

## Cooperative transport by ants and robots

C. Ronald Kube<sup>a,\*</sup>, Eric Bonabeau<sup>b</sup>

<sup>a</sup> *Edmonton Research Centre, Syncrude Canada Limited, 9421-17 Avenue, Edmonton, Alberta, Canada T6N 1H4*

<sup>b</sup> *Santa Fe Institute, 1399 Hyde Park Road, Santa Fe, NM 87501, USA*

---

### Abstract

In several species of ants, workers cooperate to retrieve large prey. Usually, one ant finds a prey item, tries to move it, and when unsuccessful for some time, recruits nestmates through direct contact or chemical marking. When a group of ants tries to move large prey, the ants change position and alignment until the prey can be moved toward the nest. A robotic implementation of this phenomenon is described. Although the robotic system may not appear to be very efficient, it is an interesting example of decentralized problem-solving by a group of robots, and it provides the first formalized *model* of cooperative transport in ants. ©2000 Elsevier Science B.V. All rights reserved.

*Keywords:* Cooperative transport; Ants; Swarm robotics; Box pushing; Collective robotics

---

### 1. Introduction

Social insect societies—ants, bees, termites and wasps—are distributed systems in which colony-level behavior emerges out of interactions among individual insects [4]. In addition to being a decentralized system, a colony of insects exhibits *flexibility* and *robustness*, two features that would be desirable in an artificial system. A recent trend in both Artificial Intelligence and Operations Research consists of viewing the social insect metaphor as a new paradigm for designing artificial problem-solving devices and optimization algorithms [3]. In Autonomous Robotics, *swarm-based*, or *collective robotics* relies on the same metaphor for the design of distributed control algorithms for swarms of robots.

There has been an upsurge of interest in swarm-based robotics in recent years [7] as it provides an interesting alternative to more classical approaches in robotics. Some tasks may be inherently too complex or impossible for a single robot to perform. For example, in the case study described in this paper, pushing a box requires the “coordinated” efforts of at least two individuals. Speedup can result from using several robots. Designing, building, and using several simple robots may be easier than designing, building and using a single complex robot. It may also be cheaper (depending on how many robots are required) because of the robots’ relative simplicity. A swarm of simple robots may also be more flexible and fault-tolerant because one or several robots may fail without affecting task completion. Furthermore, theories of self-organization teach us that randomness or fluctuations in individual behavior, far from being harmful, may in fact greatly enhance the system’s ability to explore new behaviors and find new solutions. Also, central control

---

\* Corresponding author. Tel.: 780-970-6800; fax: 780-970-6805.  
E-mail addresses: kube.ron@syncrude.com (C.R. Kube),  
bonabeau@santafe.edu (E. Bonabeau).

is usually not well suited to dealing with a large number of agents, not only because of the need for robot-to-controller-and-back communications, but also because failure of the controller implies failure of the whole system.

Self-organization and decentralization, together with the idea that interactions among agents need not be direct but can rather take place through the environment, point to the possibility of significantly reducing communications between robots: explicit robot-to-robot communications can rapidly become an issue when the number of robots increases; this issue can be to a large extent eliminated by suppressing such communications! Indirect communication among insects through modifications of the environment was coined *stigmergy* by Grassé, an entomologist who was trying to understand the regulation of building behavior in termites [14]. Stigmergy theory holds that transitions between a sequence of construction steps is regulated by the effect of previous steps. In more general terms, the theory has been used to explain and describe the process by which activity can be regulated using only local perception and indirect communication through the environment as applied to algorithms for coordinating distributed building behavior [38] and foraging tasks by multi-robot systems [2]. We will see in Section 2 that stigmergy seems to be the main coordinating mechanism in group transport by ants. That stigmergy works for a group of ants suggests that a group of robots can cooperate in group transport *without direct communication* among robots; moreover, robots do not have to change their behaviors depending on whether or not other robots are engaged in the task of carrying (or dragging, or pulling, or pushing) the item.

The current interest for collective robotics is the result of several factors:

1. The relative failure of the Artificial Intelligence program, which classical robotics relied upon, has forced many computer scientists and roboticists to reconsider their fundamental paradigm. This paradigm shift has led to the advent of connectionism, and to the view that sensori-motor intelligence is as important as reasoning and other higher-level components of cognition. Swarm-based robotics relies on the anti-classical-AI idea that a group of robots may be able to perform tasks without explicit representations of the environment and of the other robots and that planning may be replaced by reactivity.
2. The remarkable progress of mobile robotics during the last decade has allowed many researchers to experiment with mobile robots, which have not only become more efficient and capable of performing many different tasks, but also cheap(er).
3. The field of Artificial Life, where the concept of emergent behavior is emphasized as being essential to the understanding of fundamental properties of the living, has done much to propagate ideas about collective behavior in biological systems, particularly social insects; roboticists rapidly became aware of these ideas.

Using a swarm of robots has some drawbacks. For example, stagnation is one: because of the lack of a global knowledge, a group of robots may find itself in a deadlock, where it cannot make any progress. Another problem is to determine how these so-called “simple” robots should be programmed to perform user-designed tasks. The pathways to solutions are usually not predefined but emergent, and solving a problem amounts to finding a trajectory for the system and its environment so that the states of both the system and the environment constitute the solution to the problem: although appealing, this formulation does not lend itself to easy programming. Until now, we implicitly assumed that all robots were identical units: the situation becomes more complicated when the robots have different characteristics, respond to different stimuli, or respond differently to the same stimuli, and so forth; if the body of theory that roboticists can use for homogeneous groups of robots is limited, there is virtually no theoretical guideline for the emergent design and control of heterogeneous swarms.

Many potential applications of swarm-based robotics require miniaturization. Very small robots, micro- and nano-robots, which will by construction have severely limited sensing and computation, may need to *operate in very large groups or swarms to affect the macroworld* (quote from [27]). Approaches directly inspired or derived from swarm intelligence may be the only way to control and

manage such groups of small robots. As the reader will perhaps be disappointed by the simplicity of the tasks performed by state-of-the-art swarm-based robotic systems such as the one presented in this paper, let us remind her or him that it is in the perspective of miniaturization that swarm-based robotics becomes meaningful. In view of the potential applications of swarm-based robotics, it seems urgent to work at the fundamental level of what algorithms should be put into these robots: understanding the nature of coordination in groups of simple agents is a first step towards implementing useful multirobot systems.

In swarm-based robotics, cooperative transport—particularly cooperative box-pushing—has been an important benchmark for testing new types of robotic architecture. One of the swarm-based robotic implementations of cooperative transport is so closely inspired by cooperative prey retrieval in social insects that it is a genuine *model* of the phenomenon, thereby providing a unique example of a truly bidirectional exchange between biology and robotics. Ants of various species are capable of collectively retrieving large prey that are impossible for a single ant to retrieve. Usually, a single ant finds a prey item and tries to move it alone; when successful, the ant moves the item back to the nest. When unsuccessful, the ant recruits nestmates through direct contact or trail laying. If a group of ants is still unable to move the prey item for a certain time, specialized workers with large mandibles may be recruited in some species to cut the prey into smaller pieces. Although this scenario seems to be fairly well understood in the species where it has been studied, the mechanisms underlying cooperative transport—that is, when and how a group of ants move a large prey item to the nest—remain unclear. No formal description of the biological phenomenon has been developed, and surprisingly, roboticists went further than biologists in trying to model cooperative transport: perhaps the only convincing model so far is one that has been introduced and studied by roboticists [24], and although this model was not aimed at describing the behavior of real ants, it is biologically plausible. This paper first describes empirical observations of cooperative transport in ants, and then describes the work of Kube and Zhang [21–24].

## 2. Cooperative prey retrieval in ants

A small prey or food item is easily carried by a single ant.<sup>1</sup> But how can ants “cooperate” to carry a large item? Cooperative prey (or large food item) retrieval and transport has been reported in several species of ants [32,36,40]: weaver ants *Oecophylla smaragdina* [16] and *Oecophylla longinoda* [18,42], army ants *Eciton burchelli* [12], African driver ants *Dorylus* [13,29], and other species such as *Pheidole crassinoda* [35], *Myrmica rubra* [37], *Formica lugubris* [37], *Lasius neoniger* [39], the desert ants *Aphaenogaster* (ex-*Novomessor*) *cockerelli* and *Aphaenogaster albisetosus* [17,25], *Pheidologeton diversus* [29], *Pheidole pallidula* [10,11], *Formica polyctena* [8,9,28,41], *Formica schaufussi* [32,33,40] and the ponerine ants *Ectatomma ruidum* [30] and possibly *Paraponera clavata* [6]. This cooperative behavior can be quite impressive. For example, Moffett [29] reports that a group of about 100 ants *Pheidologeton diversus* was able to transport a 10 cm earthworm weighing 1.92 g (more than 5000 times as much as a single 0.3–0.4 mg minor worker) at 0.41 cm/s on level ground. By comparison, ants engaged in solitary transport of food items on the same trail were carrying burdens weighing at most five times their body weight at about 1 cm/s: this means that ants engaged in the cooperative transport of the earthworm were holding at least 10 times more weight than did solitary transporters, with only a comparatively modest loss in velocity [29].

We believe that the phenomenon of cooperative transport is much more common in ants than these few studies suggest: to the best of our knowledge, these studies are the only ones that report detailed observations of cooperative prey transport. This phenomenon involves several different aspects:

1. Is there an advantage to group transport as opposed to solitary transport? Is worker behavior in group transport different than in solitary transport?
2. When and how does an ant know that it cannot carry an item alone because it is either too large or too heavy?
3. How are nestmates recruited when help is needed?
4. How do several ants cooperate and coordinate their actions to actually transport the item?

<sup>1</sup> Portions of Section 2 have been modified from [3].

5. How do ants ensure that there is the right number of individuals involved in carrying the item?
6. How does a group of transporting ants handle deadlocks, and more generally, situations where the item to be transported is stuck either because of antagonistic forces or because of the presence of an obstacle or heterogeneities in the substrate?

All these questions, that have been more or less satisfactorily dealt with in the above-mentioned studies, are of enormous interest in view of implementing a decentralized cooperative robotic system to transport objects the locations and sizes of which are unknown.

### 2.1. Solitary transport versus group transport

In *Pheidologeton diversus*, single worker ants usually carry burdens (grasping them between their mandibles, lifting them from the ground and holding them ahead as they walk forward) rather than drag them [29]. By contrast, in cooperative transport, one or both forelegs are placed on the burden to aid in lifting it, mandibles are open and usually lie against the burden without grasping it. The movement patterns of group-transporting ants corresponding to their positions around the perimeter of a burden with reference to the direction of transport are also different than those of ants engaged in solitary transport: workers at the forward margin walk backward pulling the burden, while those along the trailing margin walk forward apparently pushing the burden; ants along the sides of the burden shuffle their legs sideways and slant their bodies in the direction of transport [29].

By contrast, Sudd [35,37] observes that individual *Pheidole crassinoda*, *Myrmica rubra*, and *Myrmica lugubris* ants appear to exhibit the same behavioral patterns in solitary and group transport: in group transport, all three species used the same method as when they work alone, including realignment and repositioning. This, however, does not exclude cooperative behavior: group transport in these species is particularly interesting because the same individual behavior is functional either in isolation or in group, and may even lead to increasing returns (up to a maximum group size: see Section 2.2) despite the lack of direct response of individuals to the presence of their nestmates.

In general, whether ants behave similarly or differently when engaged in solitary and group transport, group transport is more efficient than solitary transport for large prey. Moffett [29] observed that the weight carried by ant increases with group size: the total weight carried by a group of  $N$  workers increases as  $W \propto N^{2.044}$ , which means that the weight carried by each ant increases on average as  $N^{1.044}$ . Franks [12] made similar observations on *Eciton burchelli*: let  $W_i$  be the dry weight of transported items and  $W_a$  the total dry weight of the group of transporting ants, the relationship between both is  $W_i \propto W_a^{1.377}$ , which, assuming that  $W_a$  is proportional to  $N$ , implies that the dry weight carried by ant increases as  $N^{0.377}$ . Franks [12] also observed that items were always retrieved at a standard speed relatively independent of group size: he hypothesized that the increased efficiency of group transport with group size results from the group's ability to overcome the rotational forces necessary to balance a food item. Along the same lines, Moffett [29] found that the velocity of transport decreases as a function of the number of *Pheidologeton diversus* carriers, but decreases significantly only for large group sizes (>12 carriers). The transport efficiency per ant, measured by the product of burden weight by transport velocity divided by the number of carriers, increases with group size up to a maximum for groups of 8–10 ants, and then declines [29].

As emphasized by Traniello and Beshers [40], transport efficiency may not be the only and primary reason for group transport in ants. In *Aphaenogaster cockerelli* group retrieval of prey decreases interference competition with sympatric species [17,25], and in *Lasius neoniger* the rapid formation of a cooperative retrieval group is crucial to foraging success [39].

### 2.2. From solitary to group transport

All reports of how the decision is made to switch from solitary to group transport describe variants of the same phenomenon. A single ant first tries to carry the item, and then, if the item resists motion, to drag it (although dragging is rare in *Pheidologeton diversus*). Resistance to transport seems to determine whether the item should be carried or dragged [10,11,35,37]. The ant spends a few seconds testing the resistance

of the item to dragging before realigning the orientation of its body without releasing the item: modifying the direction of the applied force may be sufficient to actually move the item. In case realignment is not sufficient, the ant releases the item and finds another position to grasp the item. If several repositioning attempts are unsuccessful, the ant eventually recruits nestmates. Recruitment per se is examined in the next section. Sudd [37] reports that the time spent attempting to move the item decreases with the item's weight: for example, an ant may spend up to 4 min for items less than 100 mg, but only up to 1 min for items more than 300 mg. Detrain and Deneubourg [10,11] have shown that in *Pheidole pallidula*, it is indeed resistance to traction, and not directly prey size, that triggers recruitment of nestmates, including majors, to cut the prey.

### 2.3. Recruitment of nestmates

Hölldobler et al. [18] studied recruitment in the context of cooperative prey retrieval in two *Aphaenogaster* (ex-*Novomessor*) species: *Aphaenogaster albisetosus* and *Aphaenogaster cockerelli*. They show that recruitment for collective transport falls within two categories: short-range recruitment (SRR) and long-range recruitment (LRR). In SRR, a scout releases a poison gland secretion in the air immediately after discovering a large prey item; nestmates already in the vicinity are attracted from up to 2 m. If SRR does not attract enough nestmates, a scout lays a chemical trail with a poison gland secretion from the prey to the nest: nestmates are stimulated by the pheromone alone (no direct stimulation necessary) to leave the nest and follow the trail towards the prey.

Hölldobler [16] reports short-range, and more rarely long-range (rectal gland-based), recruitment in *Oecophylla smaragdina* in the context of prey retrieval. His studies indicate that the ants do not estimate the size or weight of the prey but rather adapt their group sizes, through different types of recruitment, to the difficulty encountered in first moving the prey. Hölldobler [16] further reports that the recruited ants were gathering around the prey, seeking to get access, and sometimes grasped nestmates that were already working at the prey, thereby forming a pulling chain, a common behavior in weaver ants.

### 2.4. Coordination in collective transport

Coordination in cooperative transport seems to occur through the item being transported: a movement of one ant engaged in group transport is likely to modify the stimuli perceived by the other group members, possibly producing, in turn, orientational or positional changes in these ants. This is an example of stigmergy [15], the coordination of activities through indirect interactions, which we described briefly in Section 1. The coordination mechanism used by ants in cooperative transport is not well understood, and has never really been modeled. The swarm of robots described in Section 3 is just such a model, which shows that the biology of social insects and swarm-based robotics can both benefit from each other.

### 2.5. Number of ants engaged in group transport

Apparently, the number of ants engaged in transporting an item is an increasing function of the item's weight, which indicates that group size is adapted to the item's characteristics. For example, Moffett [29] reports how the number of *Pheidologeton diversus* carriers varies with burden weight. Inverting the relationship described in Section 2.1, we obtain  $N \propto W^{0.489}$ . The fit to the data is remarkable, suggesting that the adaptation of group size is accurate. Using the same notations as in Section 2.1, Franks [14] finds that  $W_a \propto W_i^{0.726}$  for *Eciton burchelli*. However, as mentioned in the previous section, Hölldobler's [16] observations suggest that the ants adapt group size to the difficulty encountered in first moving prey: decisions rely on how difficult it is to carry the prey, and not simply on weight. A prey item that resists (either actively or passively) stimulates the ant(s) to recruit other ants. Success in carrying a prey item in one direction is followed by another attempt in the same direction. Finally, recruitment ceases as soon as a group of ants can carry the prey in a well-defined direction: in that way, group size is adapted to prey size.

### 2.6. Deadlock and stagnation recovery

Sometimes, the item's motion can no longer progress either because forces are applied by ants in opposite directions and cancel one another, or be-

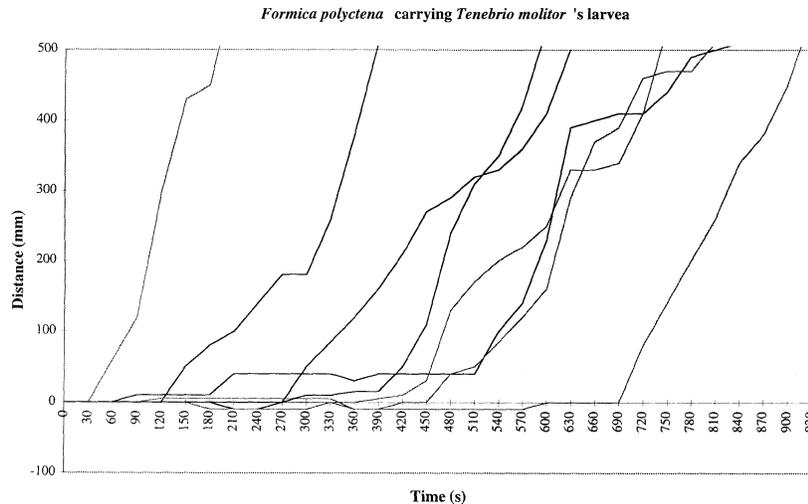


Fig. 1. Distance over which a larva of *Tenebrio molitor* has been transported by *Formica polyctena* ants as a function of time. Eight experiments are shown. After Van Damme and Deneubourg [41], reprinted by permission.

cause the group has encountered an obstacle or any significant heterogeneity on the substrate. If, for any reason, the item is stuck, ants exhibit realigning and repositioning behaviors [35,37]. The frequency of spatial rearrangements, which may result from the ants' responses to the reactive forces communicated through the item being transported [37], increases with time, and so does the rate of transport. As is the case for solitary transporters, realignments tend to occur before, and are much frequent than repositionings: only when realignment is not sufficient do ants try to find other slots around the prey.

Along the same lines, Moffett [29] reports that ants (*Pheidologeton diversus*) gather around food items at the site of their discovery, gnawing on them and pulling them; during the first 10 minutes or so, the item is moved about slowly in shifting directions, before ants "sort out" their actions and actual transport can begin. During these 10 minutes, a lot of spatial rearrangements take place. Personal observations of weaver ants *Oecophylla longinoda* confirm the existence of such spatial rearrangements in this species too. Van Damme and Deneubourg [41] studied cooperative transport of *Tenebrio molitor*'s larvae (a worm) in the ant *Formica polyctena*, and found that after a period of unsuccessful attempts to transport the larvae individually or in group, transport suddenly becomes successful, one possible reason being that the forces

applied by the various individuals engaged in cooperative transport become aligned. Fig. 1 shows the distance over which a larva has been transported as a function of the time elapsed since the larva was discovered. Distance is positive when progress has been made towards the nest and negative otherwise. It can be clearly seen that a "phase transition" occurs at some point (which, however, cannot be predicted: it varies from experiment to experiment), when group transport suddenly becomes successful. After that transition, transport proceeds smoothly until the larva reaches the nest.

### 3. Cooperative transport by robots

From the previous section, we understand better, although not perfectly, how ants cooperate in collective prey transport. In this section we introduce cooperative transport by robots, more precisely cooperative box-pushing. Box-pushing requires a cooperative effort from at least two robots to move a box along some trajectory [21,26,34]. Of the multi-robot tasks including foraging and formation marching, box-pushing has generally used a combination of centralized planning and conflict resolution with explicit communication between robots to coordinate their actions.

In the following sections we describe a series of works, by Kube and Zhang [21–24] and Kube [20], consistent in its ant-based approach to the problem of cooperative transport by a group of robots. The initial task under study was undirected box-pushing, in which a group of robots found a box and pushed it in a direction that was dependent upon the initial configuration. The task evolved into directed box-pushing, with the robots pushing the box from an initial position towards a fixed goal position. Finally, the transport task, a variant of the directed box-pushing task in which multiple goals were sequenced, is presented in which the robots push the box from one location to the next.

### 3.1. From social insects to robots

Social insects are nature’s proof-by-example of a decentralized multiagent system whose control is achieved through locally sensed information, as Section 2 clearly suggests. In previous work, we began with a simple simulation of a swarm of robots designed to locate and push a box and then implemented a subset of the behaviors in five physical robots [21,22].

Based on the simulation results the physical robots were built with controllers containing two behaviors: AVOID and GOAL. The behaviors were implemented as combinational logic which mapped a left and right obstacle sensor to left and right wheel motors, respectively, causing the robot to move away from obstacles. Left and right light sensors were mapped to right and left wheel motors causing the robot to turn towards a brightly lit box. The resulting controllers allowed the robots to locate the box, converge and push in a number of directions depending on the number of robots per side. The box was weighted such that at least two robots were required to move the box as it was pushed towards the edge of the test area [21].

The coordination demonstrated was possible by using a common goal and behaving using a simple “non-interference principle” [31]. The result demonstrated a simple cooperation without direct communication (stigmergy).

Further simulation results showed that the success rate for nondirected box-pushing<sup>2</sup> increases as a func-

<sup>2</sup> Where success was defined as pushing the box 200 units in 2000 simulated timesteps.

tion of the number of robots up to a point that appeared dependent on the size of the box. However, the system would stagnate or deadlock when an equal number of pushing robots surrounded the box resulting in an even distribution of box forces. To solve the stagnation problem we turned our attention back to cooperative prey retrieval by ants.

## 4. Stagnation recovery and mass effect

A detailed study of cooperative prey retrieval in ants by Sudd [35,37] uncovered several strategies used to combat stagnation. If during transport the food item becomes stuck ants will realign their body orientation without releasing their grasp, as was described in more detail in Section 2. This has the effect of changing the direction of the pulling or pushing forces and was often sufficient to resume motion. If after several minutes realignment failed, the ants would release their prey and reposition themselves along the perimeter. Repositioning seemed to result in larger cumulative changes in the forces acting on the transport item and was often successful in resuming motion. Could realignment and repositioning behaviors be used for stagnation recovery in box-pushing robots?

Our simulation experiments compared box-pushing controllers which included stagnation recovery behaviors [23]. The results demonstrated that the application of random pushing motions by either realigning the pushing angle or repositioning the pushing force was an effective technique against stagnation. The results also showed that the task success rate and efficiency improved as a function of the number of robots. However, efficiency measured as the number of simulation timesteps improved to a point that appeared dependent on the number of robots able to fit along the box.

The success percentage (reliability) and execution time (efficiency) was plotted as a function of the number of robots for the four different strategies: (1) without stagnation recovery; (2) REALIGNMENT only; (3) REPOSITION only; and (4) REALIGNMENT and REPOSITION behaviors. Controller reliability was improved by including stagnation recovery. For small group size strategy (2) is best, while (3) is more successful when the group size is large. Strategy (4) falls between (2) and (3) as expected since (2) then (3) are activated in

sequence. Controller efficiency as a function of simulated time was also compared. When the group size is small strategy (1) is best *provided it is successful*. When the group size is large strategy (4) is both the fastest and most successful with (2) and (3) having intermediate performance.

What do we learn from these results for real ants, assuming that this is a good model of cooperative transport in ants? There are two interesting results for biologists:

1. Although adding one or two mechanisms for stagnation recovery increases retrieval time, it also increases the probability of success. In species for which competition with other colonies or other species is not a critical factor, the probability of success should be favored: we expect stagnation recovery mechanisms in such species. On the other hand, if retrieval time is crucial, for example because of competition, then reliability is less critical but the speed of retrieval is essential: in species facing strong competition, we expect a less sophisticated or even no stagnation recovery mechanism. This prediction can be tested.
2. The probability of success in retrieving the prey depends on group size, which itself depends on prey size (see Section 2). What the results tell us is that we might observe realignment only for small prey (small groups) and both realignment and repositioning for larger prey (larger groups). It is also possible that both realignment and repositioning may be observed for all group sizes, but it is unlikely that repositioning only could be observed because it is significantly less reliable for small group sizes. These predictions, again, can be tested.

## 5. A task model for directed box-pushing

The directed box-pushing task required a new approach to task modeling. In undirected box-pushing (see Section 3.1) the state of the robot's controller was determined by selecting the highest priority behavior from a small select set. As a goal direction to push the box was added, it became apparent that accomplishing the task would involve a series of phases or steps often executed in a repetitive manner. Success would rely on the combined actions of all robots. In each step, some of the previous behaviors would not be useful

and could cause interference. For example, if a robot was correctly positioned for pushing the box towards the goal, then obstacle avoidance was not needed and if accidentally triggered would cause the progression to halt.

Describing a task as a series of steps with the transition between the steps specified as locally sensed cues formed the basis of our approach to (stigmergy-based) task modeling [24]. In this section we briefly describe the directed box-pushing model and present new results of experiments using four different box types transported between two goal positions.

### 5.1. Coherent behavior

In order to get coherent behavior from a group of robots each robot has an identical task controller which is composed of subtask controllers designed to accomplish each step of the task. The controllers are finite state machines with state transition specified using binary sensing predicates, which we call *perceptual cues*.

Pushing a box towards a goal can be divided into three phases (states): finding the box; moving towards the box; and—if correctly oriented with respect to the goal—pushing the box. Each state is then implemented as a subtask controller with two perceptual cues used to determine the state of the transport system: ?BOX-DETECT (BD) and ?BOX-CONTACT (BC). The states are shown in Table 1.

Each subtask controller is also a finite state machine with states represented as *primitive actuation* (PA) behaviors. PA behaviors use motion primitives to move the robot. An example of a subtask controller is shown in Table 2.

### 5.2. Perceptual cues for box-pushing

Transporting a box from an unknown initial position towards a final goal destination was modeled using three types of perceptual cues. Obstacle detection cues were used to detect an obstacle and trigger avoidance behaviors. Box detection cues were used to locate and track a moving box as well as to control state transitions among the subtask controllers, and a goal detection cue was used to indicate proper robot orien-

Table 1

Task execution state is determined by two perceptual cues: ?BOX-DETECT (BD) and ?BOX-CONTACT (BC)

Transport controller		
Perceptual cue (input)		Task state (output)
BD	BC	subtask controller
0	X <sup>a</sup>	FIND-BOX
1	0	MOVE-TO-BOX
1	1	PUSH-TO-GOAL

<sup>a</sup>Indicates a *don't care* term.

Table 2

The MOVE-TO-BOX subtask controller moves the robot towards any side of the brightly lit box to be manipulated

MOVE-TO-BOX subtask controller				
Perceptual cue (input) <sup>a</sup>				Behavior state (output)
?TOUCH	?CONTACT-	AVOID-	?BOX-	PA behavior
0	0	0	1	SEEK-BOX
0	0	1	X	AVOID
0	1	X	X	CONTACT
1	X	X	X	BACK-OFF

<sup>a</sup>The perceptual cues corresponding to the dashed labels are: ?CONTACT-DETECT; ?AVOID-DETECT; and ?BOX-DETECT.

tation with respect to the goal for a pushing or repositioning behavior.

### 5.2.1. Obstacle detection cues

The purpose of the obstacle detection cues are to provide obstacle distance information to the robot. Three discrete thresholds are used corresponding to the distances of: less than 25 cm, less than 12.5 cm, and in physical contact with the robot. Active infrared emitter/detector pairs are used to provide non-contact obstacle information for the left and right front of the robot. Physically touching an object is determined using a single bit contact switch. The obstacle detection cues are defined as:<sup>3</sup>

- ?AVOID-DETECT — True if an obstacle is detected within a 25 cm range.
- ?CONTACT-DETECT — True if an obstacle is detected within a 12.5 cm range.
- ?TOUCH — True if the front contact switch is pressed.

<sup>3</sup> Perceptual cues will be identified by their leading question mark.

### 5.2.2. Box detection cues

Box detection is simplified by using a bright light placed at the center of the box. The box detection cue asks the question: can the robot see the box-light? The answer depends on the robot's distance from the box and the orientation of its two forward pointing sensors with respect to the box. An adjustable threshold varies the range at which the box-light is detectable and is dynamically determined as a function of ambient light. Recognizing physical contact with the box is a combination of two different types of sensing, touch and light intensity. This combination of stimulus is unique in the task's environment thereby simplifying box recognition. Three perceptual cues are used for box detection:

- ?BOX-DIRECTION — Return right and left flags indicating the corresponding box-sensor has exceeded a threshold. The cue provides a coarse orientation towards the box.
- ?BOX-DETECT — True if either left or right box-sensors exceed a given threshold.
- ?BOX-CONTACT — True if ?TOUCH is true and either right or left box-sensors exceed a threshold.

Table 3

Behaviors that cause directional changes based on external stimuli expect a stimulus from the left and right sides of the robot similar to stimulus sensing found in insects

Positive and negative taxis mappings

Stimulus		Negative taxis		Positive taxis
L	R	AVOID	CONTACT	SEEK-BOX
0	0	<i>null</i> <sup>a</sup>	<i>null</i>	<i>null</i>
0	1	<i>left-turn</i>	<i>left-rotate</i>	<i>right-turn</i>
1	0	<i>right-turn</i>	<i>right-rotate</i>	<i>left-turn</i>
1	1	<i>right-turn</i>	<i>right-rotate</i>	<i>forward</i>

<sup>a</sup>The “null” output means the behavior does not produce a motion command.

### 5.2.3. Goal detection cue

The goal detection cue asks the question: can the robot see the goal? The answer is a function of the robot’s orientation with respect to the goal indicator, which in this instance is a spotlight placed near the ceiling. The goal detection cue is defined as:

- ?SEE-GOAL — True if a signal peak greater than a threshold is detected within the user defined field-of-view.

The final design consisted of a narrow field-of-view sensor which is swept by a motor in an upward pointing arc. If a signal peak occurs, caused by the spotlight, within an adjustable window the goal is detected.

At any given moment a robot is controlled by a single PA behavior. These behaviors issue discrete actions which affect the robot’s orientation. As in the simulated robots, orientation is based on a taxis mechanism.

### 5.3. Taxis-based discrete action

Jander defines insect orientation as “the capacity and activity of controlling location and attitude in space and time with the help of external and internal references, i.e. stimuli” [19]. In insects the behavioral act of orientation is controlled either externally, and results in a directional orientation using a taxis mechanism, or internally under kinesthetic control. Taxis is defined as a reflex translational or orientational movement by a freely motile organism in relation to a source of stimulation. Inspired by Braitenberg’s *Vehicles* [5] robot actions are based on taxis orientation or kinesthetic orientation as fixed motion patterns. The resulting ac-

tion is used to create motor behaviors used in a reactive controller. The only required knowledge about the perception side of the robot is that it corresponds to a left and right division of the mobility system used to produce the actions. In other words, the input to the action model is a stimulus as measured by a sensor and does not depend on either the stimuli’s modality or magnitude.

For the box-pushing task the PA behaviors which change robot orientation are:

- SEEK-BOX — moves the robot towards a box.
- AVOID — *turns* the robot away from obstacles.
- CONTACT — *rotates* the robot away from obstacles.

The PA behaviors and their motion primitives which cause changes in orientation are summarized in Table 3.

Kinesthetic orientation is used to produce motion in the absence of external stimuli and for stagnation recovery movements. Many behavioral acts in both insects and robots lack the external stimulus needed to guide the orientation mechanism. Rather a correct behavioral response might simply be a fixed pattern of motor activity stored in memory and released under suitable conditions. For example, a spider can return to a given location by “remembering and kinesthetically controlling its movements”, a skill also found in bees and ants [19].

For box-pushing the PA behaviors used for kinesthetic orientation and stagnation recovery are:

- RANDOM-WALK — moves the robot forward turning left or right.
- BACK-OFF — moves the robot backwards.
- PUSH-BOX — pushes the box by increasing motor voltage.

- REPOSITION — causes the robot to backup and turn left.

## 6. Group size in cooperative transport

In this section, results are presented for the integrated models of the previous sections. This global action is demonstrated in the cooperative transport task.

Global action is the effect produced when a set of identical mobile robots execute the common task of pushing an object towards an arbitrarily specified goal position. Coordination is achieved without resorting to direct inter-robot communication or robot differentiation. Instead, context sensitive subtask controllers decompose the box transport task into three phases. The phases describe *what* is to be achieved, in terms of the externally observable events described by box position, without specifying *how* the task is to be accomplished by way of a unique path.

### 6.1. Experimental system

The experimental setup used to gather the data consisted of a robot environment in which various boxes were placed along with two spotlights used to indicate final goal positions, and a set of identical mobile robots complete with sensors and task controllers. In total over 100 box-pushing trials were run using four different box types in three different venues. The final set of experiments were recorded on over four hours of video tape with an individual trial lasting between 30 seconds and 5 minutes.

The system is composed of a set of homogeneous two-wheeled robots, each weighing 1.3 kg and measuring approximately 18 cm in height and diameter as shown in Fig. 2. A battery allows for 45 minutes of operation with a 10 minute recharge time. A Motorola 68HC11 microcontroller with 8K of RAM and programmed in Forth is used to map sensor output to one of nine motion primitives. A minimum number of sensors (6) was sought in implementing the perceptual cues. The objective was to determine what could be accomplished with the minimal number of sensing bits. The hardware proved to be robust with few breakdowns.

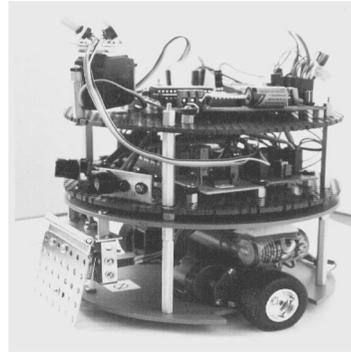


Fig. 2. Each of the robots are equipped with two forward pointing infrared obstacle sensors, one touch sensor, two forward pointing photocells, and a phototransistor to track the goal-light, all mounted on a differentially steered base.

#### 6.1.1. Directed box-pushing

Similar to our previous simulation studies, completion of an individual trial was limited to a maximum time of 5 minutes. If not successful in 5 minutes, the trial was marked “failed”. Successful trials would run between 32 and 214 seconds and were executed in three phases.

The first phase began when the robots were powered on, the box-light was off and the goal-light was on. System initialization consists of taking ambient light readings used to set the box detection threshold. The robots began executing FIND-BOX and quickly disperse themselves in the area. Shortly thereafter, the box-light was turned on and those robots that were facing the box and sufficiently close would move towards and make contact with a boxside using the MOVE-TO-BOX controller.

In the second phase, some of the robots incorrectly positioned for pushing, as determined by the PUSH-TO-GOAL controller, began moving counterclockwise around the box perimeter searching for an open spot on a correct side. This behavior is the result of several cycles through the transport controller consisting of in turn FIND-BOX, MOVE-TO-BOX and PUSH-TO-GOAL subtask controllers and can be explained as follows. Once contact is made with a boxside the ?SEE-GOAL perceptual cue determines that the robot is on the wrong side for pushing. The PUSH-TO-GOAL controller then executes the REPOSITION behavior which moves the robot away from the box in a counterclockwise direction. If the box

is within view, determined by the ?BOX-DETECT cue, MOVE-TO-BOX brings the robot into contact with a new position on the box provided it is unoccupied. The obstacle avoidance behaviors keep a robot away from occupied positions on a boxside. If the box is not within view then FIND-BOX executes and searches for the box. The PUSH-TO-GOAL controller evaluates the new position and the cycle repeats.

The third and final phase is characterized by the box moving towards the goal position. Once a net force sufficient to move the box occurs the box begins to translate and possibly rotate. During the box movement phase a robot continuously determines if it remains on the correct side for pushing using the ?SEE-GOAL cue. A robot located at the edge of the pushing swarm may suddenly lose sight of the goal and begin repositioning. The resulting drop in pushing force may be sufficient to halt the box movement until another robot joins the group effort. The dynamics of both the box and robots is such that the path taken by the box towards the goal is seldom straight. Rather, box movement can be said to converge towards the goal since its trajectory is the net result of several force vectors applied by individual robots.

### 6.1.2. Pushing different box types

To evaluate the controller's sensitivity to object geometry, 39 successful trials were performed using six robots and four different box types. The initial box, Box A, tested was 42 cm square and large enough for two 18 cm robots on a side. A second 84 cm square box, Box C, was built by extending the initial box with a second frame. This increased the box dimensions, but used the same base on which the box slid along the floor. A third 84 cm box, Box B, was built on a new base which increased the number of points in contact with the floor and therefore its sliding friction. The fourth box, Box D, was round with a diameter of 84 cm and the results of the 39 trials can be summarized as follows:

- Box A. A total of 10 trials were successful in pushing Box A from the initial position to the goal position. In general as the number of robots increased the task took longer to complete as the robot interference was high since the limited box side space created competition among the robots.

- Box B. A total of eight trials were successful in transporting Box B from its initial position using six robots.
- Box C. A total of seven successful trials were recorded in which Box C was moved to the goal area by six robots. This box had the highest failure rate among the four boxes used and was due to a robot getting caught on the frame.
- Box D. A total of 14 trials using a round box, Box D, and four to six robots were successful in moving the box between two goal positions. The round box was the last box built and experienced the most success of the four types tested.

### 6.1.3. Changes in goal position

The initial success of the directed box-pushing task led to the following extension which increased the task difficulty. Pictured in Fig. 3 are two goal positions labeled  $P_A$  and  $P_B$ . The robots start and a goal-light at position  $P_A$  is illuminated causing the robots to push the box towards  $P_A$ . Once reached the goal-light at  $P_A$  is turned off and the goal-light at  $P_B$  is switched on. The robots reposition around the box and begin pushing towards the goal at  $P_B$ . Fig. 4 is a sequence of three images taken from a video segment in which two goals were used.

In the following discussion some interesting results are presented which compare execution times as a function of system size in the first experiment and as a function of object geometry in the second experiment along with the following caveat. In experiments involving physical mobile robots, holding the many system variables invariant is near impossible making comparisons based on execution runtimes tenuous at best. In this experimentalist approach to robotics "things change" is axiomatic. Coefficients of friction change because the floor gets dusty, force is reduced because batteries run down, motors wear reducing repeatability, wheels slip in response to changes in load and the list goes on. However, in general there still seems to be a trend in the data which is worth presenting.

### 6.1.4. System size

The mean execution time for moving the smaller 42 cm square box from its initial position to the goal positions were compared for two to six robots as

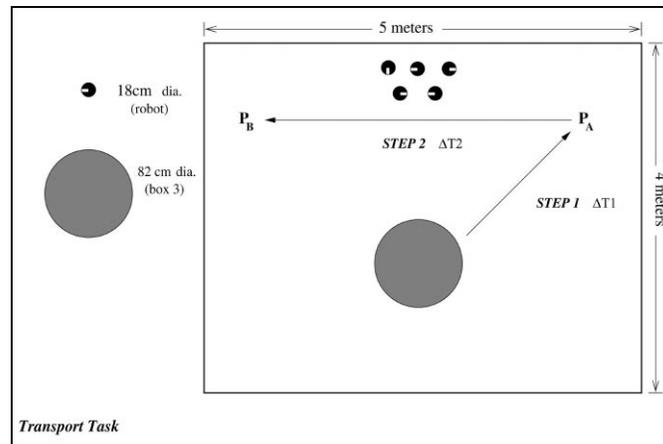


Fig. 3. A schematic of the lab environment used to test the transport of a round box between two goal positions. Shown are the initial positions of the five robots and the box. The first step is to move the box from its initial position to the goal located at  $P_A$ . The second step moves the box from  $P_A$  to position  $P_B$ .



Fig. 4. Shown are five robots pushing a round box from its initial position first towards a goal-light in the right of the picture and then towards a goal-light on the left of the picture. The mpeg video from which this sequence was taken is available at <http://www.cs.ualberta.ca/~kube/>.

shown in Fig. 5. Starting positions for the robots were varied with the final end position of the box recorded for timing to be the upper left corner of the lab. Indicated in each plot are the number of trials used to compute the mean. The large variance in runtimes was due to the robots starting at the goal position which could result in long repositioning phases.<sup>4</sup> In general, execution times increased as a function of the number of robots due to the increase in robot interference competing for the limited box space.

#### 6.1.5. Convex object geometry

Our previous simulation study had shown that in a box-pushing task performance, as measured by com-

<sup>4</sup> Both the maximums indicated in the case of three and five robots occurred from the goal position.

pletion time or success rate,<sup>5</sup> could be improved if stagnation recovery behaviors were added to the controller to avoid deadlock from occurring when the robots applied an equal distribution of forces to the box [26]. What was also noted was the sudden drop in performance as the number of robots in the system grew for controllers without stagnation recovery. This was conjectured to be due to the number of robots able to fit on a boxside. To test this hypothesis, simulations were run for the same controller and the robot diameter (RD) was tested for  $RD = 10$  and compared with the results using  $RD = 20$ . The results are shown in Fig. 6. If the diameter of the robots were reduced, for a fixed box side, the performance increases, which leads

<sup>5</sup> Success was defined to be the movement of the box by 200 units in under 2000 simulation timesteps.

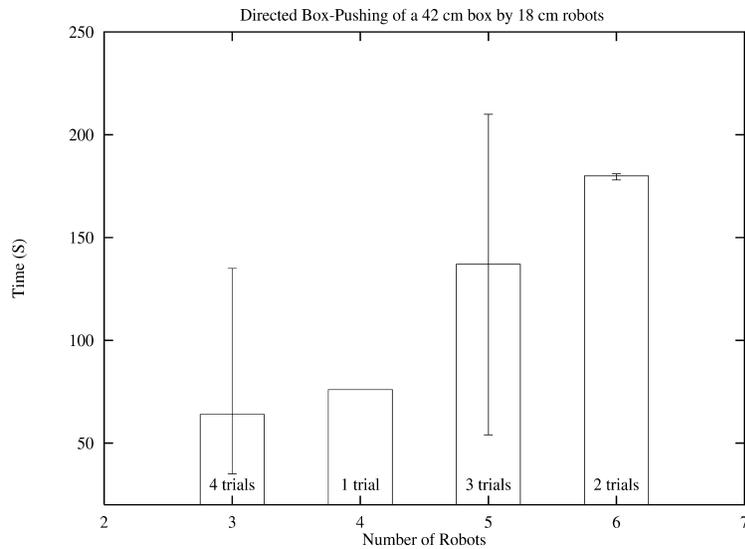


Fig. 5. The mean execution time of moving a  $42 \times 42 \text{ cm}^2$  box 2.5 m towards a goal position as a function of the number of robots. For each plot the number of trials as well as the minimum and maximum run times are indicated. A boxside is approximately twice the robot's diameter and increasing the number of robots increases the robot interference as they compete for the limited space available.

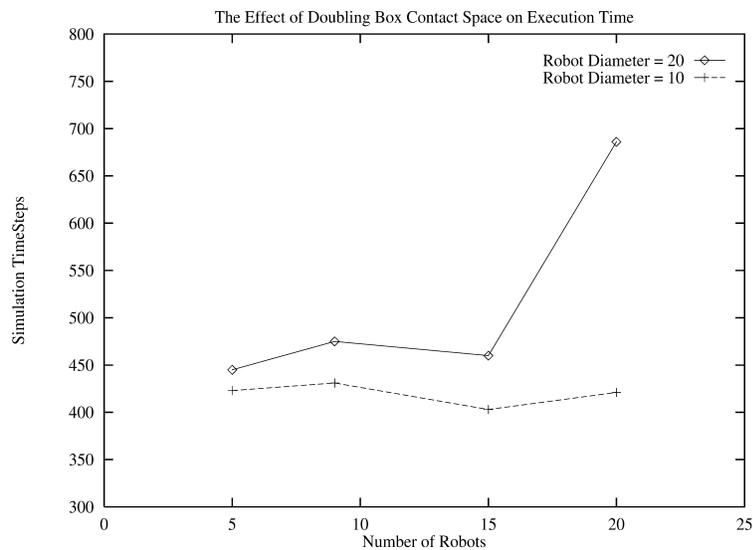


Fig. 6. The effects of doubling box contact space on execution time. The results from two simulation experiments showing execution time versus system size. The only parameter varied was the size of the robot; the size of the box side was held constant at 90 units.

to the conjecture that for a given task, performance is dependent on some yet to be determined *task density* function.

In Fig. 7 the mean execution times were compared for the four box types and six robots starting

from the same initial position. In general, it appears that as the available contact space increases more robots are able to participate in pushing at the same time reducing the time taken to complete the task. However, due to the sparseness of the

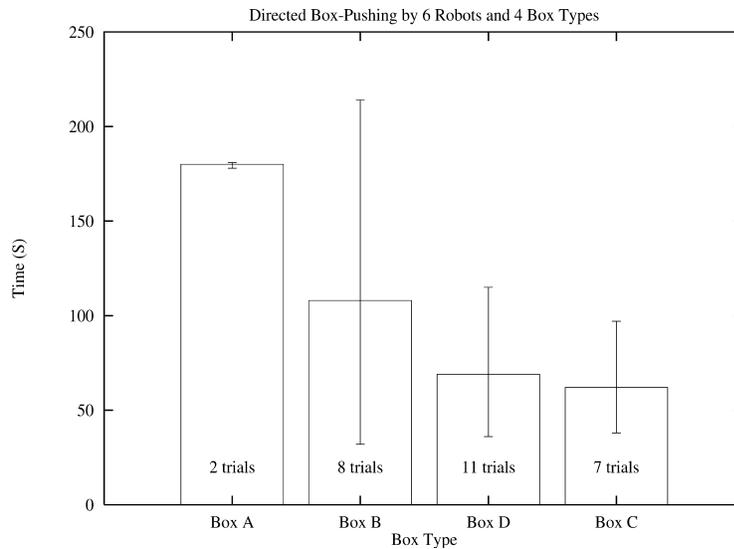


Fig. 7. The mean execution time of moving a box towards the goal as a function of box type. Box A is a 42 cm square box, Boxes B and C are 84 cm square boxes with B having a higher sliding friction than Box C, Box D is an 84 cm diameter round box. All box types are approximately the same weight and can be pushed by at least two robots. For each plot the number of trials as well as the minimum and maximum run times are indicated. All trials used six robots.

data additional experiments are needed for statistical validation.

## 7. Discussion: from ants to robots and back

Visualize a room in which a group of robots sit in one corner and a large box sits approximately center with a spotlight placed in another corner. The robots begin moving and soon disperse into the room. Soon after the box-light comes on the robots begin moving towards it and eventually come into contact with a side. Then some of the robots begin to reposition themselves by moving around the box in a counter-clockwise fashion, while others which are correctly positioned begin to push the box towards the spotlight. The box begins to move in the direction of the lit corner of the room, but the path is not quite straight and veers to the right and the box movement stops. Again some of the robots begin their counter-clockwise repositioning and assume a new position more correctly oriented for pushing. Finally, the box begins to move in a new direction towards the goal-light. The dynamics of the swarm of robots is very reminiscent of the dynamics of ants represented

in Fig. 1: given that the implementation of individual robot behavior is based on ant behavior, it is encouraging that the robotic *model* produces the same kind of emergent collective behavior as ants, and it suggests that the robotic implementation constitutes a plausible model of cooperative transport in (some species of) ants.

Once the box reaches the goal position the spotlight turns off and a second goal light on the opposite corner of the room is illuminated. Now all the robots begin repositioning, eventually making it to the opposite side and begin to once again push the box towards the new goal destination. Robots leave the task, seemingly at random, and wander off only to return and join the group effort in transporting the box towards its goal. The experiments are repeated, this time with boxes of different shapes and sizes and the number of robots in a group are varied. Our video recordings show, and those that have seen them agree, that the robots make a coordinated effort in pushing the box in a direction that converges towards the indicated goal position.

The results show in the many successful trials of directed box-pushing that *a coordinated group effort is possible without use of direct communication or robot*

*differentiation*. Rather a form of indirect communication (stigmergy) takes place through the environment by way of the object being manipulated. For directed box-pushing, the control strategy was shown to be insensitive to system size, some convex object geometries and changing goal positions. The results of experiments with physical robots presented here adds support to Arkin's simulation studies which showed that cooperation in some tasks is possible without direct communication [1].

From their local perception to the mass effect that results in a global action social insects serve to elucidate the mechanisms thought to be at the heart of self-organizing behavior and help create new paradigms for collective robotics. Of course, the use of ant behavior as a basis for designing robot swarms has its limits. For example, the cooperative transport of ants, if it is self-organized, is not always efficient: it takes 10 minutes to first get the object to move! An artificial system inspired by ants can (and should if it is not to be a model) overcome this type of limitation by not being purely ant-based.

In return, the robotic system described in this paper tells us a lot about cooperative transport in ants. We have seen that the model makes predictions about the kind of stagnation recovery mechanism (if any) to be expected depending on ecological conditions, and about the combination of realignment and repositioning that should be observed depending on prey size. At a more fundamental level, because the model is able to reproduce many of the collective features of cooperative transport in ants with a minimum of plausible assumptions, it suggests that these assumptions may be sufficient to explain the behavior observed in ants. The predictions of the model can now be tested empirically. More predictions would be welcome, especially predictions related to the response of the system to perturbations. The model should also eventually be tested against alternative models.

### Acknowledgements

CRK's research is supported by the University of Alberta and the Ralph Steinhauer Award of Distinction. EB's work at the Santa Fe Institute is supported through the Interval Research Fellowship.

### References

- [1] R.C. Arkin, Cooperation without communication: Multiagent schema-based robot navigation, *Journal of Robotic Systems* 9 (1992) 351–364.
- [2] R. Beckers, O.E. Holland, J.L. Deneubourg, From local actions to global tasks: Stigmergy and collective robotics, in: *Proceedings of the Fourth International Workshop on the Synthesis and Simulation of Living Systems Artificial Life IV*, 1994, pp. 181–189.
- [3] E. Bonabeau, M. Dorigo, G. Théraulaz, *Swarm Intelligence: From Natural to Artificial Systems*, Oxford University Press, Oxford, 1998.
- [4] E. Bonabeau, G. Théraulaz, J.-L. Deneubourg, S. Aron, S. Camazine, Self-organization in social insects, *Trends in Ecological Evolution* 12 (1997) 188–193.
- [5] V. Braitenberg, *Vehicles: Experiments in Synthetic Psychology*, MIT Press, Cambridge, MA, 1984.
- [6] M.D. Breed, J.H. Fewell, A.J. Moore, K.R. Williams, Graded recruitment in a ponerine ant, *Behavioral Ecology and Sociobiology* 20 (1987) 407–411.
- [7] Y.U. Cao, A.S. Fukunaga, A.B. Kahng, Cooperative mobile robotics: antecedents and directions, *Autonomous Robots* 4 (1997) 2–7.
- [8] R. Chauvin, Sur le transport collectif des proies par *Formica polyctena*, *Insectes Sociaux* 25 (1968) 193–200.
- [9] R. Chauvin, Les lois de l'ergonomie chez les fourmis au cours du transport d'objets, *Comptes Rendus Académie des Sciences Paris D* 273 (1971) 1862–1865.
- [10] C. Detrain, J.-L. Deneubourg, Origine de la diversité des réponses collectives des fourmis lors de la récolte de proies, *Actes Coll. Ins. Soc.* 10 (1996) 57–65.
- [11] C. Detrain, J.-L. Deneubourg, Scavenging by *Pheidole pallidula*: A key for understanding decision-making systems in ants, *Animal Behaviour* 53 (1997) 537–554.
- [12] N.R. Franks, Teams in social insects: Group retrieval of prey by army ants (*Eciton burchelli*, Hymenoptera: Formicidae), *Behavioral Ecology and Sociobiology* 18 (1986) 425–429.
- [13] W.H. Gotwald, Death on the march, *Rotunda* Fall/Winter (1984/1985) 37–41.
- [14] P. Grassé, La reconstruction du nid et les coordinations interindividuelles chez *Bellicositermes natalensis* et *Cubitermes* sp. La théorie de la stigmergie: Essai d'interpré, *Insectes Sociaux* 6 (1959) 41–81.
- [15] P.-P. Grassé, *Termitologia*, Tome II. Fondation des Sociétés. Construction, Masson, Paris, 1984.
- [16] B. Hölldobler, Territorial behavior in the green tree ant (*Oecophylla smaragdina*), *Biotropica* 15 (1983) 241–250.
- [17] B. Hölldobler, R.C. Stanton, H. Markl, Recruitment and food-retrieving behavior in *Novomessor* (Formicidae: Hymenoptera). I. Chemical signals, *Behavioral Ecology and Sociobiology* 4 (1978) 163–181.
- [18] B. Hölldobler, E.O. Wilson, The multiple recruitment systems of the African weaver ant *Oecophylla longinoda* (Latreille), *Behavioral Ecology and Sociobiology* 3 (1978) 19–60.
- [19] R. Jander, Insect Orientation, *Annual Review of Entomology* 8 (1963) 95–114.

- [20] C.R. Kube, Collective robotics: From local perception to global action, Ph.D., University of Alberta, Edmonton, Alberta, 1997.
- [21] C.R. Kube, H. Zhang, Collective robotic intelligence, in: Proceedings of the Second International Conference on Simulation of Adaptive Behavior: From Animals to Animats 2, MIT Press, Cambridge, MA, 1992, pp. 460–468.
- [22] C.R. Kube, H. Zhang, Collective robotics: From social insects to robots, *Adaptive Behavior* 2 (1994) 189–218.
- [23] C.R. Kube, H. Zhang, Stagnation recovery behaviors for collective robotics, in: Proceedings of the 1994 IEEE/RSJ/GI International Conference on Intelligent Robots and Systems, IEEE Computer Society Press, Los Alamitos, CA, 1995, pp. 1883–1890.
- [24] C.R. Kube, H. Zhang, Task modelling in collective robotics, *Autonomous Robots* 4 (1997) 53–72.
- [25] H. Markl, B. Hölldobler, Recruitment and food-behavior in *Novomessor* (Formicidae, Hymenoptera). II. Vibration signals, *Behavioral Ecology and Sociobiology* 4 (1978) 183–216.
- [26] M.J. Mataric, M. Nilsson, K.T. Simsarian, Cooperative multi-robot box-pushing, in: Proceedings of the IEEE International Conference on Intelligent Robots and Systems, 1995, pp. 556–561.
- [27] C. Melhuish, O. Holland, S. Hoddell, Collective sorting and segregation in robots with minimal sensing, Preprint, 1998.
- [28] J.-A. Meyer, Sur les lois régissant l'accomplissement d'une tâche collective complexe chez *Formica polyctena*, *Comptes Rendus de l'Académie des Sciences Paris D* 270 (1970) 2111–2114.
- [29] M.W. Moffett, Cooperative food transport by an Asiatic ant, *National Geographic Research* 4 (1988) 386–394.
- [30] S.C. Pratt, Recruitment and other communication behavior in the ponerine ant *Ectatomma ruidum*, *Ethology* 81 (1989) 313–331.
- [31] S. Premvuti, S. Yuta, Consideration on the cooperation of multiple autonomous mobile robots, in: Proceedings of the IEEE International Workshop on Intelligent Robots and Systems, 1990, pp. 59–63.
- [32] S.K. Robson, J.F.A. Traniello, Resource assesment, recruitment behavior, and organization of cooperative prey retrieval in the ant *Formica schaufussi* (Hymenoptera: Formicidae), *Journal of Insect Behaviour* 11 (1998) 1–22.
- [33] S.K. Robson, J.F.A. Traniello, Key individuals and the organisation of labor in ants, in: C. Detrain, J.-L. Deneubourg, J.M. Pasteels (Eds.), *Information Processing in the Social Insects*, Birkhauser, Basel, 1999, 239–259.
- [34] D.J. Stilwell, J.S. Bay, Toward the development of a material transport system using swarms of ant-like robots, in: Proceedings of the IEEE International Conference on Robotics and Automation, Atlanta, GA, 1993, pp. 766–771.
- [35] J.H. Sudd, The transport of prey by an ant *Pheidole crassinoda*, *Behaviour* 16 (1960) 295–308.
- [36] J.H. Sudd, How insects work in groups, *Discovery* 24 (1963) 15–19.
- [37] J.H. Sudd, The transport of prey by ant, *Behaviour* 25 (1965) 234–271.
- [38] G. Theraulaz, E. Bonabeau, Coordination in distributed building, *Science* 269 (1995) 686–688.
- [39] J.F.A. Traniello, Social organization and foraging success in *Lasius neoniger* (Hymenoptera: Formicidae): Behavioral and ecological aspects of recruitment communication, *Oecologia* 59 (1983) 94–100.
- [40] J.F.A. Traniello, S.N. Beshers, Maximization of foraging efficiency and resource defense by group retrieval in the ant *Formica schaufussi*, *Behavioral Ecology and Sociobiology* 29 (1991) 283–289.
- [41] T. Van Damme, J.-L. Deneubourg, Cooperative transport in *Formica polyctena*, submitted for publication.
- [42] J. Wojtusiak, E.J. Godzinska, A. Dejean, Capture and retrieval of very large prey by workers of the African weaver ant *Oecophylla longinoda*, *Tropical Zoology* 8 (1995) 309–318.



**C. Ronald Kube** is a senior research scientist with Syncrude Canada at their Edmonton research centre where he works on intelligent mining systems. He holds a B.Sc. (1990), M.Sc. (1992) and Ph.D. (1997) from the University of Alberta all in computing science. His research interests include collective robotics, machine vision, and sensor-based robotics.



**Eric Bonabeau** is the CEO of Euro Bios, a Paris, France-based consultancy that applies complex systems science to business problems. Prior to that he was the Interval Research Fellow at the Santa Fe Institute, where he studied the emergent collective intelligence of social insects. The author of three books and more than 80 scientific articles, Dr Bonabeau is the Editor-in-Chief of *Advances in Complex Systems*