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**IRIDIA – Technical Report Series**

Technical Report No.
TR/IRIDIA/2004-013

October 12, 2006

Published in *ACM Transactions on Autonomous and Adaptive Systems*, vol. 1, num. 1, pages 4–25

**IRIDIA – Technical Report Series**
ISSN 1781-3794

Published by:
IRIDIA, *Institut de Recherches Interdisciplinaires*
*et de Développements en Intelligence Artificielle*
UNIVERSITÉ LIBRE DE BRUXELLES
Av F. D. Roosevelt 50, CP 194/6
1050 Bruxelles, Belgium

Technical report number TR/IRIDIA/2004-013

# Division of Labour in a Group of Robots Inspired by Ants' Foraging Behaviour

THOMAS H. LABELLA and MARCO DORIGO
IRIDIA - Université Libre de Bruxelles - Brussels, Belgium
and
JEAN-LOUIS DENEUBOURG
CENOLI, Université Libre de Bruxelles, Brussels, Belgium

In this paper, we analyse the behaviour of a group of robots involved in an object retrieval task. The robots' control system is inspired by a model of ants' foraging. This model emphasises the role of learning in the individual. Individuals adapt to the environment using only locally available information. We show that a simple parameter adaptation is an effective way to improve the efficiency of the group, and that it brings forth division of labour between the members of the group. Moreover, robots that are best at retrieving have an higher probability to become active retrievers. This selection of the best members does not use any explicit representation of individual capabilities. We analyse this system and point out its strengths and its weaknesses.

Categories and Subject Descriptors: I.2.9 [**Artificial Intelligence**]: Robotics

General Terms: Algorithms, Performance

Additional Key Words and Phrases: adaptive systems, ant algorithms, bio-inspired systems, adaptation, multi robot system modelling

## 1. INTRODUCTION

Nature is full of examples of animals that can co-operate efficiently in big groups. Ants are probably the most cited: they can collectively retrieve big prey, adapt to the richness of the environment or find the shortest path to food [Hölldobler and Wilson 1990]. Other examples are termites, which are able to build big and complex nests, and bees, which collectively choose a new location for their nest. Amazingly, direct communication is seldom observed: these insects use only locally available information, exploit features present in the environment and use indirect communication—for instance *stigmergy* [Grassé 1959].

Such collective insect behaviour tends to be robust in the face of uncertainty and environmental change. Also noteworthy is the fact that in most cases the individual group members seem to lack an internal map of the environment. Nor do the individuals seem to have in any sense a global plan to which they adhere. Indeed the individuals have a limited knowledge and perception of their environment. The results of collective insect behaviour are usually well beyond the capabilities of a single insect. The key mechanism at work tends to be that of *self organisation* [Camazine et al. 2001]. Researchers in the field of *Multi Robot Systems* look with interest at such examples because they might suggest new ideas for developing robust and adaptive robotic control algorithms. At the same time, biologists see robotics as a useful experimental tool for checking and validating their theories [Webb 2000].

In this paper, we study the collective behaviour of a group of robots, both real and simulated, performing an object search and retrieval task. The control algorithm of each individual was inspired by a model of ants' foraging, developed observing the behaviour of *Pachycondyla apicalis* (previously named *Neoponera apicalis*). The robots we used for our experiments are quite simple. They have very limited computational power, they do not communicate with each other and they are equipped with simple sensors, too simple to allow them to build a map or any other model of the environment. Nevertheless, we show in this paper that they are able to cooperate in order to increase the efficiency of the group. The control algorithm we use induces division of labour at the group level. The controller also encourages a selection mechanism at the group level—robots more suited to the task are more likely to carry out the task than less capable robots. These results are achieved in a distributed fashion, without the use of explicit models either of the environment or of the capabilities of the robots.

This work is part of a larger research agenda. We started from implementing in real and simulated robots a model of ants' foraging. This is studied, to the best of our knowledge, only theoretically in the literature. The first steps, discussed in this paper, are the validation of the theoretical model and the analysis of its features. Some of the results might be easily foreseen from the model, but they need a formal validation to be useful. The results of the analysis will be used then to perform comparisons with similar algorithms that are found in the literature and eventually to improve and test them in other contexts. These last steps are on-going work and are not presented here.

The analytical methodology used in this work makes extensive use of statistical tools and concepts (e.g., non-parametric tests and the "blocking design" of experiments). In fact, our experiments were designed in such a way as to obtain statistically significant results even when using a limited number of runs. This is useful especially when experimenting with real robots, a highly time-consuming activity. While such concepts are extensively used in other disciplines, we are aware of very few works that make use of this methodology in robotics, or that at least explicitly mention it. We hope that this paper can be an inspiration for other researchers to improve the efficiency of their experimental work.

The next section describes the task of our robots. Section 3 fixes some issues with the terminology, Section 4 explains the methods that we used for our experiments, reported and discussed in Section 5. Section 6 summarises related works in the literature and Section 7 draws some conclusions and indicates the directions of our future research.

## 2. THE APPLICATION DOMAIN: PREY RETRIEVAL

The test application we chose for our experiments is object search and retrieval: a group of robots has to look for objects, termed *prey*, spread in the environment and retrieve them to a special area, termed *nest*. In this paper, we refer to this task as *prey retrieval* to emphasise the similarity with the corresponding behaviour observed in ants.

Prey retrieval is often used as a model for other real-world applications (such as toxic-waste cleanup, search and rescue, demining or collection of terrain samples in unknown environments) and is among the canonical tasks for collective robotics [Cao et al. 1997]. The main scientific question is whether there is an actual performance gain in using more than one robot, since the task can be accomplished by a single one [Cao et al. 1997]. Stated in another way, the question is whether more robots are also more efficient.

There are two components that must be taken into account in a prey retrieval task in order to measure the efficiency of the group. On the one hand, retrieved prey may be seen as an *income* for the group. On the other hand, searching and retrieving also has drawbacks that can come from dangers in the environment, from the interferences among robots (such as blocking the way to others, or collisions that slow down their speed), or from the fact that robots spend energy while moving. All these are *costs* for the group.

Income and costs depend on the number, $X$, of robots that are exploring the environment. Both income and costs increase with $X$, but not in the same way. The income saturates when $X$ becomes too high (robots can not retrieve more prey than their actual number in the environment), but costs potentially increase without limit. A straightforward definition of *efficiency* is

$$\eta = \frac{income}{costs} \quad . \tag{1}$$

We indicate as "*performance* of the group" the number of retrieved prey items, that is, the income.[1]

We see three possible strategies for increasing the efficiency of a group of robots performing prey retrieval: increase the income by providing better sensors or better search strategies; decrease the costs, for example by introducing communication in order to reduce interference; use an optimal number of robots.

The third strategy, the one that we follow in this paper, comes from the observation that if $X = 0$, the income is null and so is the efficiency (costs are never null because they include also the energy spent by the robots in the nest). When $X$ becomes too high, costs increase faster than income and the efficiency tends towards 0. Therefore, there is a value $\hat{X}$ that maximises $\eta$. We refer to the mechanism that tunes the number of the robots involved in the retrieval task as *division of labour*.[2]

The optimal number of robots can be estimated *a priori* if the characteristics of the environment are well known and fixed, as done for instance by Hayes [2002].

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[1] Note that the words "performance" and "efficiency" have been used with different meanings in the robotics literature. For instance in some works, "performance" refers to the time it takes to retrieve all the prey in the environment, while in others it refers to the number of retrieved prey. The choice of which definition to use depends, in our opinion, on the particular application the researcher has in mind: for instance, time is an important factor when considering search and rescue applications, but the number of collected items is a more interesting measure in the case of spatial exploration.

[2] In the robotics literature, the terms "division of labour" and "task allocation" are often used synonymously. We see however some important differences in their use. "Division of labour" is more typical for bio-inspired studies and the problem is usually "how many robot should perform a single task?". "Task allocation" is often used in more traditional robotic studies. In this case, there are many tasks which can be executed by one or more robots and the problem is to find the best assignment robots/tasks, once the robots' qualities are known (see Gerkey and Matarić [2004]).

Otherwise, the group of robots should use some form of adaptation in order to cope with uncertain and dynamic environments. The robotic literature already offers algorithms for learning and adaptation (some of them are described in Section 6), but we are at the moment interested in studying the properties of the biological model described in the following section.

### 2.1 A Model of Ants' Foraging

Although many aspects of ants' foraging behaviour are still under study, we can summarise its main features as follows [Detrain and Deneubourg 1997; Hölldobler and Wilson 1990]:

(1) ants explore randomly the environment till one of them finds a prey; if the prey is not too heavy, the ant tries to pull it to the nest; otherwise, it tries to cut it or to use short or long range recruitment (by spreading some chemical substance in the environment or going back to the nest while leaving a pheromone trail);

(2) the prey is pulled straight to the nest (pushing is never observed), both in case of individual or collective retrieval;[3]

(3) after the retrieval, the ant returns directly to the location where it found the prey.

It has been noted that the foraging behaviour of a single ant may be influenced by several factors, like age or genetic differences. Among the few authors that pointed out that learning might play a key role, we refer to the work by Deneubourg et al. [1987]. They model each ant of the species *Pachycondyla apicalis* as an agent that has a probability to leave the nest $P_l$ that changes according to previous successes or failures. If an ant retrieves a prey, its $P_l$ increases by a constant $\Delta$. If it spends too much time without retrieving a prey, its $P_l$ decreases by the same constant. $P_l$ is always kept between a minimum and a maximum value. They show, through numerical simulations, that this model can explain the division of labour observed in ants and how the colony is able to adapt to the environment.

The model that Deneubourg et al. [1987] propose emphasises the role played by learning during individual lifetime. No direct communication, not even signalling, is necessary for the colony to adapt to the environment.

The simplicity of this division of labour model indicates that it might be well suited for use in the context of group robotics. This is the key idea we study in this paper. We have two goals. To date, the model has only been tested using purely numerical simulations. Our first goal is, therefore, to subject the model to further testing in a more real environment. Our second goal is to provide a deeper level of analysis, with a view to identifying the salient features of the model that can then be reused in other contexts.

## 3. TERMINOLOGY

There are a few terms that we need to clarify before proceeding with our discussion. In fact, these terms are used with different meanings by roboticists and biologists.

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[3] In this paper, we consider only the simple case in which one robot can retrieve one prey without either recruitment of other robots or dividing up (cutting) the prey.

Moreover, some of the definitions are still subject of debate in the research community. It is out of the scope of this work to argue for one definition or another: here we limit ourselves to clearly stating what we mean when we use these terms in this paper.

We have so far used the word "learning" only when discussing ants. For a biologist, learning is in fact a behaviour observed in animals. It produces a "durable modification of [another] behavior in response to information acquired from specific experiences [within a given time scale]" [Alcock 1995]. Researchers in robotics tend to associate "learning" with "Reinforcement Learning" (RL), a field which studies "how to map situations to actions so as to maximise a numerical reward signal" [Sutton and Barto 1998].[4] As the setup for our experiments and the algorithm we study are far simpler than those typically studied in RL, we use the term "adaptation", which seems more appropriate and avoids confusion.

In this paper, we use the concept "indirect" communication, but unfortunately there is still a lot of debate on how to define and classify the different forms of communication. By "indirect" communication, we mean that there is nothing in the robots' controller that an observer can interpret as an act of transmitting information to other robots. In our experiments, robot use neither wireless communication nor signalling. Nevertheless, they do communicate by modifying the environment—for instance, by retrieving a prey.

It might be argued also that what we show is more a form of "specialisation" than of "division of labour". The former has indeed a meaning in biology that is different from what we show in Section 5.2, but we use it in a robotics context to refer to the process of tuning the number of robots performing a task. Moreover, some of the definitions given for "specialisation"[5] imply some form of individual adaptation (behavioural or physical) in order to better perform a task. This is not what we show either: some of our robots will perform a task more and more often. However, how well the individual robot performs the task does not change.

## 4. METHODS

This section describes the tools and the methodology that we used in our experiments. Before doing so, we briefly explain the rationale behind our choices. We used two different set-ups: real robots, built with Lego Mindstorms$^{\text{TM}}$, and simulated *s-bots*.[6] This choice was driven by the concepts explained below and by the tools available at the time of experimentation.

Different set-ups allow us to draw conclusions that are less dependent on particular experimental conditions and that are potentially more generally valid. The conclusions have a more qualitative than quantitative nature, given that different platforms with different characteristics are compared.

As we wrote previously, we need to validate a theoretical model. Real robots are preferable for this purpose in order to avoid erroneous validation due to ill-chosen

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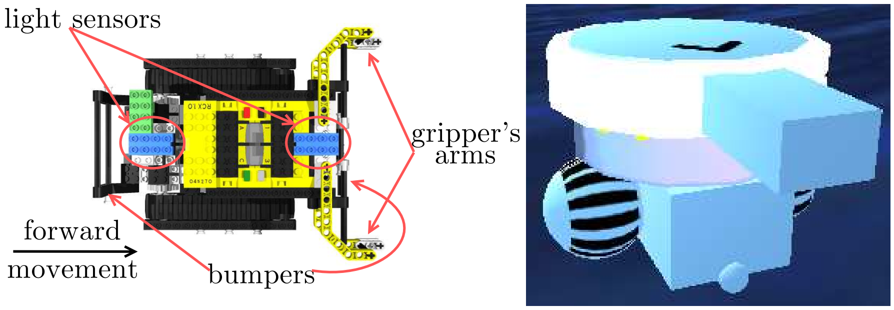
[4] RL is in fact a particular mechanism of implementing learning—in the biological meaning.

[5] For example, the following taken by the Merriam-Webster English dictionary: "structural adaptation of a body part to a particular function or of an organism for life in a particular environment".

[6] *S-bots* are small autonomous robots produced within the SWARM-BOTS project [Dorigo et al. 2004; Mondada et al. 2004]. See also the web site of the project at `http://www.swarm-bots.org`.



(a) The *MindS-bot*. (b) The *s-bot*.

Fig. 1. The robots, real and simulated, used for the experiments. Left: top view of a *MindS-bot*. The circled bricks are light sensors and are used to locate prey and nest. There are two bumpers, one on the front and one on the back, to avoid obstacles. The gripper is made of two arms that close by rotating around two vertical axes relative to the *MindS-bot* (coming out of the picture). Right: an *s-bot*. It has simulated light sensors placed around the main circular body and an omnidirectional camera (not shown in the picture). The frontal parallelopiped is the gripper, which can stick to the prey for retrieval.

simulation models or parameters. Once we know that the model is valid through experiments with real robots, we can use simulation, after having verified it against the empirical evidence brought by the real robots. The advantage of simulation is that it speeds up analysis because it can produce more data in shorter time.

We designed the experiments in order to exploit the best characteristics of each set-up. With real robots, we validate the theoretical model and define the path for further analysis. With simulation, we first crosscheck the results with those obtained with real robots, before continuing with more in depth analysis.

## 4.1 Real Robots

The robots, which we call *MindS-bots* (Fig. 1(a)), were built using Lego Mindstorms$^{\mathrm{TM}}$. The CPU is a Hitachi H8300-HMS 1 MHz, with 32Kb for both the operating system and the user program. Figure 1(a) shows a top view of a *MindS-bot* and its sensors. Two light sensors are used to sense prey, which are black cylinders, and the nest, which is spotted in the experimental arena by a light above it. Two bumpers are used for obstacle avoidance. The CPU controls three motors, two for the tracks and one for the gripper. Random numbers where generated using the random number generator of BrickOS (the operating system of the robots), which is "inspired by Press et al. [1992], p. 279–281 [sic]".[7] Detailed instructions to replicate the *MindS-bot* can be found in Labella [2003].

## 4.2 Simulation

The simulator used for the experiments, named `swarmbots3d`, was developed by the members of the SWARM-BOTS project and is described by Mondada et al. [2004] in more detail. It is a dynamics simulator, based on Vortex, a commercial

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[7] From BrickOS source code. See `http://brickos.sourceforge.net/`.

dynamics engine.[8] It simulates the *s-bots*, robots that can explore the environment autonomously and connect to each other whenever the environmental contingencies require it. Among other features, `swarmbots3d` can simulate the *s-bots* with different levels of detail, ranging from a simple cylinder with wheels to a nearly exact replica of the real *s-bot*. Obviously, the more detailed the simulation is, the slower it runs. Figure 1(b) shows the model used in our simulations.

Simulated light sensors placed around the main body and an omnidirectional camera, which has limited perceptual range, are used to locate prey and nest. Infrared sensors, also around the main body, are used to detect and avoid obstacles. The simulation of the gripper is somewhat simplified but still functional: the parallelopiped in front of the *s-bots* can stick and un-stick to the prey by dynamically creating and deleting a joint between the *s-bots* and the prey. Random numbers are generated using the "Mersenne Twister" algorithm, in the implementation of the GNU Scientific Library.[9]

### 4.3 Control

Figure 2 depicts the control program both of the *MindS-bots* and of the *s-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 robot looks for a prey randomly exploring the environment and changes direction when it encounters an obstacle. If a prey is found, the robot grasps it. If a timeout occurs before the robot has grasped a prey, the robot gives up searching.

**Retrieve**: the robot looks for the nest and pulls the prey toward it.

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

**Return**: the robot looks for the nest and returns to it.

**Rest**: the robot rests in the nest.

Transitions between states occur when the labels on the edges in Fig. 2 are true, except the one from **Rest** to **Search** which occurs with probability $P_l$ every second. More details about the implementation of the behaviours are given in Labella [2003].

### 4.4 Adaptation

The robots change from **Rest** to **Search** with probability $P_l$ each second, whose value is updated during the transitions from **Search** to **Return** (henceforth called *failure*) and from **Deposit** to **Rest** (henceforth called *success*). The probability to leave the nest $P_l$ is adapted in a fashion similar to the one described by Deneubourg et al. [1987] and is shown in Alg. 1. While Deneubourg et al. [1987] increment and decrement $P_l$ by a fixed constant $\Delta$, in our algorithm $\Delta$ is multiplied by the number of consecutive successes or failures. Also in our case, $P_l$ is bounded in the range $[P_{\min}, P_{\max}]$.

It is out of the scope of this paper to discuss different methods for adapting $P_l$, but the origin of the difference between the method studied by Deneubourg et al.

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[8] `http://www.cm-labs.com`.

[9] `http://www.gnu.org/software/gsl/`.

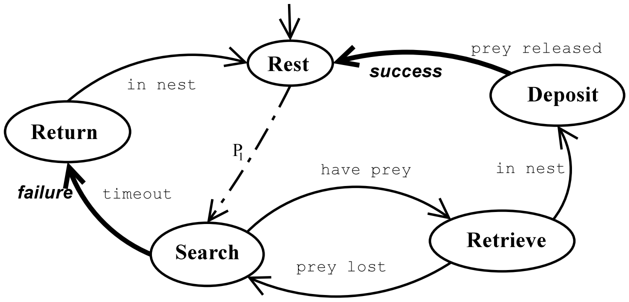

Fig. 2. Sketch of the control system of the robots. The states represent different phases of retrieval (see text). The labels on each edge represent the conditions under which the robots change state. The robots start in the **Rest** state. The transition from **Rest** to **Search** (dash-dotted) is based on the probability $P_\mathrm{l}$. The transition from **Deposit** to **Rest** (bold arrow) represents a successful retrieval ($P_\mathrm{l}$ is increased), the one from **Search** to **Return** (also a bold arrow) is a failure ($P_\mathrm{l}$ is decreased).

**Algorithm 1** Adaptation rule of $P_\mathrm{l}$, the probability to leave the nest. The variables *succ* and *fail* are the number of consecutive successes and failures.

```
$succ \leftarrow 0$;    $fail \leftarrow 0$;    $P_\mathrm{l} \leftarrow P_\mathrm{init}$;

if success then
    $succ \leftarrow succ + 1$
    $fail \leftarrow 0$
    $P_\mathrm{l} \leftarrow min\{P_\mathrm{max}, P_\mathrm{l} + succ \cdot \Delta\}$
fi

if failure then
    $succ \leftarrow 0$
    $fail \leftarrow fail + 1$
    $P_\mathrm{l} \leftarrow max\{P_\mathrm{min}, P_\mathrm{l} - fail \cdot \Delta\}$
fi
```

[1987] and ours deserves some explanation. In fact, some preliminary tests showed that the dynamics of adaptation would have been too slow if the original algorithm had been used [Labella 2003]. With our modification, individuals adapt faster, although the experiments with real robots still took 40 min each.[10]

### 4.5 Experimental Set-up

For the experiments, we used a circular arena (Fig. 3) 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 in the experiments with the real robots, prey are black. The search timeout is fixed to 228 s for the *MindS-bots* and 71.2 s for the *s-bots*.[11]

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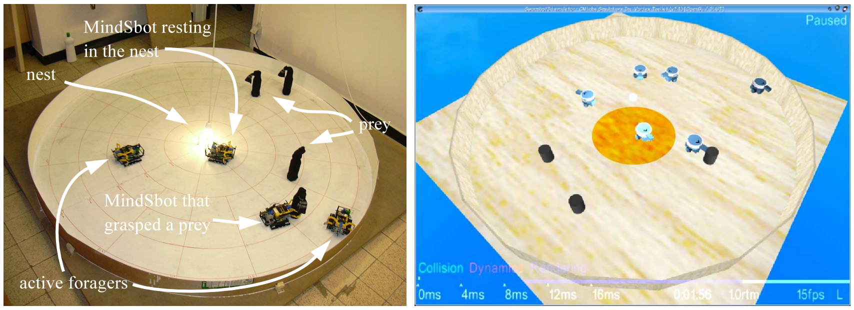
[10] The length of the experiments is generally affected not only by the speed of adaptation, but also by other factors like the speed of the robots and how effective their search for prey is. The latter are in fact the most limiting factors. For instance, the mean time for a *MindS-bot* to find and retrieve a prey is nearly 300 s. As an approximation, under the hypothesis that there is no timeout, that the *MindS-bot* is always successful, and that it never rests in the nest, the average number of prey retrieved in 40 min is 8. Therefore, in each experiment $P_\mathrm{l}$ can be updated maximum 8 times.

[11] These values are the estimated median times needed by a single robot to find one prey when it is alone in the arena. Notice that these values do not depend only on the speed of the robots, but also on their sensors. The *s-bots* can detect a prey in their surroundings with the omnidirectional camera more easily than the *MindS-bots*, which need to have the prey in front of their light sensor



(a) Snapshot of an experiment with four *MindS-bots*.

(b) Snapshot of an experiment with six *s-bots*.

Fig. 3. Set-up of the experiments. The nest is indicated by a light in the centre. The robots in the nest are resting and not active. The other robots are searching the environment, and one in each picture has found and is retrieving a prey.

$P_{\text{min}}$ is set to 0.0015, $P_{\text{max}}$ to 0.05, $P_{\text{init}}$ to 0.033, which correspond to a mean time spent in the nest of approximately 11 min, 20 s and 30 s respectively. $\Delta$ is set to 0.005. Prey appear randomly in the environment during the experiments. The probability with which this happens each second is referred to as *prey density* and changed between experiments. A new prey is placed randomly in the arena so that its distance from the centre is in $[0.5\text{ m},\ 1.1\text{ m}]$. We chose the values of the above parameters based on some *a priori* reasoning about the dynamics of the system. The purpose was to find the set of parameter values that better shows the effects of adaptation. More detail about the choice of the parameters are given in Labella [2003].

### 4.6 Efficiency Index

It is not possible to directly measure the value of $\eta$ (as given by Eq. 1) because the costs, as we defined them, are hard to, or cannot be, quantified. In fact, they comprise too many factors, some of which are generally unknown. Therefore, we decided to use the *group duty time* as an estimate of the costs. The group duty time is the sum of the time that each robot spent in searching or retrieving, that is, the time it was "on duty". The group duty time is directly related to the costs: the higher it is, the higher the probability that some robot gets lost or brakes down, the higher the energy consumption, and so forth. Thus, as an efficiency index we used

$$\nu = \frac{performance}{\sum_{robots} duty\ time} \ , \qquad (2)$$

where *performance* is the number of retrieved prey. It is easy to see that if $\nu$ increases, $\eta$ increases too.

### 4.7 Experimental Methodology

The results of our experiments are strongly stochastic. The randomness induced by our particular adaptation algorithm adds to the natural noise coming from the

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to perceive it.

sensors. The final result of an experiment is therefore a random variable, with an unknown distribution. In order to draw sound conclusions, we need to give statistical relevance to the results.

Some of the experiments described in Section 5 are designed in order to identify the impact of varying a single experimental parameter (e.g., adapting vs. non-adapting robots). The experiments were designed according to the concept of "block design" [Montgomery 2000]. We generated a set of random *instances* before running the experiments. An instance, parametrised by prey density, describes where and when prey appear in the environment. Then, we tested different set-ups against *the same* instances. Finally, the results were compared using preferentially non-parametric statistical tests [Siegel and Castellan Jr. 1988]. This procedure often allows statistical significance to be demonstrated with fewer experiments. This in turn greatly speeds up research, especially when working with real robots.

## 5. EXPERIMENTS AND RESULTS

We now analyse the effects of individual adaptation on the group of robots. We focus mainly on three features: efficiency improvement (Section 5.1), division of labour (Section 5.2) and selection of best individuals (Section 5.3). We also describe some of the limitations that we observed and these will be used as a basis for further research.

### 5.1 Efficiency

5.1.1 *Real Robots.* We used groups of four *MindS-bots* chosen out of a pool of six. The four robots were changed after each experiment.[12] Each trial lasted 2400 s (40 min). We created ten instances with prey density set to $0.006\,\mathrm{s}^{-1}$. We repeated each experiment with a control group made of the same robots with $P_l$ fixed to 1 and using the same instances.[13] Figure 4 summarises the results: on the left side, there are the values of $\nu$ for both the adapting and the control group; on the right side, we show the ratio between the number of retrieved prey and the total number of prey that appeared during the experiment. When the robots used adaptation, there were 2.57 active robots and 2.44 prey on average in the arena in the period between 1000 s and 2400 s. In the control experiments, there were 3.63 active robots and 3.49 prey.

5.1.2 *Simulation.* The simulation experiments used groups which varied from 2 to 8 *s-bots* with increments of two units. The groups were tested with prey density equal to $0.005\,\mathrm{s}^{-1}$, $0.01\,\mathrm{s}^{-1}$, $0.02\,\mathrm{s}^{-1}$ and $0.04\,\mathrm{s}^{-1}$. We generated fifty instances to be used for each combination of prey density/group size. As a base result, we tested a single robot also on the same instances. The experiments lasted 2400 s (simulated time). As we did with the *MindS-bots*, the experiments were replicated using the same instances but with a control group that did not use adaptation. The results are summarised in Fig. 5, which reports the final distribution of the values

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[12] The choice was not completely random but was biased by the status of the *MindS-bots* after each experiment. For instance, those with low battery or those which needed some maintenance were taken out and new ones were added to the group.

[13] In both original and control experiments, a computer next to the arena signalled the experimenter the time and the position of the new prey.

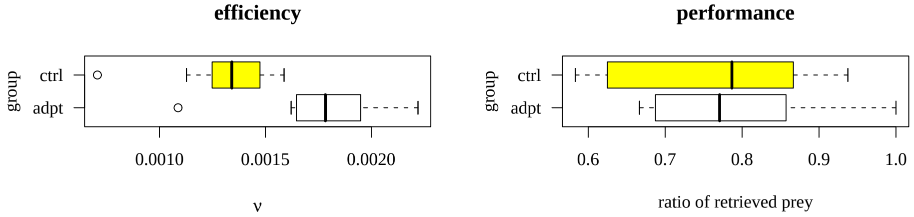

Fig. 4. Left: Value of $\nu$ (Eq. 2) when $P_l$ is adapted (bottom) and when it is not (top) in the *MindS-bots*. Right: relative performance of the adapting and control group (1 on the $x$ axis means 100% of prey retrieved in an experiment). The right and left limits of a box extend from the first to the third quartile of the distribution of the results. The line in the box shows the median value. The whiskers extend to the most extreme data point which is no more than 1.5 times the inter-quartile range from the box. Circles are considered outliers. See text for the discussion.

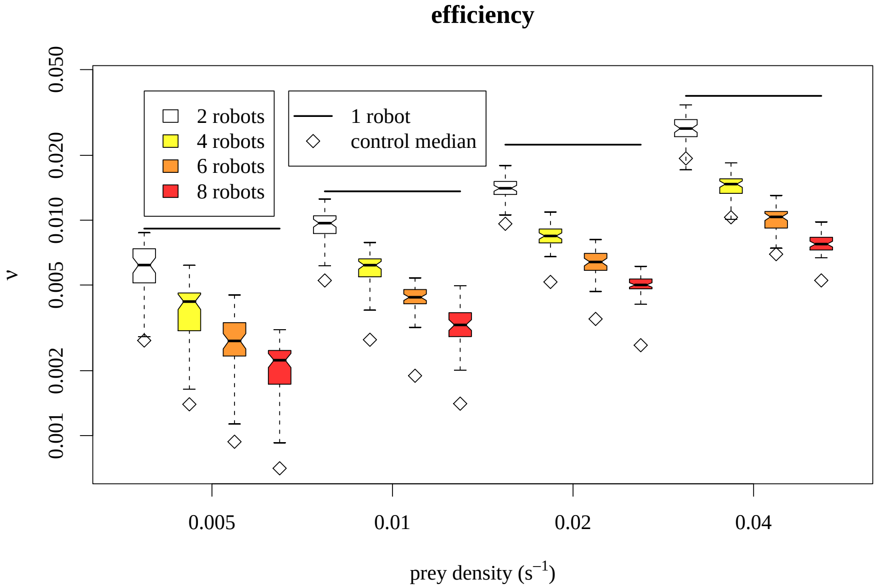

Fig. 5. Effects of prey density and group size on the efficiency of retrieval in the simulated *s-bots*. The plots report the results of fifty experiments for each prey density (on the $x$ axis), for each group dimension (different filling of the boxes). Both the $x$ and the $y$ axes use a logarithmic scale. The horizontal black line shows the median value of the efficiency of one adapting robot tested in the same conditions as the other groups. The diamonds show the median value obtained in the control experiments. We show only the median values and not the whole distribution for the sake of readability of the plot. See text for the discussion.

of $\nu$ for different combination of prey density and group size. Fig. 6 reports the final distribution of the performances of the different groups in each environment.

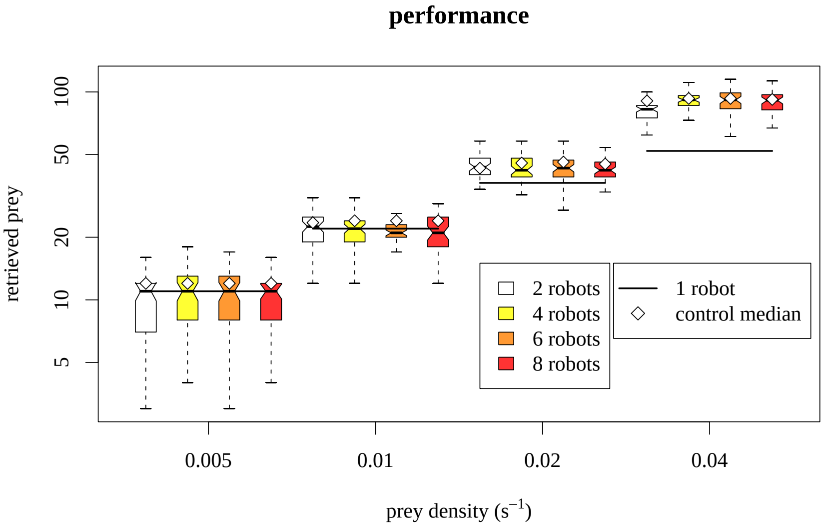

Fig. 6. Performance of different set-ups in simulation. The $x$ and $y$ axes are in logarithmic scale. The value plotted is the number of retrieved prey. For the meaning of the boxes and the other symbols, see Fig. 4 and Fig. 5. See text for the discussion.

5.1.3 *Discussion.* The group that uses adaptation is significantly more efficient both in the case of the real robots (after 1400 s)[14] and of simulation[15] (confidence level 95%).

There is no statistical difference in the performances between the two groups of *MindS-bots*,[16] while in simulation the control group performs better.[17] In the latter case the average difference of retrieved prey is 3.4 units, that is, a negligible amount with respect to the total.[18] The group size seems not to have effect on the performance of the group, but this is mainly due to the fact that the relative number of retrieved prey, that is, the number of retrieved prey divided the total number of prey, is on average already close to 1.

Both in simulation and with the real robot, the differences in performance, if any, are not enough to explain the difference in efficiency. Therefore, the improvement is due to the decrease of the group duty time. We show in Section 5.2 that this is achieved by division of labour.

We see in Fig. 5 that the gap between the adapting group and the control group tends to decrease when the prey density increases. This is not surprising, because it is better to use all available robots, as the control group does, in rich environments.

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[14] Sign test for paired data (Siegel and Castellan Jr. [1988], p. 80–87). Null hypothesis: $\nu$ is the same in the two colonies. Alternative hypothesis: $\nu$, and therefore the efficiency, improves with adaptation.

[15] Wilcoxon rank sum test. The null and alternative hypotheses are the same as in footnote 14.

[16] Permutation test, null hypothesis: the performances are the same. Alternative hypothesis: the performances are different. The $p$-value is 0.53.

[17] Wilcoxon rank sum test. The null and alternative hypotheses are the same as in footnote 16.

[18] The only exception is for prey density 0.04 s$^{-1}$ and 2 *s-bots*, where the control group retrieved on average 8.9 prey more.

It is important to observe that $\nu$ decreases with the group size also when adaptation is used. One possible explanation is that our adaptation algorithm is not good at reducing the number of explorers. For instance, if the optimal number of explorers is 2 for a given prey density, our robots might end up with 2.5 for a group of 4 *s-bots* and 3.5 for 8 *s-bots*. An alternative explanation is related to the way we measure $\nu$, which depends on the group duty time. The latter depends on the group size. In fact, all the robots in a group spend some time in searching because none of them can have $P_l = 0$ (remember that $P_l \in [P_{\min}, P_{\max}]$ and $P_{\min} > 0$), so each robot contributes to the final group duty time. These two explanations are not mutually exclusive, but it is important to test if the first case does occur, as this would demonstrate a limitation of our adaptation algorithm. Section 5.2 provides a partial answer to this issue.

## 5.2 Division of Labour

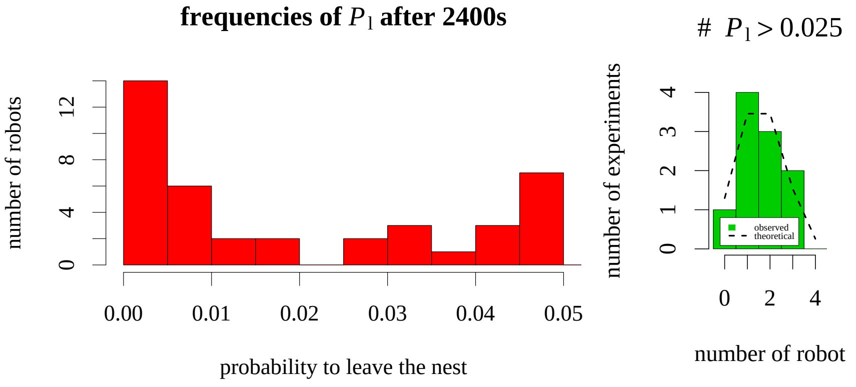
We showed that adaptation improves the efficiency of the group. The differences of the performances in both simulation and hardware, when present, are not enough to explain the improvement. Therefore, we deduce that adaptation reduces the group duty time. There are two ways in which the group can achieve this: in the first case, all robots end up having the same, albeit low, $P_l$ so that the mean number of robots in the foraging area is reduced; in the second case, only few robots are active foragers with high $P_l$ and the others have low $P_l$. Obviously, the robots with high $P_l$ would spend more time in searching than the others, therefore we could observe division of labour.

At any given instant $t$ after the beginning of the experiment, the value of $P_l$ in a robot is a random variable which has different values for every robot and every experiment. Whether the group uses division of labour or not can be observed in the distribution of $P_l$: in case division of labour occurs, then at the end of the experiments the distribution of $P_l$ will have two peaks; otherwise it will have only one peak.

5.2.1 *Real Robots.* During the experiments of Section 5.1.1, we recorded the value of $P_l$ for each *MindS-bot* in order to estimate the distribution. The result after 2400 s, plotted in Fig. 7(a), clearly shows two peaks. Figure 8 reports the distribution of $P_l$ over time.

5.2.2 *Simulation.* We used the data from the experiments of Section 5.1.2 to analyse the effects of group size and prey density on division of labour. We observed that the evolution of the distribution of $P_l$ is similar to Fig. 8, for each combination of prey density and group size (data not shown). We also noticed a wider gap between the two peaks of the distributions.

We classify the robots in three classes: *foragers*, *loafers* and *undecided*. *Foragers* are those *s-bots* whose $P_l$ is bigger than 0.042, while *loafers* have $P_l$ lower than 0.007, and the rest are undecided (notice that this last group spans over a range of values for $P_l$ that is five times bigger than the others). Figure 9 plots the proportions of *s-bots* belonging to each class at 2400 s. The graphs clearly show a strong division of labour in the colonies. Individuals tend to have either high or low $P_l$ but seldom



(a) (b)

Fig. 7. (a) Frequency of $P_1$ observed in the *MindS-bots* 2400 s after the beginning of experiments. The two peaks demonstrate the occurrence of division of labour. 40% of the observation are above 0.025. (b) Distribution of the number of *MindS-bots* with $P_1 > 0.025$ observed in each experiment compared with the theoretical binomial distribution with $p = 0.4$.

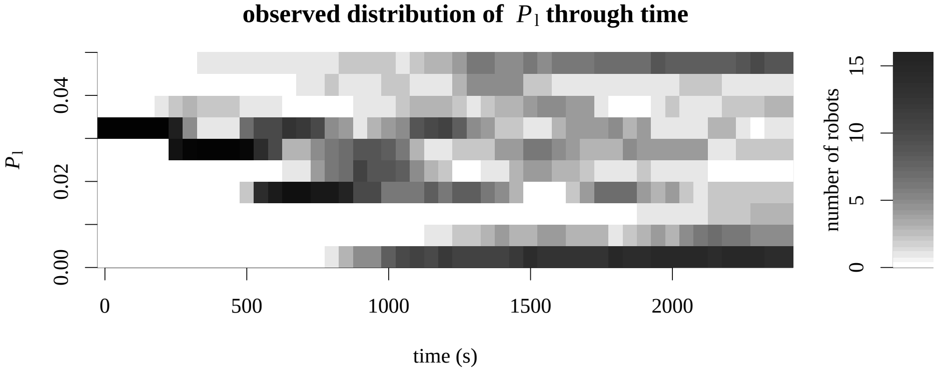


Fig. 8. Dynamics of the observed frequency of $P_1$ in the *MindS-bots*. The darkness of a cell in position $(t, p)$ is proportional to the number of *MindS-bots* with $p = P_1$ after $t$ seconds from the beginning of the experiment. The relationship is given by the bar on the right. At $t = 0$ all the *MindS-bots* have $P_1 = 0.033$ (see the black stripe on the left). After 1000 s the number of *MindS-bots* with low $P_1$ drastically increases (see the dark stripe on the bottom). Similarly, after 1500 s, the number of robots with high $P_1$ increases, although slowly and reaching a lower value than that of the loafers (top-right part of the plot).

values in between.[19]

5.2.3 *Discussion.* One might object that the right peak of Fig. 7(a) could be the result of a few experiments in which all the *MindS-bots* happened to have high $P_1$. To see that this is not the case, it is enough to look at the number of

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[19] The *undecided* category spans a broader range of $P_1$ than either *forager* or *loafer* categories. Note that in Fig. 9, therefore, even in cases where the percentages of *undecided s-bots* is similar to the percentage of *foragers* or *loafers*, the *undecided s-bots* are still more sparsely distributed over $P_1$.

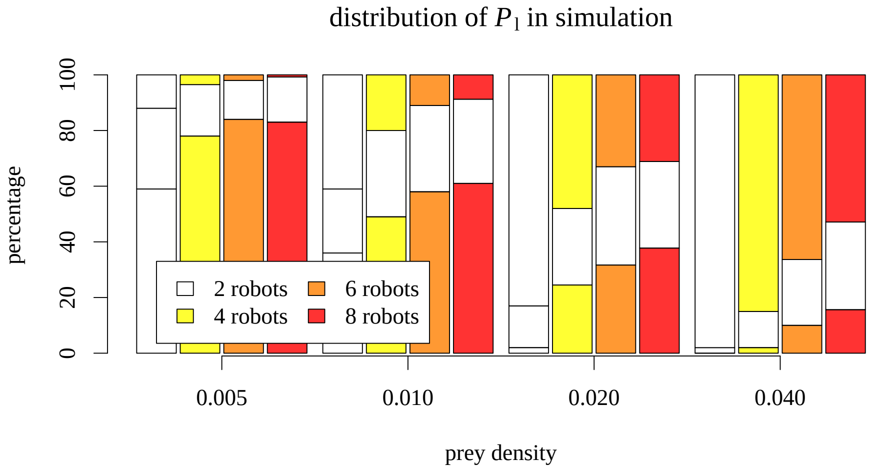

Fig. 9. Division of labour in the *s-bots*. Each group of four columns refers to different environments with increasing prey density. Each bar refers to a group size (see the legend). Each bar is divided into three parts whose height is proportional to the ratio of robots belonging to the following groups: *foragers* ($P_l > 0.043$) on the top, *loafers* ($P_l < 0.007$) at the bottom, and *undecided* ($0.007 \leq P_l \leq 0.043$) in between. For example, if the top part is 25% of the total height of the bar for a group of 8 robots, it means that on average 2 robots were foragers.

*MindS-bots* with $P_l > 0.025$ at the end of the experiments, and how this number is distributed. From the data in Fig. 7(a), we know that 40% of the population has $P_l > 0.025$. Therefore, we expect that the number of *MindS-bots* with $P_l > 0.025$ in each experiment follows a binomial distribution with $p = 0.4$. Figure 7(b) shows that the profiles of the theoretical and the observed distributions are indeed very similar.

The evolution of the distribution of $P_l$ over time (Fig. 8) shows that the *MindS-bots* with high $P_l$ appear later than those with low $P_l$ (the former at 1500 s, the latter at 1000 s). It may by hypothesised that the presence of robots with low $P_l$ are necessary for the group with high $P_l$ to appear. All *MindS-bots* start with the same $P_l$, as can be seen from the black stripe for $t = 0$ and $0.03 \leq P_l \leq 0.035$. After some time, some *MindS-bots* reduce their $P_l$ because they are not successful (see the black stripes that start at 250 s and 500 s for $P_l = 0.025$ and $P_l = 0.015$), while the others alternate successes with failures (indicated by the region in the middle of $y$ range that remains dark till 1500 s). The number of *MindS-bots* in the arena decreases, that is, there are less competitors for those which managed to keep their $P_l$ high enough. Less competitors implies more and easier retrievals, which increase the $P_l$ of the remaining foragers.

As we expected, the ratio of foragers in the *s-bot* group increases with higher prey density for fixed group size. More interestingly for most prey densities, the proportions of foragers for group of six and eight *s-bots* are nearly the same, and thus there are in average more foragers in the latter group.[20] This phenomenon could explain the loss in efficiency when increasing the group size even when *s-bots* adapt. Because of the particular set-up we used, we could not test colonies with more than eight individuals: if more robots had been used, there would not have been room enough in the nest for all of them. We speculate that the particular rule we implemented, or the set of parameters we used, can be effective only to a certain extent and that other rules or other parameter settings could work better in such conditions.

### 5.3 Best-Individual Selection

The adaptation mechanism we are studying is based only on individual successes or failures. If one robot, for any reason, is better than the others for the task of retrieving, then it will be more successful and therefore it is more likely to become a forager. We might, in fact, have come to this conclusion intuitively. It is still important, however, to validate it experimentally.

Generally speaking, the differences can be artificially created or intrinsic in the robots. In the first case, for instance, some robots can be intentionally designed for the task of retrieving while the others are designed to explore the environment to find and mark dangerous spots. In the second case, the differences come from the imperfections of the robots' components, which can never be identical (e.g., one motor that is less powerful than another). Any mechanism for division of labour should take into account this type of heterogeneity of the group.

This section shows that individual adaptation can be effective to select the best suited individuals for the retrieving task. We want to stress the fact that the algorithm we are studying does not take into account the presence of other robots. In fact, a robot neither knows how many nest-mates are present, nor whether it is working in a group or alone. There is no explicit model either of the environment or of the robot's own capabilities.

The *MindS-bots* are built identically. The only differences come from the components. With the simulated *s-bots*, we artificially introduced some heterogeneity. In the following, we are interested in those robots whose $P_l$ is greater than 0.025. Slightly modifying our earlier definition, we refer to them as *foragers*.[21] Given the stochastic nature of the experiments, we can model the fact that a robot $i$ is a forager at the end of an experiment as a random event.

5.3.1 *Real Robots.* We took data from the experiments of Section 5.1, where we use groups of 4 robots selected out of a pool of $N = 6$ robots. Table I reports the number of times each *MindS-bot* was observed to be a forager at the end of the experiments.

5.3.2 *Simulation.* We created six different *s-bots* that differ in their maximum speed. More precisely, we set the maximum speed of the first *s-bot* to half the speed

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[20] This is true also for prey density 0.04 $\mathrm{s}^{-1}$, where there are on average 4.23 foragers in a group of 8 robots vs. 3.98 in a colony of 6.

[21] Note that both with *MindS-bots* and *s-bots* the robots are not aware of such concepts as “being a forager” or “being undecided”. These are categories defined *a posteriori* by us, that is, they are arbitrary definitions, whose purpose is to help us in the discussion. Therefore, we can modify them, if this helps to explain better the results of our experiments.

Table I. For each *MindS-bot*, identified by an unique name, the total number of experiments in which it was used and the number of times it was a forager ($P_1 > 0.025$) are reported. Data refers to ten experiment, four *MindS-bots* per experiment.

| ID | Tot. Exp. | $\#_{foragers}$ |
|---|---|---|
| *MindS-bot*1 | 6 | 5 |
| *MindS-bot*2 | 3 | 2 |
| *MindS-bot*3 | 9 | 1 |

| ID | Tot. Exp. | $\#_{foragers}$ |
|---|---|---|
| *MindS-bot*4 | 9 | 4 |
| *MindS-bot*5 | 3 | 0 |
| *MindS-bot*6 | 10 | 4 |

of the *s-bots* used in Section 5.1.2 and 5.2.2. The speed of each of the other five robots was the speed used in Section 5.1.2 and 5.2.2, scaled respectively by 0.7, 0.9, 1.1, 1.3, 1.5. The six robots were combined into all possible colonies of four robots, forming fifteen different groups. Each group was tested in the same fifty instances randomly created with prey density 0.01 $\mathrm{s}^{-1}$. The groups were simulated for 2400 s and we counted how many times each *s-bot* in each group ended up being a forager. The results are not shown for reasons of space.

5.3.3 *Discussion.* If adaptation takes into account differences among individuals, the probability that each robot becomes a forager at the end of an experiment either depends on the other robots in the same group, or is different for at least one robot. Adaptation does not consider differences among robots if the probability of becoming a foragers is constant for all the robots.

For the *MindS-bots*, the data in Table I allows us to reject the hypothesis that the probability of becoming a forager is constant with confidence 95%.[22] Thus one of the other two conditions can be assumed to be true. Both of them prove that adaptation considers individual differences for the division of labour.

This way of proving our thesis might seem complex but it has a great advantage: it allows us to reach significant conclusions with only 10 experiments. Consider the simpler approach of testing all possible groups with different instances: it would require 15 experiments (all the combinations of 4 robots out of 6) for each instance.

A two-way ANOVA test on the data from simulation shows statistically relevant differences both among robots and groups (confidence level 95%), therefore we can conclude that both individual characteristics and average abilities of the group are crucial to the selection of the best individuals. Not surprisingly, the probability of becoming a forager is always higher for faster robots.[23]

## 6. RELATED WORK

When working with several robots, interference between them reduces the efficiency of the group [Balch 1999; Goldberg and Matarić 1997]. To reduce interference, smarter behaviours can be implemented, as in Goldberg and Matarić [1997]. The authors estimate where the interferences occur the most, by counting the number of collisions or manoeuvres to avoid other robots. With this data, they design a control algorithm that avoids the most problematic zones. Schneider-Fontán and

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[22] $\chi^2$ test. Null hypothesis: all the probabilities are equal. Alternative hypothesis: there is at least one robot with different probability.

[23] Paired Wilcoxon tests among the data for each robot, applying Bonferroni correction for multiple tests.

Matarić [1996] reduce interference by assigning a predefined part of the arena to each robot, and each robot to one particular area.

It is not surprising that co-operation and task allocation are extensively studied in the robotic literature as a means of reducing the interference problem. Jin et al. [2003] and Flint et al. [2004] give some examples of distributed control and task allocation for Unmanned Air Vehicles (UAV). Gerkey and Matarić [2004] recently proposed a taxonomy of task allocation problems and analysed some of the known solutions which use *intentional* cooperation [Parker 1998]. In these examples, however, robots have enough information in order to create explicit models of the environments and of their own capabilities, unlike our case.

Our working conditions are more akin to those usually found in *swarm robotics* [Dorigo and Şahin 2004] or *minimalistic robots*, as in Jones and Matarić [2003]. They suggest a method for division of labour when robots have to collect items of two different types. Their robots collect one type or the other with a probability that changes according to estimates of the relative number of items in the environment and of the relative number of robots already focusing on one type. Krieger and Billeter [2000] show an example of division of labour in a group of robots using the activation-threshold model [Bonabeau et al. 1996]. The thresholds of the robots are assigned at the beginning and do not change during the experiments. Their work is interesting because it is one of the first showing that complex group behaviour can be produced using simple control algorithms.

Among the works that use adaptation or learning, we would like to highlight a few which show some similarity with our work. In the L-ALLIANCE framework [Parker 1998], each robot has a set of behaviours associated with each task. Two values, *impatience* and *acquiescence*, are associated with each set. Impatience increases every time a robot is not performing a task, till it reaches a particular threshold. Then the robot executes the task, and its acquiescence starts growing. The robot gives up performing the task when the acquiescence is too high. Individual impatience and acquiescence rates of growth are adjusted by each robot according to their experience and to the information coming from other robot. The system can, however, work without communication.

Ijspeert et al. [2001] showed how robots can collaborate in order to pull a stick out of a hole without using communication. The behaviour of the robots is characterised by a *gripping time parameter* (GTP), which sets the time to wait for help from other robots. Li et al.[2004] proposed an adaptation algorithm to adjust the GTP in order to improve the collaboration rate. They tested it only in simulation and in an extended version of the problem where $k$ robots are needed. Their algorithm works by incrementing (or decrementing) the GTP by a variable value. Both local information (that is, the rate of personal successful collaborations) and global information (that is, the swarm collaboration rate evaluated globally and broadcast to all the robots) are used by each robot to decide how to modify the GTP.

Agassounon et al. [2004] propose an architecture, based on the threshold model to allocate workers in a puck clustering application. Their algorithm is also characterised by a time constant, that is, the time spent without finding a puck to transport. If this time expires, a robot returns to the nest and does not exit any more. They use a form of adaptation which consists in estimating the density of pucks at the beginning of the experiment and setting the time constant accordingly.

The three works described above show some fundamental differences with respect to ours. Unlike L-ALLIANCE, our approach neither needs intentional communication, nor a model of other robots. Unlike the two other works, our actions are not deterministic. It is still an open question whether the other adaptation algorithms differ from ours in terms of performance or efficiency. Unfortunately, the applications used by the authors and the set-ups are too different to draw any scientifically sound conclusion.

## 7. CONCLUSIONS

We implemented and analysed an algorithm for division of labour which is inspired by a model of ants' foraging. The model stresses the role that learning plays in the collective behaviour of ants' foraging. A simple form of adaptation, which occurs in each individual and which uses only information locally available, can improve the efficiency of a group of robots. Efficiency improves by means of division of labour, which implicitly takes into account heterogeneity among robots. The robots do not need to communicate with each other, and in fact their control algorithms do not need to know how many other robots, if any, are present.

We are convinced that our work can be useful both for biologist and roboticists. Biologist tend to downplay the importance of learning in collective behaviours. Many biologists still think that complex phenomena (like prey retrieval) must imply some form of communication or some form of social hierarchy. Our work is a strong argument against this point of view. Roboticists can take advantage of the methodology that we used. For instance, to the best of our knowledge, very few works exploit, at least explicitly, control groups for the statistical assessment of hypotheses. In this way, we obtained statistical significance with a few experiments.

We also pointed out some limitations of our adaptation algorithm. We showed the negative effects of group size on the global efficiency and noticed that the ratio of foragers seems to reach a fixed value for some prey density. We also note that adaptation occurs quite slowly (the experiments with *MindS-bots* took forty minutes). This still might not be a problem if the group is designed to work for a long time, as in the case of planetary explorations.

Future work will try to identify the causes of the problems in order to improve the efficiency of the group and the division of labour. We will also compare our approach with similar ones, like those described in Section 6. The comparison will be done by porting the different algorithms to a common application and by analysing the result in the same way as we did in this paper. Hopefully, we will be able to say if different algorithms yield different results and, if so, which are their strong and weak points.

Finally, another future research line will investigate the effect of combining our adaptation algorithm with signalling and more complex communication. We expect that the the group will be more efficient, although it is an open question whether communication and adaptation will interact synergically or destructively. The results will integrate the conclusion already given by Balch and Arkin [1994], who considered only the effect of communication on the group performance.

## ACKNOWLEDGMENTS

This work was supported by the "SWARM-BOTS project", funded by the Future and Emerging Technologies programme (IST-FET) of the European Commission, under grant IST-2000-31010. The information provided is the sole responsibility of the authors and does not reflect the Community's opinion. The Community is not responsible for any use that might be made of data appearing in this publication. Marco Dorigo acknowledges support from the Belgian FNRS, of which he is a Research Director, through the grant "Virtual Swarm-bots", contract no. 9.4515.03, and from the "ANTS" project, an "Action de Recherche Concertée" funded by the Scientific Research Directorate of the French Community of Belgium. Jean-Louis Deneubourg acknowledges support from the Belgian FNRS, of which he is a Research Associate. The authors want to thank the anonymous reviewers for their precious comments on this paper.

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Received January 28, 2005; revised July 26, 2005; November 12, 2005; accepted XXX XXX