Multiagent systems: Lessons from social insects and collective robotics

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Abstract

Multiagent systems used in the AI community are typically knowledge based, consisting of heterogeneous unembodied agents carrying out explicitly assigned tasks, and communicating via symbols. In contrast, many extremely competent natural collective systems of multiple agents (e.g. social insects) are not knowledge based, and are predominantly homogeneous and embodied; agents have no explicit task assignment, and do not communicate symbolically. A common method of control used in such collective systems is stigmergy, the production of a certain behaviour in agents as a consequence of the effects produced in the local environment by previous behaviour. This paper shows how stigmergy is used successfully in a collective robot system modelled on ants, and considers the possibility of extending the use of stigmergy and other forms of collective control to conventional multiagent or hybrid systems.

Introduction

Most of the multiagent systems forming the background to this symposium are built, however loosely, on the conceptual model of human groups, and have certain characteristics: agents are knowledge based, communicate symbolically, are not embedded in an environment, are not embodied, and are heterogeneous; real time considerations are minimal or absent, symbolic communication with humans is typical, and tasks and task assignment are explicit. In almost perfect contrast, there is a large class of systems also consisting of multiple agents but having opposite characteristics: agents (almost certainly) have no internal representations, but follow simple if-then rules, communicate by analogue quantities or tokens, exist in an environment, operate directly on the environment, are embodied, and are homogeneous; real time considerations are vital, symbolic communication with humans is impossible, and tasks and task assignment are implicit and emergent. The latter systems, which may usefully be called collective systems rather than multiagent systems, are mostly formed by the social insects. There are two exceptional subclasses:

(i) Many animals move in flocks, herds, or schools. During this movement, they operate as very simple rule-based systems responding to local sensory input, whatever their degree of cognitive complexity in dealing with other behaviours (Reynolds, 1987).

(ii) A very few collective task-achieving robot systems have been built (e.g. Beckers, Holland, & Deneubourg 1994; Altenberg 1994; Mataric 1994; Kube & Zhang 1992; for reviews, see Taipale & Hirai 1992, and Cao et al. 1995). Of course, very many more have been simulated.

Collective systems have a number of generic characteristics which make them useful in a variety of applications. For example, they are robust with respect to individual agent failure and to environmental disturbance; they can carry out tasks requiring spatially separated sensing and action; they can vary the allocation of resources to tasks to achieve optimal division of labour; and they use simple, and therefore intrinsically reliable and cheap agents.

Multiagent systems and artificial collective systems thus represent computational abstractions of the two most powerful natural types of social system. It is sensible to ask whether the principles underlying these systems will allow the design of hybrid systems which have some advantage over either type of system acting alone, and whether indeed there are any examples of such systems in nature. There are no examples of natural collective systems incorporating any of the features listed under multiagent systems, although claims are made from time to time that insects are capable of operating at a cognitive level. However, groups of humans (normally multiagent systems) can show some features of collective systems when they are constrained by circumstance or mutual agreement to behave as if blindly following a simple set of locally-based rules rather than behaving as knowledge-based cognitive agents using global information. Such situations arise in the organisation of movement (traffic conventions), queuing, some economic activities, riots, and other crowd phenomena. In some of these cases, especially traffic, there are clear benefits from this approach; the computational load on the agents is much reduced, improving real-time performance, and the homogeneity of responses often produces locally coherent and appropriate group behaviour which may appear as an emergent characteristic. In other cases, the effects are deleterious and even catastrophic; to appreciate the downside of some types of emergence in traffic situations, see Nagel & Rasmussen 1994.

Because both collective systems and multiagent systems are very varied and complex, it is not possible to consider all the ways in which their features could be combined. A more profitable approach at this stage might be to make available to the multiagent system community details of some of the mechanisms used by collective systems, and to attempt to relate them to the existing multiagent system mechanisms which they might enhance or replace; the community may then form a view on which collective mechanisms, if any, might offer advantages over existing multiagent practice. The principal mechanism discussed in this paper is stigmergy, a type of indirect communication which is one of the most powerful but least known principles underpinning successful collective action. It is preented in the context of a collective robot system; this is both a demonstration that biological techniques can be successfully adapted for use in artificial systems, and also a means of obtaining more experimental control over a collective system than is possible with a natural system.

Stigmergy

The subject of stigmergy is best approached by considering the ways in which embodied agents (call them robots) can interact. At any instant, a robot can affect another robot directly and immediately in three main ways:

- by affecting the other robot's sensors: for example, by being sensed as an obstacle
- by applying force to the other robot, actively or passively (possibly through the environment): for example, by colliding with it
- by communicating with the other robot

A robot can also affect another robot indirectly, and with a delay, by changing a part of the environment which the other robot may subsequently encounter. The changes may influence the other robot in the following ways when it arrives at the altered location:

- by affecting its sensors, and consequently its choice of behaviour
- by altering the effect of its actions (for example, if the environmental change is the laying down of a film of oil, the effect may be to cause the robot to lose traction and therefore to follow a different trajectory than it would have without the change)

The effects of these indirect interactions constitute stigmergy (Grassé, 1959). Active stigmergy (Holland & Beckers 1996) occurs when the effect is to influence the choice of behaviour of the second robot through sensory input. There are two types of active stigmergy: cue based stigmergy, where the sensory input is a by-product of the performance of the task by the first robot (e.g. laying a brick in a building task changes the local sensory input); and sign based stigmergy, where the sensory change is produced by an action (e.g. laying a chemical marker) which is not a by-product of task performance but has only the function of affecting subsequent behaviour at that location. Passive stigmergy (Holland and Beckers, 1996) is less obvious, but a version of it is present in almost every system operating in a mutable environment; it is essentially the mechanism of the formation of rivers, meanders, oxbow lakes, deltas, sand dunes, ruts, etc., extended to the realm of agents.

Stigmergy can be thought of as a type of low-overhead communication which can be used by computationally simple agents. When the agents are homogeneous, the effect of a local change on any robot in the locality will be the same as its effect on any other robot, other things being equal, and so the message will be consistent. Since the effect may take the form of the activation of an if-then rule, real time performance can be excellent. As the change persists in the environment (possibly decaying with time) there is no need for an agent to remember it or to forget it. As the change stays at a location, and acts on the behaviour of agents at the location, there is no need for the agent to compute the required site of action from the communication, because if the change can be sensed, the agent is at the required location. Changes made in the same locality by the same or different robots can interact physically, providing some processing of information external to the agents; this processing is therefore both reliable and free. For example, pheromone concentrations can sum locally so that a single agent sampling the local concentration at two points can in effect evaluate a time-weighted spatiotemporal pattern made up from many individual pheromone trails, and by moving up the sensed concentration gradient can move towards the currently richest food source in the environment.

Sign based stigmergy is found in any social insect behaviour mediated by pheromone deposits - for example, trail following, termite building, and avoidance of previously visited nectar sources in bees. Cue based stigmergy controls much building behaviour; cues derived from a building in progress are known as sematectonic cues (Wilson 1975), and recent progress has been made in identifying some formal constraints on successful stigmergic construction algorithms (Theraulaz and Bonabeau, 1995). Passive stigmergy has only recently been identified (Holland and Beckers, 1996) and has not yet been used in the analysis of social insect behaviour.

A robotic model of a social insect system

In order to study the possible use of social insect control techniques in collective robotics, a system was designed around a very simple ant behaviour - corpse gathering. The dead ants from a colony are sometimes found placed together in heaps ('cemeteries') some distance from the nest. The development of these heaps was studied by Deneubourg and his colleagues (Deneubourg et al. 1991) who showered 4000 dead ants onto a nest, and recorded the outcome. Ants from the nest would occasionally pick up a dead ant, carry it for a while, apparently aimlessly, and then drop it, apparently at random. However, after a few hours, the dead ants were seen to be arranged in many small piles. As time went by, these small piles were succeeded by a smaller number of much larger piles, and eventually the characteristic cemetery arrangement appeared. In a computer simulation, Deneubourg showed that the qualitative aspects of this sequence of events could be reproduced by a very simple model in which individual ants wandered at random, picking up dead ants with a probability that decreased, and dropping them with a probability that increased, with the sensed local density of dead ants. The stigmergic links were thus the change in the probability of picking up or dropping a dead ant as a function of the number of dead ants having been picked up or dropped in that area previously.

The robot system consists of up to five identical fully autonomous robots (Beckers, Holland, and Deneubourg, 1994). A differential drive wheel geometry allows each robot to move forwards or backwards in a straight line or curve, and also allows it to turn on the spot. At the front of the robot is a horizontally arranged C-shaped pusher blade (known as the gripper) with which it can push objects; the ends of the C are bent inwards so that the objects are retained during a turn. The objects used are circular pucks 4cm in diameter and 2.5cm in height. When the force on the gripper from the pucks being pushed exceeds some value, the gripper is moved towards the body, where it triggers a microswitch. For these experiments, the control value was adjusted so that the microswitch was triggered whenever three or more pucks were pushed. This is an extremely crude way of sensing the local density of pucks; note that it cannot differentiate between three pucks and any number greater than three. The robots have two active infra-red sensors at the front for obstacle avoidance. Pucks are too low to be sensed as obstacles; boundary walls and other robots are good targets.

The robots are programmed with three behaviours; only one behaviour is active at any time. Behaviours are selected by the input from the IR sensors and the gripper microswitch as follows:

Move Forward: if neither the IR sensors nor the gripper sensor is triggered, move forward at a constant speed. When moving forward, the robot can push one or two pucks; it will also tend to scoop into the gripper any pucks in its path.

Reverse and Turn: if the gripper sensor is triggered, and the IR sensors are not triggered, reverse for one second, and execute a random turn. If the robot was pushing one or two pucks before the gripper was triggered, it will leave them behind, next to the pucks which helped to trigger the microswitch. If the robot was not pushing any pucks, but had collided with a group of three or more pucks, the group will be moved slightly by the impact of the gripper, but will remain a group.

Avoid Obstacle: if one or both IR sensors are triggered, halt and make a random turn away from the sensor that was first triggered. If the robot was pushing any pucks, they will usually be retained during the turn by the hooked ends of the gripper. The robots are operated in a flat arena 2.5x2.5m, bounded by a reflective barrier. At the start of each experiment 81 pucks are positioned throughout the arena at 25cm intervals in a grid arrangement, and the required number of robots are placed in the centre of the arena facing away from one another, and switched on. Every 10 minutes of runtime, the robots and the clock are stopped, the sizes and positions of clusters of pucks are recorded, and the robots and the clock are restarted. A cluster of pucks is defined as a group which cannot be divided into smaller groups by a continuous line of width equal to a puck diameter.

The behaviour of the system

To the observer, experiments seem to have three more or less distinct phases. In the initial phase, robots move forward scooping up single pucks; when three have been collected, or when the robot encounters a cluster of pucks making the total in the gripper three or more, the gripper switch is triggered, and the robot reverses and turns, leaving a cluster of three or more. Within a short time, most pucks are in clusters of three or more which cannot be pushed.

In the second phase, robots acquire pucks by striking clusters obliquely so that only one or two pucks fall inside the gripper opening; these pucks will usually be deposited on the next cluster to be struck, although sometimes a robot will be able to take single pucks from two clusters in succession. In this phase, the number of clusters reduces quite fast, and some clusters grow much more rapidly than others. At the end of the phase, only a small number of relatively large clusters remain.

In the third and final phase, robots will occasionally remove one or two pucks from the edge of a cluster, and, typically after pushing them around the almost empty arena for some time, will deposit them on one of the remaining clusters, often on the same cluster they came from. This phase can be quite protracted, but it eventually results in the formation of a single cluster. If the experiment is allowed to run on, the odd puck may be taken from this cluster, but is eventually returned to it. If a robot fails, the remaining robots will finish the task. Robots can be added or subtracted at any time, but the cluster formation continues without interruption. If the pucks are disturbed or rearranged by some external factor such as an experimenter, the end result is still the same.

The collective robot system is thus able to perform a task analogous to the ants' corpse collection, and shows significant robustness with respect to variation in robot numbers, robot failure, and disturbance. Three interesting questions arise:

- how does the speed of task completion vary with the number of robots?
- how does the total energy used vary with the number of robots?

- what are the mechanisms which lead to cooperative completion of a global task when only local information is available?

Before comparing the performance of different numbers of robots, it will be useful to look at the fine structure of an individual experiment. There are two readily available measures for task progress: the size of the largest cluster, and the total number of clusters.

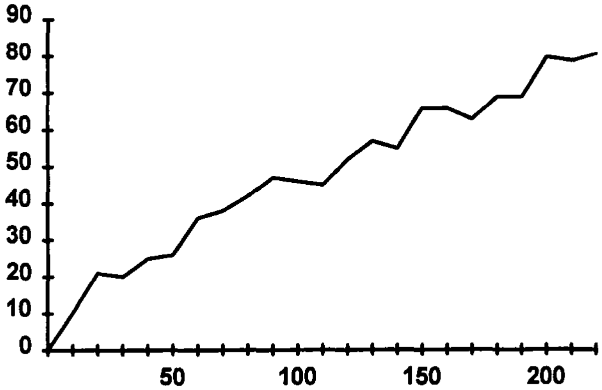

Figure 1. The largest cluster plotted against elapsed time in minutes for a three robot experiment.

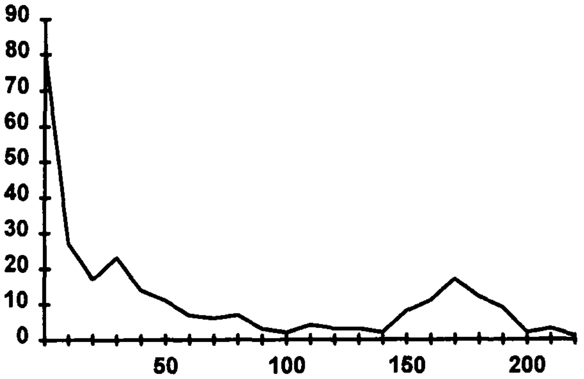

Figure 2. The number of clusters plotted against elapsed time for a three robot experiment.

Figures 1 and 2 show the progress of these measures during a typical three robot experiment. Although there is a certain amount of irregularity, it is clear that task completion is the result of a more or less steady accumulation of 'useful work' and so the simple measure of time to completion should be good enough for comparing the performance of different numbers of robots.

As can be seen from Figure 3, the mean time to completion is greatest for a single robot, decreasing for two and three robots, and then increasing gradually for four and five robots. Two processes seem to be in operation. Robots which are not interacting with one

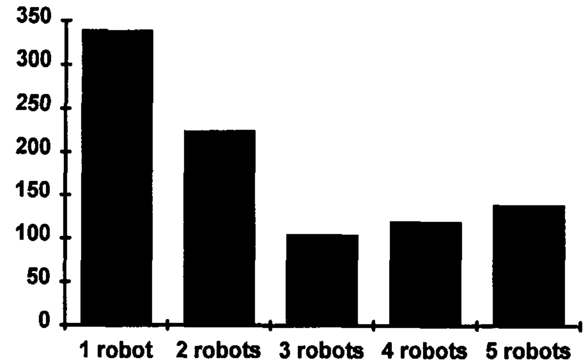

Figure 3. The time to completion for different numbers of robots, averaged over three replications.

another are essentially working in parallel, and so gains would be expected - providing that they are working on the same task, of course. However, interactions between robots, in the form of avoiding one another, have two deleterious effects: they take a certain amount of time, and they can cause damage to clusters because the avoidance reaction has priority over all others. The rate of occurrence of interactions will clearly be a function of the density of robots in the arena. Figure 4 shows the way in which the number of interactions observed in a 20-minute period varied with the number of robots.

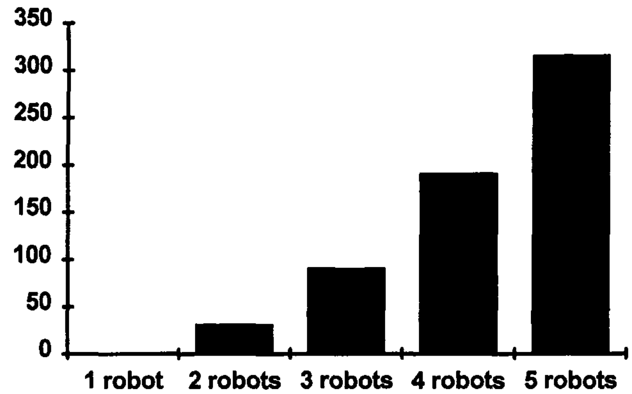

Figure 4. Number of observed interactions between robots in a 20-minute period

Each interaction lasts around four seconds for each of at least two robots. This alone is not sufficient to lead to diminishing returns when four and five robots are used, since the number of robot minutes gained by adding the extra robots is not less than the number lost by interaction, and so the observed destructive effects of interactions on the clusters must be responsible for the upturn of the curve in Figure 3.

The second question concerned the total energy used by different numbers of robots in the completion of the task. This is simply the total number of robot minutes used, and is obtainable by multiplying each column in Figure 3 by the appropriate number of robots. The results are shown in

Figure 5. The single robot situation, although by far the slowest at achieving the task, is the second most efficient. This is interesting, because it is the only condition in which no time is wasted due to interactions, and there might be some grounds for expecting it to be the most efficient. Although it is possible that a modest level of interactions might be beneficial in breaking up medium-sized clusters so that pucks can be taken from them more easily and delivered to larger clusters, it would be unwise to give too much weight to this in view of the small number of replications of these experiments. In biological terms, it might be better for a system to carry out a task as quickly as possible if there is a risk arising from delay (for example, if a food source could be discovered and captured by some competing species); however, in the absence of risk, energetic efficiency would be the best choice. If the maximum values of speed and efficiency are achieved by different numbers of agents, then the system can ensure the appropriate outcome simply by deploying the appropriate number of agents.

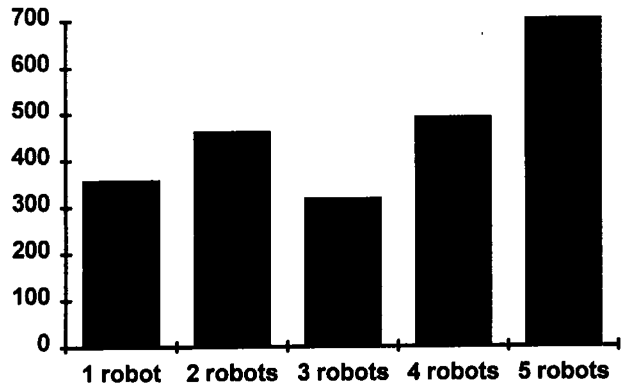

Figure 5. The efficiency with which different numbers of robots complete the task, measured in total robot-minutes.

The third question, concerning the way in which the local information is apparently used to perform the global task, is rather more difficult. However, some simplifying assumptions can be made. (For a more detailed treatment, see Holland & Beckers 1996.) Since the robots turn randomly during Avoid Obstacle and Reverse and Turn, and move in straight lines otherwise, they can be regarded as pursuing a series of random straight-line paths through the arena. Most clusters are fairly dense and compact, and so they can be regarded as roughly circular. The probability that a given robot will strike a given cluster will therefore be roughly proportional to the diameter of the cluster - the position of the cluster can be ignored because the robot's path is random. If a robot pushing two pucks strikes the cluster, it will leave them on the cluster. If it is carrying one puck, and if it strikes the cluster tangentially, it may remove a further puck; if it strikes the cluster more frontally, it will leave the puck it carries. The width of the zone providing this tangential contact will tend to stay the same or decrease with cluster size, and so the width of the zone providing frontal contact will increase with cluster size. Larger clusters are therefore more likely to gain any pucks being carried by robots than are smaller clusters.

A similar argument can be used to show that the probability of tangential contact with a cluster is likely to stay the same or decrease with cluster size. Since the rate of losing pucks will be determined by the frequency of tangential contacts, larger clusters are therefore equally or less likely to lose pucks than smaller clusters. The net effect of these two processes will be a stochastic growth of larger clusters relative to smaller clusters; for a fixed number of pucks, the inevitable outcome will therefore be a single cluster.

Although these arguments can persuade us that the outcome is inevitable, they do not go deeply into the causes of the outcome; in particular, they do not enable us to say what it is about the agents and their putative interactions that leads to the result. There are in fact three separable factors involved: the physics of the environment, active stigmergy, and passive stigmergy. They will be discussed in turn.

Consider a given distribution of clusters. The rate at which each cluster gains and loses pucks is simply a function of its size, and of the sizes of the other clusters. Even if gaining and losing pucks did not affect the effective cluster size (as might happen if pucks were piled up vertically on a base of a given size) until it became zero, the relative net rates of flow would still favour the larger clusters, and at least the smallest cluster must therefore always have a net rate of loss. At some point, the cumulative net rate of loss for at least the smallest cluster will mean that it ceases to exist. As each one ceases to exist, and can no longer supply or acquire pucks, then at least the next smallest will have to have a net rate of loss. The end result will therefore be a single cluster. This is achieved by a pattern of actions which does not change as a result of changes in the environment; the end result is a consequence of the interaction of the environmentally-determined actions with the physics of the environment - in this case, the conservation of matter, and the exhaustion of finite resources when consumed at a finite rate.

Active stigmergy occurs when the consequence of an action affects a subsequent choice of action at the same location. When a robot drops a puck on a cluster, it increases the size of the cluster. A robot on a trajectory which would previously have led it to detach two pucks could then be caused to strike the cluster relatively less tangentially. If this resulted in Reverse and Turn rather than continuing with Move Forward, the previous dropping of the puck would have altered the subsequent action at the location, yielding an instance of active stigmergy. In the same way, the previous removal of a puck can lead to a robot striking the cluster more rather than less tangentially, and so producing Move Forward rather than Reverse and Turn, another example of active stigmergy. Note that active stigmergy can operate both to add and to subtract pucks.

Passive stigmergy can occur when the addition of a puck to a cluster causes a robot which would previously have struck the cluster too tangentially to remove a puck, to strike slightly more frontally and succeed. The action in both cases will be Move Forward; it is the consequence which is changed. Similarly, the previous removal of a puck can cause a robot to fail to remove a puck which it would previously have managed to remove; passive stigmergy can therefore both add and subtract pucks.

The three factors operate at all times in the system. However, stigmergy is most apparent during the second phase, when cluster sizes change very rapidly. In the third phase (the end game) the effects of the relative sizes of clusters (environmental physics) seem more important.

Discussion

This collective robot system shows that some principles of behaviour and control used in social insect systems can be successfully adapted for use in multiple robot systems; this confirms our understanding of the principles. Now the focus of this paper is intended to be on whether collective principles can usefully be integrated with multiagent principles. For this to be possible, it must be possible to give the members of one class at least the necessary architecture to support some of the features of the other class. Multiagent systems typically use knowledge-based agents; can a successful agent be at the same time knowledge based and behaviour based (or based on a small set of simple rules)? The answer is yes. Connell's (1992) SSS robot architecture has three layers: a Servo layer controlling actuator and sensor interfaces, a Subsumption or behaviour based layer controlling the robot at the behaviour level, and a Symbolic layer dealing with maps, planning, and strategic navigation. The Behaviour Synthesis Architecture (Barnes & Gray 1991) integrates both behaviour based and symbolic control for the control of small numbers of real robots engaged in cooperative tasks. However, using a physical robot automatically provides much of the necessary substrate for using collective techniques - a physical environment within which the robot has a location, and an embodied agent. (Note that the use of stigmergy requires in addition that the robot must be able to act on and change the environment; this is an option not available to robots which simply move through fixed environments, as is the case with many research robots). In general, classical multiagent systems will lack anything corresponding to location within a mutable environment; this will preclude the use of stigmergy. However, some multiagent systems - for example, switching networks with node-based agents - may have an analogue of location, and others - for example, switching networks supporting mobile software agents - may have both location and the capacity for moving between locations; provided that location also influences the agent's capacity for receiving input and producing output, it is therefore at least conceivable that some multiagent systems may be able to use and benefit from stigmergy. It may also be possible to introduce some analogue of location into an arbitrary multiagent system and then to exploit this extra dimension to solve problems within the original non-spatial system by using stigmergy within the added spatial dimension.

References

Altenberg K. 1994. Adaptive resource allocation for a multiple mobile robot system using communication. TR NDSU-CSOR-TR-9404, North Dakota State University

Barnes D. & Gray J. 1991. Behavioural synthesis for cooperant mobile robot control. Proc. Intl. Conf. on Control, pp1135-1140

Beckers R., Holland O.E. and Deneubourg J.L. 1994. From local actions to global tasks: stigmergy and collective robotics. In Brooks & Maes, *Artificial Life 4*, Bradford-MIT

Cao Y.U., Fukunaga A.S., Kahng A.B., & Meng F. 1995. Cooperative mobile robotics: antecedents and directions. IROS '95

Connell J. 1992. SSS: a hybrid architecture applied to robot navigation. ICRA 1992

Deneubourg J.L., Goss S., Franks N., Sendova-Franks A., Detrain C., & Chrétien L. 1991. The Dynamics of Collective Sorting: Robot-like Ants and Ant-like Robots. In Meyer J-A. & Wilson S.W. (eds) *From animals to animats*, MIT-Bradford.

Grassé P.P. 1959. La reconstruction du nid et les coordinations interindividuelles chez Bellicositermes natalensis et Cubitermes sp. La théorie de la stigmergie: Essai d'interpretation du comportement des termites constructeurs. *Ins. Soc.*, 6, 41-83

Holland O.E. and Beckers R. 1996. The varieties of stigmergy: indirect interaction as a control strategy for collective robotics. *Robotica*. Forthcoming.

Kube C.R & Zhang H. 1992. Collective robot intelligence. In Meyer J-A., Roitblat H.L., & Wilson S.W. (eds) *From Animals to Animats 2*. Bradford-MIT

Mataric M. 1994. Interaction and intelligent behaviour. MIT AI Lab Technical Report AI-TR-1495

Nagel K. and Rasmussen S. 1994. Traffic at the edge of chaos. In R. Brooks and P. Maes, eds, *Artificial Life IV*. Proceedings of the Fourth International Workshop on the synthesis and simulation of living systems. MIT Press

Reynolds C. 1987. Flocks, Herds, and Schools: a distributed behavioural model. *Computer Graphics* 21 (4), 25-34

Taipale T. and Hirai S. 1992. A comparative study of multirobot systems. *Bulletin of the Electrotechnical Laboratory (Japan)* pp. 30-60

Theraulaz G. and Bonabeau E. 1995. Modeling the Collective Building of Complex Architectures in Social Insects with Lattice Swarms. *J. theor. Biol.* Forthcoming.

Wilson E.O. 1975. *Sociobiology*. Belknap Press, Harvard University Press