Intelligent Autonomous Systems 9
T. Arai et al. (Eds.)
IOS Press, 2006

Group Transport Along a Robot Chain in a Self-Organised Robot Colony

Shervin Nouyan [a], Roderich Groß [a,b], Marco Dorigo [a], Michael Bonani [c] and Francesco Mondada [c]

[a] *IRIDIA, Université Libre de Bruxelles, Belgium*
[b] *Yamakita Lab, Tokyo Institute of Technology, Japan*
[c] *Autonomous Systems Lab, École Polytechnique Fédérale de Lausanne, Switzerland*

Abstract.
We study groups of autonomous robots engaged in a foraging task as typically found in some ant colonies. The task is to find a prey object and a nest object, establish a path between the two, and transport the prey to the nest. Once a path is established, robots are recruited to the prey, self-assemble into a pulling structure and collectively transport the prey—which is too heavy for a single robot to move it—along the path to the nest. We follow a swarm-intelligence based control approach. All robots have the same controller. They self-organise into teams and sub-teams that accomplish a number of different tasks concurrently. To solve the subtask of exploration and path formation we propose a new approach, that is, chain formation based on *cyclic directional patterns* (CDP chains). At present, we believe this study to be the most complex example of self-organisation in the robotics field. Experimental results with groups of 2, 4 and 8 physical robots confirm the reliability and robustness of the system.

Keywords. Swarm intelligence, swarm robotics, self-organisation, prey retrieval, path formation, self-assembly, group transport

1. Introduction

There are several advantages in using a group of robots instead of a single one: (i) the lack of ability (of a single robot), (ii) increased efficiency, (iii) increased redundancy and fault tolerance, and (iv) reduced costs [1]. However, many challenges arise when controlling a group of robots. Especially for large group sizes, centralised control architectures and complex communication protocols rapidly reach their limits due to individual failure or limited bandwidth. To overcome these problems, and to reach both tight cooperation and scalability at the same time, swarm robotic control algorithms [4] emphasise principles such as decentralisation and exploitation of local sensory information and communication. These principles are assumed to form the basis of the behaviour of social insects when addressing challenging tasks [5].

In this paper, we demonstrate the utility of swarm robotic control algorithms in a complex foraging scenario as typically found in some ant colonies: the robots are randomly scattered in a bounded arena containing two objects—the *prey* and the *nest*. The former has to be retrieved to the latter. The following constraints are given:

- C_1: the prey requires the cooperative effort of n robots to be moved, with $n > 1$.
- C_2: the robots have no a priori knowledge about the dimensions of the environment, or about the position of any robot or other object.
- C_3: the robot's perception range is small when compared to the distance between the nest and the prey.
- C_4: communication is unreliable and limited to a small set of simple signals that can only be perceived by those robots that are in the immediate neighbourhood.

These constraints have strong implications on the organisation of labour within the group. To illustrate this, we refer to the generic definition of teamwork recently proposed by Anderson and Franks [1]. To solve our task it is required for some robots to engage in the transport (C_1), while others have to direct the transporters towards the nest (C_2, C_3 and C_4). Thus, two *different* subtasks have to be performed *concurrently*. Therefore, our task can be considered to be a *team task*. Both subtasks require the cooperation of multiple robots. Moreover, each subtask can be considered as a team task [1].

In this paper, we present a distributed controller for the *team task* described above. To the best of our knowledge, the three different tasks of path formation, self-assembly, and group transport have been tackled only separately with real robots. We present the first attempt to solve these three tasks as parts of an integrated scenario, using a robot team that is homogeneous both in hardware and control. Roles are assigned dynamically as the result of a self-organised process.

Furthermore, we introduce the concept of chains with cyclic directional patterns (termed *CDP-chains*). CDP-chains are a new method in robotic exploration of unknown environments. These chains serve (a) to explore the environment, (b) to establish a path between prey and nest, (c) to recruit workers to the prey along this path, and (d) to guide the transport group back to the nest.

The remainder of this paper is organised as follows. In Section 2, we give a brief overview of related work in path formation, self-assembly, and group transport. In Sections 3 and 4, we detail the robot's hardware and control. In Section 5, we present the experimental results. Finally, in Section 6 we draw some conclusions.

2. Related Work

Path Formation. When foraging, ants of many species lay trails of pheromone, a chemical substance that attracts other ants. Deneubourg *et al.* [6] showed that laying pheromone trails is a good strategy for finding the shortest path between a nest and a food source. Even though a colony of social insects is capable to solve such complex tasks, individuals are governed by simple rules. These often serve as a source of inspiration when designing distributed exploration strategies.

Robotic chains, where the robots act as trail markers themselves, mimic the idea of pheromone trails. The concept of robotic chains stems from Goss and Deneubourg [9]. In their approach, every robot in a chain emits a signal indicating its position in the chain. A similar system was implemented by Drogoul and Ferber [7]. Both works have been carried out in simulation.

Werger and Matarić [21] used real robots to form a chain in a prey retrieval task. Neighbouring robots within a chain sense each other by means of physical contact: one robot in the chain has to regularly touch the next one in order to maintain the chain.

The use of virtual pheromones for environment exploration has been studied by Payton *et al.* [18] and by Mamei and Zambonelli [15].

Self-Assembly. Self-assembly is a particularly interesting mechanism in social insects [2]. Insects physically connect to each other to form aggregate structures with capabilities exceeding those of an individual insect. Some observed uses have strong implications for robotic system design (e.g., the formation of pulling structures [12]).

Most modular robotic systems are not capable of self-assembly—modules are pre-assembled by the experimenter or by a separate machine [22]. Other systems can self-assemble if the modules are pre-arranged in specific patterns. Rare instances of less constrained self-assembly with up to three robots have been reported [8].

Recently, self-assembly has been demonstrated with the *swarm-bots* system [16]. Experiments were conducted on different terrains and with up to 16 physical robots [10].

Group Transport. Almost half a century ago, Sudd [19] studied solitary transport and group transport of prey by ants of the species *Pheidole crassinoda*. Although he observed that single ants would mostly behave similarly to those engaged in group transport, he reported that group transport "showed co-operative features".

Object transportation has extensively been studied in groups of mobile robots.

In multi-robot box pushing, most studies consider two robots pushing a wide box simultaneously from a single side, a few systems with more than two robots have been studied [14].

Another strategy is to grasp and/or lift the object. In this case, each robot's motion is highly constrained. Typically, systems of 2–3 physical robots have been studied. Often the planning is accomplished by a *leader* robot. While in some systems the *leader* sends explicit high- or low-level commands to the *followers* [20], in others, robots communicate through the object being transported [13].

3. Hardware

We use a robotic system called *swarm-bot* lying at the intersection between collective and self-reconfigurable robotics [16]. A *swarm-bot* is formed by a number of basic robotic units, called *s-bots*, which are fully autonomous and mobile, and capable of autonomously connecting to each other.

Fig. 1a shows the physical implementation of the *s-bot*. The robot has a diameter of $12\,\mathrm{cm}$ and weighs approximately $700\,\mathrm{g}$. In the following, we briefly overview the actuators and sensors that are used in this study. For a more comprehensive description of the *s-bot*'s hardware see [16].

The *s-bot* has five degrees of freedom (DOF) all of which are rotational, including two DOF for the traction system, one DOF to rotate the *s-bot*'s upper part (called the *turret*) with respect to the lower part (called the *chassis*), one DOF for the grasping mechanism of the gripper (in what we define to be the *s-bot*'s front), and one DOF for elevating the arm to which the gripper is attached (e.g., to lift another *s-bot*).

The robot's traction system consists of a combination of tracks and two external wheels, called *treels*©. An *s-bot* can connect with another by grasping the connection ring. An *s-bot* can receive connections on more than two thirds of its perimeter.

In this study we make use of a variety of sensors, including 15 proximity sensors distributed around the turret, four ground sensors mounted underneath, an accelerom-

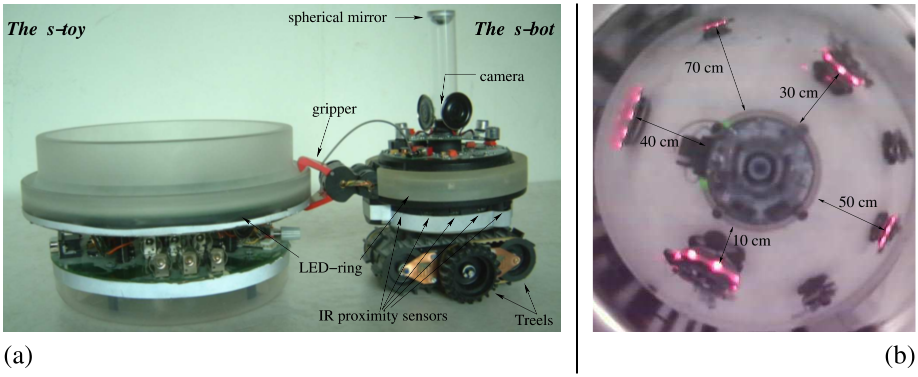

Figure 1. The hardware. (a) The *s-toy* and the *s-bot*. (b) An image taken with the omni-directional camera of the *s-bot*. It shows other *s-bots* and an *s-toy* activating their red LEDs at various distances.

eter, two optical barriers integrated in the gripper, four omni-directional microphones, one X-Y force sensor between the turret and the chassis, as well as proprioceptive sensors. Moreover, a VGA camera directed towards a spherical mirror provides an omni-directional view.

Next to the *s-bot*, Fig. 1a shows the *s-toy*, an object which we use either as nest or as prey (depending on its colour). It has a diameter of $20\,\mathrm{cm}$ and, like the *s-bot*, it is equipped with an RGB LED-ring. The nest is immobile. The prey weighs $800\,\mathrm{g}$ and requires the cooperative effort of two or more *s-bots* to be moved.

A snapshot taken from an *s-bot*'s camera is shown in Fig. 1b. Due to differences among the robots' cameras, there are some variations in the perceptual range. The software we use to detect coloured objects allows a recognition of the red coloured prey up to a distance of $70 - 90\,\mathrm{cm}$, and of the three chain colours, blue, green and yellow, up to $35 - 60\,\mathrm{cm}$ (depending on which robot is used).

4. Controller

We decompose the task into two subtasks: (i) exploration of the environment to form a path between nest and prey, and (ii) assembly to the prey or already connected robots to transport the prey along the path towards the nest.

We realized our controller using the behaviour based architecture illustrated in Fig. 2. The *exploration module* and the *transport module* are detailed in the following. In addition to these two main modules, there is the reset behaviour in which a robot moves back to the nest and rests.

4.1. Exploration Module

The robots are initially located at random positions. They have to search the nest, which can be considered as root of each chain. Robots that have found the nest start self-organising into visually connected chains relying on the concept of cyclic directional patterns. As displayed in Fig. 3a, each robot emits one out of three signals depending on its position in the chain. By taking into account the sequence of the signals, a robot

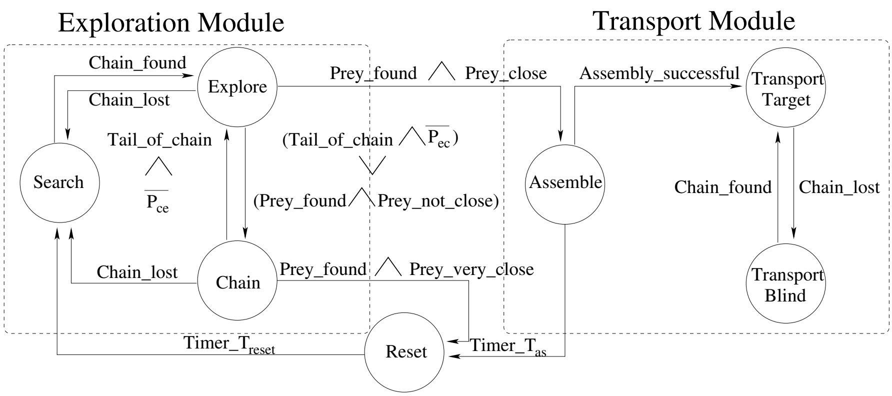

Figure 2. State diagram of the control. Each circle represents a state (i.e., a behaviour). Edges are labelled with the corresponding conditions that trigger a state switch. The initial state is the search state. $\overline{P_{ec}}$ (and $\overline{P_{ce}}$ respectively) is a boolean variable which is set to *True*, if $R \leq P_{ec}$ ($R \leq P_{ce}$), and to *False* otherwise, where R is a stochastic variable sampled from the uniform distribution in $[0, 1]$.

can determine the direction towards the nest. Each signal is realized by the activation of a dedicated colour with the LED ring. Robots that are part of a chain may leave it under certain conditions. This is fundamental for the exploration of the environment as it allows the formation of new chains in unexplored areas. The process of chain formation and decomposition is continued until a chain encounters the prey. The members of this chain do not decompose any more and automatically lead the other robots to the prey.

The prey, the nest, and members of a chain can be recognised by their colour. A chain member is either blue, green or yellow. The nest is considered as a chain member, and is blue. The prey is red.

Behaviours. Three behaviours are employed to realize the exploration module:

- **Search**: the robot performs a random walk which consists of straight motion and turning on the spot when an obstacle is encountered. No LEDs are activated.
- **Explore**: an explorer moves along a chain towards its tail. In case a robot becomes an explorer by leaving a chain, it moves back to the nest from where it might then

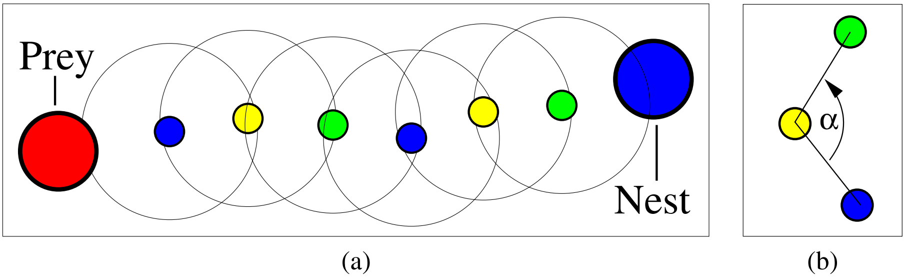

Figure 3. (a) CDP-chains. The small coloured circles represent robots that have formed a CDP-chain that connects a nest with a prey. Three colours are sufficient to give a directionality to the chain. The large circles surrounding the robots indicate their sensing range. (b) Alignment of a chain member. If the angle α is less than 120^o, the central chain member aligns with respect to its closest neighbours.

start to follow a different chain. No LEDs are activated.
- **Chain**: a chain member activates the appropriate colour with its LEDs. To avoid loops in chains and to improve the length of the chains, we implemented an alignment behaviour, that is, the robot aligns with its two closest neighbours in the chain in case the angle between them is smaller than 120^o (see Fig. 3a). Otherwise there is no movement.

The behaviours are realized following the motor schema paradigm [3]. For each behaviour, a set of motor schemas is active in parallel. Active motor schemas are added and translated into motor activation at the beginning of each *control time step*.[1] Common to all behaviours is a motor schema for collision avoidance.

Behaviour Transitions. A set of conditions trigger behaviour-transitions:

- **Search** → **Explore**: if a chain member is perceived.
- **Explore** → **Search**: if no chain member is perceived.
- **Explore** → **Chain**: (i) if the tail of a chain is reached (i.e., only one chain member is perceived), the robot joins the chain with probability P_{ec} per time step, or (ii) if the prey is detected at a distance larger than $30\,\mathrm{cm}$.
- **Explore** → **Assemble**: if the prey is detected at a close distance (i.e., less than $30\,\mathrm{cm}$).
- **Chain** → **Search**: if the previous neighbour in the chain is no longer detected.
- **Chain** → **Explore**: if a chain member is situated at the tail of a chain, it leaves the chain with probability P_{ce} per time step.
- **Chain** → **Reset**: if the prey is perceived at a very close distance (i.e., less than $5\,\mathrm{cm}$), which only occurs if the prey is transported towards the chain member.
- **Reset** → **Search**: after resting for the time $T_{reset} = 60s$.

The two probabilistic parameters P_{ec} and P_{ce} have a significant effect on the overall behaviour of the robot group. This concerns in particular the number and length of the formed chains, and the speeds of the processes that lead to the formation and to the destruction of chains. For instance, low values for P_{ec} result in a rather patient behaviour; in most cases a single chain is formed slowly. For P_{ec} close to 1, several chains are formed fast and in parallel. The second parameter, P_{ce}, determines the stability of the formed chains, directly influencing their lifetime and the frequency of chain disbandment. After having conducted tests in simulation [17] and on the real *s-bot*, we have fixed the values of the probabilities to $P_{ec} = 0.14$ and $P_{ce} = 0.007$.

4.2. Transport Module

The transport module controls the *s-bots* to form a pulling structure, a *swarm-bot*, connected with the prey. This *swarm-bot* transports the prey along a path established by other robots back to the nest. In the following the behaviours and behavioural transitions are detailed.

Behaviours. The transport module comprises three behaviours:

- **Assemble**: the robot approaches and connects with a red object (e.g., the prey). It is controlled by a reactive neural network taking input from the camera and the

[1] A control time step has a length of approximately 120 ms. This value is not constant because it depends on the time required for image processing.

proximity sensors [10]. In the moment the robot connects, it activates its LED ring in red. Therefore, it becomes itself an object with which to establish a connection.
- **Transport-Target**: the robot aligns its chassis towards the closest chain member, which indicates the direction to the nest, and starts pulling.
- **Transport-Blind**: if no chain member is perceived, the robot monitors the force acting between the turret and the chassis. Moreover, it estimates if there is stagnation using the torque sensors of the tracks. Based on this information, a recurrent neural network computes the speed and the desired direction of the chassis [11].

Behaviour Transitions. Again, a set of conditions trigger behaviour-transitions:

- **Assemble** → **Reset**: if the robot does not succeed in connecting to an object within $T_{as} = 90\,\mathrm{s}$.
- **Assemble** → **Transport-Target**: if the robot succeeds in connecting to an object.
- **Transport-Target** → **Transport-Blind**: if the robot perceives no chain member.
- **Transport-Blind** → **Transport-Target**: if the robot perceives a chain member.

5. Results

We conducted experiments in a bounded arena of size $500\,\mathrm{cm} \times 300\,\mathrm{cm}$. The nest was positioned in the centre and the prey was put at distance D (in cm). N robots are positioned on a grid composed of 60 points uniformly distributed in the arena. The initial position of each *s-bot* is assigned randomly by uniformly sampling without replacement. The *s-bot*'s initial orientation is chosen randomly from a set of 12 possible directions.

We examined different setups (N, D), keeping a linear relationship between N and D. We studied distances (D) of 30, 60 and $120\,\mathrm{cm}$, for group sizes (N) of 2, 4 and 8 *s-bots*, respectively. In each case, at least two robots are required to transport the object. In the case $(N, D) = (2, 30)$, the completion of the task does not require a chain as the prey can be seen from the nest and vice versa. In the case $(N, D) = (4, 60)$, it is possible that the prey is recognised from within the vicinity of the nest. However, the nest cannot be perceived from within the proximity of the prey (remember that *s-bots* can perceive red at a further distance than other colours). Therefore, the transport requires a chain consisting of one or more *s-bots*. In case of $(N, D) = (8, 120)$, a chain of three or more *s-bots* is required to complete the task.

The criterion of success is satisfied if the prey retrieval is completed, that is, if the prey, or a robot transporting it, touches the nest.

We conducted 10 trials for each setup. In total 30 trials have been performed. In 29 cases the task was successfully completed. Only in one replication of the setup $(N, D) = (8, 120)$ this was not the case. This failure was due to an *s-bot* that incorrectly assumed that it was gripping the prey.

Fig. 4 shows a series of six images taken from a typical trial with $N = 8$ *s-bots*. Within $120\,\mathrm{s}$, three *s-bots* found the nest and the prey, and established a path between them. After another $60\,\mathrm{s}$ one of the five remaining *s-bots* connected with the prey, and signalled this by activating its red LEDs. This robot alone was not strong enough to pull the prey. However, shortly after, a second *s-bot* connected and the prey started to move. The group of *s-bots* transporting the prey reached the nest after a total of $300\,\mathrm{s}$.

There are three main phases in the accomplishment of the task: path formation, assembly and transport. We denote the completion times of these phases by T_p, T_a and T_t.

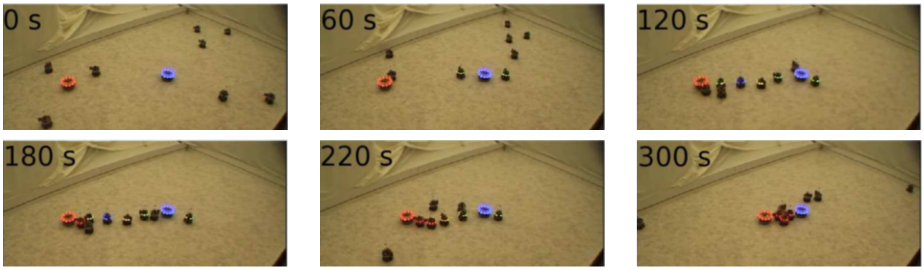

Figure 4. Sequence of images taken at different moments of a typical trial with 8 *s-bots*.

We consider the path formation phase to be completed as soon as a path connecting the prey with the nest can be traversed in both directions. The assembly phase is considered to be completed as soon as two *s-bots* are connected to the prey so that it can be moved. Table 1 summarises the results for the three completion times.

For the experiments with 2 and 4 *s-bots* the shortest phase was path formation. In case of 2 *s-bots* no path needs to be formed at all. In case of 4 *s-bots*, one *s-bot* finding the nest and forming a chain in the direction of the prey is sufficient to complete the first stage. Indeed, in 9 out of 10 trials, the time to form a path is approximately equivalent to the time until the first *s-bot* found the nest (see Fig. 5).

The largest fraction of time was required for the assembly phase: 89.9 % and 63.6 % for 2 and 4 *s-bots*, respectively. This phase is dominated by the relatively long time it takes to gather at least two *s-bots* at the prey location from their random starting positions. In fact, to find the nest or a chain, an *s-bot* performs a random walk. As the arena is rather large compared to an *s-bot*'s perceptual range, it can take a considerable amount of time until 2 out of 2, or 3 out of 4 *s-bots* have encountered the area from which they can perceive either the nest or a chain connected to it.

The situation is different for 8 *s-bots*. Only 31.4 % of the time was spent in the assembly phase, which is far less than for groups of 2 and 4 *s-bots*, respectively. One possible explanation for this observation is the higher degree of redundancy in the system; only 5 out of 8 *s-bots* are required to accomplish the overall task, which is a lower fraction than for the other group sizes. However, the time until a sufficient number of *s-bots* have found the nest drops from slightly more than 100 seconds for the group sizes 2 and 4, to approximately 50 seconds for group size 8 (see Fig. 5): this can not any more be explained with the smaller absolute fraction of *s-bots* required. A possible explanation is that the larger the group size, the more *s-bots* join the chains, in this way extending the area from which a path to the nest can be found. This in turn makes it more likely to encounter a chain member and thus a connection to the nest.

Table 1. Summary of the results. The value of T_p denotes the time required to form a path between nest and prey, T_a is the time until at least two *s-bots* are assembled to the prey so that the transport phase can start, and T_t is the time required to finish the transport. Mean and standard deviations are over ten experiments.

	2 *s-bots*			4 *s-bots*			8 *s-bots*		
	T_p (s)	T_a (s)	T_t (s)	T_p	T_a	T_t	T_p	T_a	T_t
Mean	0 (0%)	211.9 (89.9%)	23.9 (10.1%)	24.5 (11.7%)	133.3 (63.6%)	51.8 (24.7%)	93.6 (33.8%)	87.4 (31.6%)	95.6 (34.6%)
Std. Dev.	0	127.5	6.3	10.8	72.8	39.8	51.9	59.7	46.6

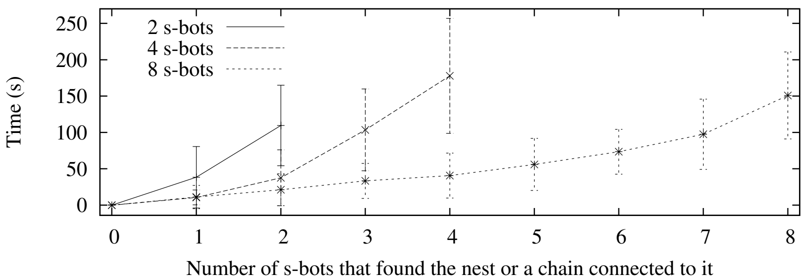

Figure 5. Time until the n-th *s-bot* finds either the nest or a chain connected to it.

The absolute amount of time spent during transport grows approximately linearly with the distance between nest and prey: 23.9, 51.8, and 95.6 seconds are required for the three setups, suggesting that for the transport it is not beneficial to increase the number of *s-bots*. Indeed, we observed that a pulling structure of 2–3 *s-bots* seems to be the optimal configuration for this particular transport task.

6. Conclusions

We presented an experimental study in which a group of autonomous robots engage in a foraging scenario, as found in some ant colonies. The task comprised the following three complex subtasks: (i) environment exploration and path formation, (ii) self-assembly to form a pulling structure connected with an object, and (iii) group transport of a heavy object. Inspired by the natural counterparts, we developed a swarm robotic control algorithm. The system is fully decentralised, and homogeneous in control.

Experimental results with up to eight physical robots confirm the reliability and robustness of the system. As, (i) the number or robots is relatively large when compared to most other examples of *teamwork* in multi-robot systems [1], (ii) not only the task but also its subtasks can be considered as team tasks, and (iii) our homogeneous robots dynamically solve the problem of task allocation, we believe that to date this study is the most complex example of self-organisation in the robotics field.

Acknowledgments

This work is supported by the “ANTS” project, an “Action de Recherche Concertée” funded by the Scientific Research Directorate of the French Community of Belgium, and 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 Swiss participants of the project were supported under grant 01.0012 by the Swiss Government. 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. Roderich Groß acknowledges additional support from JSPS.

References

[1] C. Anderson and N. R. Franks. Teamwork in ants, robots and humans. *Adv. Stud. Behav.*, 33:1–48, 2004.

[2] C. Anderson, G. Theraulaz, and J.-L. Deneubourg. Self-assemblages in insect societies. *Insect. Soc.*, 49(2):99–110, 2002.

[3] R.C. Arkin. *Behavior-Based Robotics*. MIT Press, Cambridge, MA, 1998.

[4] E. Bonabeau, M. Dorigo, and G. Theraulaz. *Swarm Intelligence: From Natural to Artificial Systems*. Oxford University Press, New York, NY, 1999.

[5] S. Camazine, J.-L. Deneubourg, N. Franks, J. Sneyd, G. Theraulaz, and E. Bonabeau. *Self-Organization in Biological Systems*. Princeton University Press, Princeton, NJ, 2001.

[6] J.-L. Deneubourg, S. Aron, S.Goss, and J.-M. Pasteels. The self-organizing exploratory pattern of the argentine ant. *J. Insect Behavior*, 3:159–168, 1990.

[7] A. Drogoul and J. Ferber. From Tom Thumb to the Dockers: Some experiments with foraging robots. In *From Animals to Animats 2. Proc. of the 2nd Int. Conf. on Simulation of Adaptive Behavior (SAB92)*, pages 451–459. MIT Press, Cambridge, MA, 1992.

[8] T. Fukuda and T. Ueyama. *Cellular Robotics and Micro Robotic Systems*. World Scientific Publishing, London, UK, 1994.

[9] S. Goss and J.-L. Deneubourg. Harvesting by a group of robots. In *Proc. of the 1st European Conf. on Artificial Life*, pages 195–204. MIT Press, Cambridge, MA, 1992.

[10] R. Groß, M. Bonani, F. Mondada, and M. Dorigo. Autonomous self-assembly in a swarm-bot. In *Proc. of the 3rd Int. Symp. on Autonomous Minirobots for Research and Edutainment (AMiRE 2005)*, pages 314–322. Springer, Berlin, Germany, 2006.

[11] R. Groß and M. Dorigo. Group transport of an object to a target that only some group members may sense. In *Parallel Problem Solving from Nature – 8th Int. Conf. (PPSN VIII)*, volume 3242 of *LNCS*, pages 852–861. Springer Verlag, Berlin, Germany, 2004.

[12] B. Hölldobler and E. O. Wilson. *The Ants*. Harvard University Press, Cambridge, MA, 1990.

[13] K. Kosuge and T. Oosumi. Decentralized control of multiple robots handling an object. In *Proc. of the 1996 IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, volume 1, pages 318–323. IEEE Computer Society Press, Los Alamitos, CA, 1996.

[14] C. R. Kube and E. Bonabeau. Cooperative transport by ants and robots. *Robot. Auton. Syst.*, 30(1–2):85–101, 2000.

[15] M. Mamei and F. Zambonelli. Spreading pheromones in everyday environments through RFID technology. In *Proc. of the 2nd IEEE Symposium on Swarm Intelligence*, pages 281–288. IEEE Press, Piscataway, NJ, 2005.

[16] F. Mondada, L. M. Gambardella, D. Floreano, S. Nolfi, J.-L. Deneubourg, and M. Dorigo. The cooperation of swarm-bots: Physical interactions in collective robotics. *IEEE Robot. Automat. Mag.*, 12(2):21–28, 2005.

[17] S. Nouyan. Path formation and goal search in swarm robotics. Technical Report TR/IRIDIA/2004-14, Université Libre de Bruxelles, Belgium, September 2004. DEA Thesis.

[18] D. Payton, M. Daily, R. Estowski, M. Howard, and C. Lee. Pheromone robotics. *Auton. Robots*, 11:319–324, 2001.

[19] J. Sudd. The transport of prey by an ant *Pheidole crassinoda*. *Behav.*, 16:295–308, 1960.

[20] T. G. Sugar and V. Kumar. Control of cooperating mobile manipulators. *IEEE Trans. Robot. Automat.*, 18(1):94–103, 2002.

[21] B. Werger and M. Matarić. Robotic food chains: Externalization of state and program for minimal-agent foraging. In *From Animals to Animats 4, Proc. of the 4th Int. Conf. on Simulation of Adaptive Behavior (SAB96)*, pages 625–634. MIT Press, Cambridge, MA, 1996.

[22] M. Yim, Y. Zhang, and D. Duff. Modular robots. *IEEE Spectr.*, 39(2):30–34, 2002.