The work described in this paper has also the aim of identifying the physical features of the environment that *must* be modelled in a simulator. The results of our experiments will be used to tune a simulator in future work.

No *s-bot* was available at the time of the experiments yet. Therefore, in our experiments we used Lego MindstormsTM to build the robots, which we call *MindS-bots* (Fig. 4). *MindS-bots* are based on a Hitachi H8300-HMS 1 MHz microprocessor with 32Kb RAM. They have one light sensor and one bumper on both the front and the back side, for a total of four sensors. The traction system, based on two tracks controlled by two motors, resembles the one of the *s-bot*. Two arms on the front side form the gripper that is used to grasp prey and that is controlled by another motor.

BrickOS,³ a POSIX-like operating system, runs on the *MindS-bots*. The control program is written in C and then downloaded on the robots. The finite state machine in Fig. 5 represents the control program of the *MindS-bots*. Different states are the different phases of prey retrieval, that is, the sub-tasks in which the overall prey retrieval task is decomposed. These sub-tasks are as follows:

Search: the *MindS-bot* looks for a prey randomly exploring the environment (as ants do) and changing direction when a bumper is pressed. If a prey is found, the *MindS-bot* grasps it. If a timeout occurs without having grasped a prey, the *MindS-bot* gives up foraging.

Retrieve: the *MindS-bot* looks for the nest and pulls the prey toward it. Since the gripper is on the front, the *MindS-bot* uses the sensors on its back for this purpose.

Deposit: the *MindS-bot* leaves the prey in the nest and turns toward the point from which it came (to mimic ants' behaviour).

Give Up: the *MindS-bot* looks for the nest and returns to it.

Rest: the *MindS-bot* rests in the nest.

³ <http://brickos.sourceforge.net/>

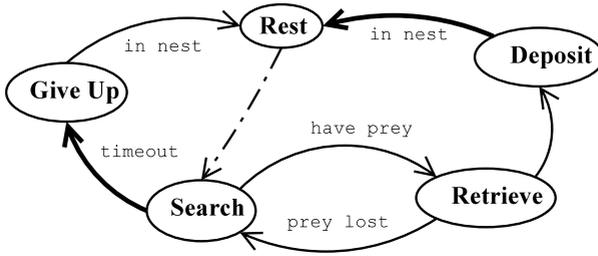


Fig. 5. Sketch of the control system of a *MindS-bot*. The states represent different phases of retrieval (see text). The labels on each edge represent the conditions under which the *MindS-bot* changes state. The transition from **Rest** to **Search** is based on the probability P_1 . The transition from **Deposit** to **Rest** represents a successful retrieval (P_1 is increased), the one from **Search** to **Give Up** is a failure (P_1 is decreased).

Algorithm 1 Adaptation mechanism: Variable Delta Rule

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initialisation: successes  $\leftarrow$  0; failures  $\leftarrow$  0;  $P_1 \leftarrow P_{\text{init}}$ 
if prey retrieved then
    successes  $\leftarrow$  successes + 1; failures  $\leftarrow$  0
     $P_1 \leftarrow P_1 + \text{successes} * \Delta$ 
    if  $P_1 > P_{\text{max}}$  then
         $P_1 \leftarrow P_{\text{max}}$ 
    end if
else
    if timeout then
        successes  $\leftarrow$  0; failures  $\leftarrow$  failures + 1
         $P_1 \leftarrow P_1 - \text{failures} * \Delta$ 
        if  $P_1 < P_{\text{min}}$  then
             $P_1 \leftarrow P_{\text{min}}$ 
        end if
    end if
end if

```

Transitions between states occur when the labels on the edges in Fig. 5 are true, except the one from **Rest** to **Search** which is controlled by P_1 . The transition from **Search** to **Give Up** represents a failure in retrieval, whilst the transition from **Deposit** to **Rest** is a success.

4.1 Adaptation Mechanism

MindS-bots adapt their P_1 according to the algorithm depicted in Alg. 1, called *Variable Delta Rule* (VDR). Its parameters are: Δ (the base increment), P_{min} , P_{max} (the minimum and maximum value that P_1 can reach) and P_{init} (the initial value of P_1). Two counters store the number of successes and failures in a row of the *MindS-bot* and multiply Δ before being added or subtracted to P_1 . The

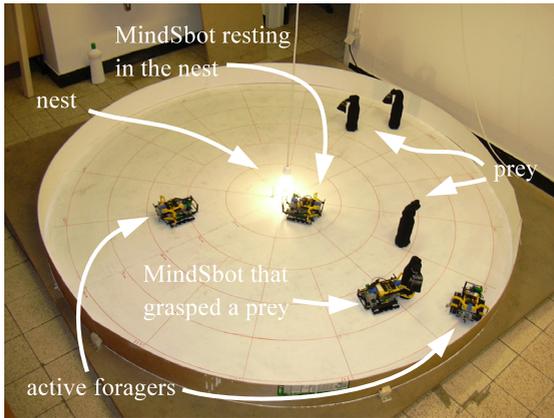


Fig. 6. Snapshot of an experiment. Four *MindS*-bots are looking for three prey. The nest is indicated by a light in the centre. One *MindS*-bot is resting in the nest and is therefore inactive. Two others are exploring the environment. One found a prey. It grasped it and is searching for the nest to retrieve it.

effect is that the reward is much bigger for those *MindS*-bots that can repeatedly retrieve more prey than for the others.

5 Experiments and Results

For the experiments, we used a circular arena (Fig. 6) with a diameter of 2.40 m. A light bulb is used to signal the position of the nest in the centre of the arena. Walls and floors are white, prey are black. The search timeout is fixed to 228 s.⁴ Δ is set to 0.005, P_{\min} to 0.0015, P_{\max} to 0.05, P_{init} to 0.033. Prey appear randomly in the environment. The probability that a prey appears each second is 0.006. A new prey is placed randomly in the arena so that its distance from the nest is in [0.5 m, 1.1 m]. Values were chosen on the base of a trial-and-error methodology.

5.1 Efficiency of the System

The first of our hypotheses is that the use of adaptation of P_1 increases the efficiency of the foraging task with respect to a group that does not use it and whose available robots are all foragers. In order to test this hypothesis, it is not possible to look at the value of (1) in the colony because the costs cannot be quantified. In fact, they comprise too many factors, some of which are unknown.

⁴ This value is the estimate of the median time needed by a single *MindS*-bot to find one prey when it is alone in the arena.

Thus, as efficiency index we used

$$\nu = \frac{\text{performance}}{\text{colony duty time}} , \quad (2)$$

where *colony duty time* is the sum of the time each *MindS-bot* of the colony spent in searching or retrieving and *performance* is the number of retrieved prey. The *colony duty time* is directly related to the costs: the higher it is, the higher is the probability that some robot gets lost or brakes down, the higher the energy consumption, and so forth. Therefore, if ν increases, η increases too.

The quantitative improvement of the efficiency was measured in a series of ten experiments lasting 2400 s each. Four *MindS-bots* out of a pool of six were used in each experiment, and changed among experiments. For each experiment, we conducted a control, with the same robots, in which P_1 was not adapted and set to 1. Moreover, the prey in the control experiments did not appear randomly, but at the same time and place as in the original experiments. Figure 7 plots the mean value of ν in time for both experiments. The difference is statistically significant after 1400 s.⁵

The colony that uses adaptation is more efficient because it has less colony duty time. The ratio between the final ν in the two colonies is 1.41, but the ratio of their performances (Table 1) is only 1.04. Moreover, there is no statistical difference in the performances between the two colonies.⁶ Therefore, we deduce that the improvement is due to the colony duty time. This means that, in the colony that uses adaptation, foragers can do their job easily and in less time because of less interferences.

When the Variable Delta Rule was used, there were 2.57 foragers and 2.44 prey on average in the arena in the period between 1000 s and 2400 s (Fig. 8(a)). In the control experiments, there were 3.63 foragers and 3.49 prey (Fig. 8(b)). In both cases the ratio is nearly one robot per prey but there are less robots out of the nest when adaptation is used. We were surprised to see that fewer foragers did not correspond to a worse performance. The explanation could be in the fact that in our setup 3.49 *MindS-bots* represent an overcrowded environment in which there are many interferences and in which the robots can not perform well their job.

5.2 Task Allocation

The second hypothesis regards task allocation. We expect that the adaptation mechanism leads to the creation of two classes of *MindS-bots* in the colony: *foragers* and *loafers*. The task of the first group is to search and retrieve prey

⁵ Sign test for paired data [23, p. 80–87]. Null hypothesis: ν is the same in the two colonies. The p -value is 0.01074 from 1400 s to 1500 s and 0.00098 from 1500 s on.

⁶ Permutation test on the data of Table 1. This kind of non-parametric test is among the most powerful because it uses all the information available in a data set [23, p. 95]. Null hypothesis: the performances are the same. Alternative hypothesis: the colony with adaptation performs better. The p -value is 0.2637.

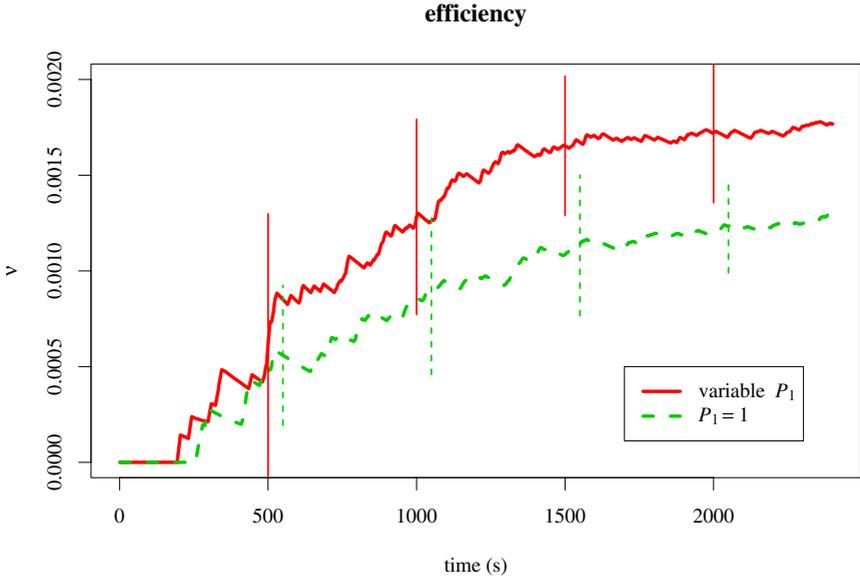
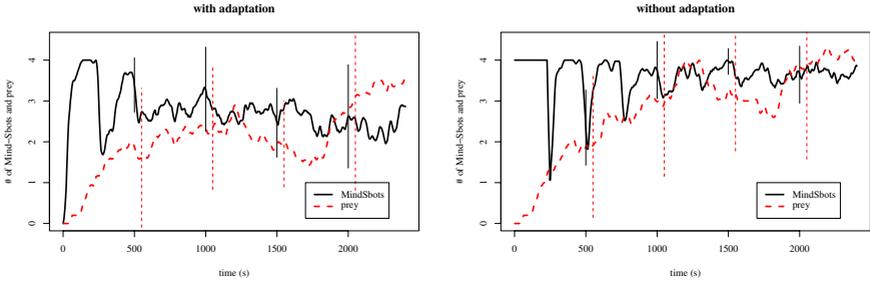


Fig. 7. Value of ν (2) when P_1 is adapted (continuous line) and when it is not (dashed line). The average over 10 experiments is plotted. Vertical lines represent the standard deviation. The two curves are statistically different after 1400 s (see footnote 5).

Table 1. Performances of colonies with and without adaptation of P_1 . The first column contains the experiment number and the second the total amount of prey that appeared during the experiment. The third column is the number of prey retrieved when the VDR is used, the fourth refers to the the control experiments. The last row sums the results. Bold numbers are used to indicate which setup retrieved more prey. There is no statistical difference in the performance of the two colonies.

Exp.	Tot. prey	prey retrieved	
		with adaptation	without adaptation
1	15	14	13
2	17	14	14
3	12	8	7
4	18	12	11
5	16	11	12
6	21	18	15
7	14	10	12
8	16	12	15
9	16	16	14
10	24	19	15
<i>Total:</i>	169	134	128



(a) Mean number of *MindS-bots* and prey when the VDR was used. Between 1000s and 2400s, when the system is at regime, there are on average 2.57 foragers and 2.44 prey.

(b) Mean number of *MindS-bots* and prey in control experiments with $P_1 = 1$. Between 1000s and 2400s, when the system is at regime, there are on average 3.63 foragers and 3.49 prey.

Fig. 8. Mean number of foragers and prey observed during the first 2400 seconds in experiments with adaptation and in control experiments. The continuous line represents *MindS-bots*, whilst the dotted one represents prey. Vertical lines show the standard deviation. Data is collected over 10 experiments.

while the second group stays in the nest and avoids to interfere with the activity of the others.

The only means by which the VDR can allocate tasks is the modification of P_1 . We consider an instant t when the colony reached its regime. The value of P_1 of each *MindS-bot* at time t is a random variable that assumes different values for different experiments according to an unknown distribution. The estimate of this distribution can give us enough information to test our hypothesis: if it is a single-peak distribution, then there is no separation in classes; if there are two peaks, then task allocation occurs.

We collected the value of P_1 of each *MindS-bot* in the ten experiments of Sec. 5.1 after 2400s (four robots times ten experiments) and we obtained the histogram in Fig. 9. We deduce from its U-shape that the *MindS-bots* have higher probability to have P_1 next to one of the two peaks of the distribution. 60% of the *MindS-bot* in the population have $P_1 \leq 0.02$ and represent the loafers. The remaining 40% have $P_1 \geq 0.025$ and are the foragers. Few *MindS-bots* have P_1 around 0.02 and 0.025, suggesting that the VDR prevents the maintenance of a high fraction of unspecialised robots pushing them toward one of the two peaks.

Since we ran few experiments, it could be that the right peak of the distribution is due to a few lucky experiments. Table 2 shows on the contrary that foragers were present in nearly all the experiments.⁷

⁷ No foragers were present in experiment 3, that is also the one in which less prey appeared, as shown in Table 1.

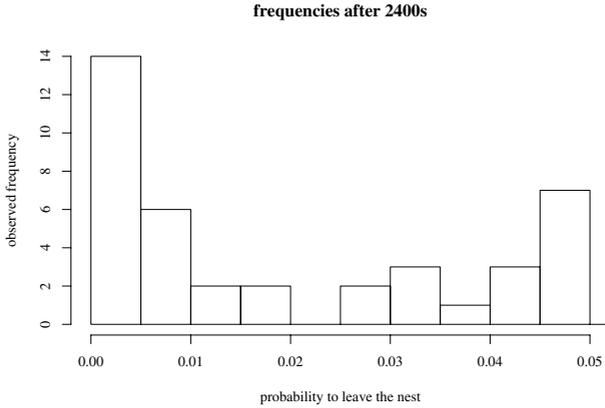


Fig. 9. Histogram of the observed P_1 in the *MindS-bots* at 2400s. The distribution has two peaks, showing that some of the *MindS-bots* are allocated to the foraging task (those with high probability) and the others are loafers (low probability). 60% of the observations are below 0.025. Data refers to ten experiments, four *MindS-bots* per experiment.

Table 2. Number of *MindS-bots* that are foragers and loafers per experiment. The presence of forager is nearly systematic. Bold numbers refer to the only experiment without foragers. Data refers to ten experiment, four *MindS-bots* per experiment.

Exp.	# loafers	# foragers	Exp.	# loafers	# foragers
1	3	1	6	2	2
2	3	1	7	3	1
3	4	0	8	2	2
4	1	3	9	1	3
5	3	1	10	2	2

6 Related Work

Interferences among robots, mostly due to physical collisions, are known to be a problem in collective robotic tasks [4,13]. We briefly discuss here other techniques that have been developed to reduce them.

A group of solutions to the interference problem works at the level of the control program. For instance, Schneider-Fontán and Mataric [22] introduced *a priori* territoriality in their programs, so that each robot is assigned to a region of the environment and can not trespass its borders. Each robot brings the objects in its area to the border nearest to the nest, where another robot takes care of them. Balch [4] reimplemented, for a retrieval task with more prey types, this approach and two others (homogeneous controls and robot specialisation by item type). He noticed that robots with homogeneous controllers gave the best performance. The two works reach contradictory conclusions, but in [4] the

author suggests two possible reasons: bad reimplementation of the algorithms or different set of test conditions.

Another group of solutions relies on inter-robot communications. Balch and Arkin [5] tested the effects of increasing communication complexity, starting from no communication, on the performance of a group of robots. They tested the group with different tasks, including foraging. Their conclusion is that communication appears unnecessary when implicit communication already exists, but it significantly improves the performance in the other cases. The difference between simple and complex forms of communication is negligible. Rybsky et al. [21] tested the influence of signalling on foraging with respect to a system without communication, but no statistical difference was found.

Hayes [15] follows an analytical approach. He provides an equation to suggest the optimal number of robots to use in an environment with given conditions. His approach requires however some knowledge of the environment, which is not always available.

Agassounon et al. [1,2] follow a swarm-intelligent approach. They use a threshold-based model developed in biology [7] to allocate tasks among the robots in a clustering experiment. Each robot switches to the execution of a task only if the level of an external stimulus is higher than a threshold. In their case, the stimulus is given by the time spent to search for an object. If it is higher than the threshold, the robot goes back to the nest, reducing the total number of foragers. Once a robot stops to explore the environment, it can not switch back to the search behaviour. Their approach works well for a clustering task, but it could have some problems in prey retrieval where the density of prey can change abruptly.

7 Conclusions

We showed that a group of robots can self-organise in order to work more efficiently using only a form of adaptation, inspired by ants' behaviour, that is based on information locally available to each robot. Only communication that uses the environment itself as a media is used. Interferences, which are considered as a negative factor in robotic retrieval, are exploited as a source of information: robots perceive their effects, e.g. a failure, and adjust the behaviour consequently. The amplification mechanism of the adaptation, combined with random fluctuations is also responsible for the task allocation.

Future research will follow different paths. First of all, we will analyse the effects of changing the initial density of robots. Then we will also study the self-regulatory mechanism of this adaptation by changing the distribution of prey during the experiments. The aim is to relax some of the constraints that define the experimental environment that we used. Furthermore, we will study the robustness of the adaptation to the perturbation of its parameters. For instance, if Δ decreases, we expect the dynamics to be slower and, if Δ increases, we expect the system to show an oscillatory behaviour in which, for example, *MindS-bots* frequently switch back and forth from low to high P_1 values.

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