FROM LOCAL ACTIONS TO GLOBAL TASKS: STIGMERGY AND COLLECTIVE ROBOTICS

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Abstract

This paper presents a series of experiments where a group of mobile robots gather 81 randomly distributed objects and cluster them into one pile. Coordination of the agents' movements is achieved through stigmergy. This principle, originally developed for the description of termite building behaviour, allows indirect communication between agents through sensing and modification of the local environment which determines the agents' behaviour. The efficiency of the work was measured for groups of one to five robots working together. Group size is a critical factor. The mean time to accomplish the task decreases for one, two, and three robots respectively, then increases again for groups of four and five agents, due to an exponential increase in the number of interactions between robots which are time consuming and may eventually result in the destruction of existing clusters. We compare our results with those reported by Deneubourg et al. (1990) where similar clusters are observed in ant colonies, generated by the probabilistic behaviour of workers.

1. Introduction

There is a class of natural systems in which large numbers of simple agents collectively achieve remarkable feats through exploiting a single principle. They offer a spectacular existence proof of the possibility of using many simple agents rather than one or a few complex agents to perform complex tasks quickly and reliably. It is therefore surprising that the systematic exploitation of this principle has been neglected within the field of robotics. The natural systems we refer to are social insects - ants, termites, wasps, and bees. The principle is that of stigmergy, recognised and named by the French biologist P.P. Grassé (1959) during his studies of nest building in termites. Stigmergy is derived from the roots 'stigma' (goad) and 'ergon' (work), thus giving the sense of 'incitement to work by the products of work'. It is essentially the production of a certain behaviour in agents as a consequence of the effects produced in the local environment by previous behaviour.

When they start to build a nest, termites modify their local environment by making little mud balls and placing them on the substrate; each mud ball is impregnated with a minute quantity of a particular pheromone. Termites deposit their mud balls probabilistically, initially at random. However, the probability of depositing a mud ball at a given location increases with the sensed presence of other mud balls and the sensed concentration of pheromone. The first few random placements increase the other termites' probability of putting their loads at the same place. By this blind and random game little columns are formed; the pheromone drifting across from neighbouring columns causes the tops of the columns to be built with a bias towards the neighbouring columns, and eventually the tops meet to form arches, the basic building units. Finally, as the influence of other stigmergic processes comes into play (e.g. processes involving water vapour and carbon dioxide concentrations, and modulated by the presence of the queen), the whole complex and highly differentiated nest structure is produced, with the royal cell, brood nurseries, food stores, air circulation, communication and foraging tunnels, and other areas all contained within one of the largest non-excavated structures built by any creature except man.

The use of stigmergy is not confined to building structures. It also occurs in cooperative foraging strategies such as trail recruitment in ants, where the interactions between foragers are mediated by pheromones put on the ground in quantities determined by the local conditions of the environment. For example, trail recruiting ant species are able to select and preferentially exploit the richest food source in the neighbourhood (Pasteels *et al*. 1987; Beckers *et al*. 1989) or the shortest path between the nest and a food source (Beckers *et al*. 1992). This strategy takes advantage of the characteristics of the trail-laying and trail-following mechanisms of the ants in combination with their essentially probabilistic behaviour: the probability that an ant follows a trail is a non-linear function of the trail's pheromone concentration, and the probability that an ant lays a pheromone spot depends on the characteristics of the recently-encountered food source and the environment. When a trail between a single food source and the nest is first established, its pheromone concentration is low, and a high proportion of ants lose the path before reaching the food or the nest. As more and more journeys are made along the trail, the pheromone concentration increases progressively and so does the accuracy of trail following; finally the majority of the foragers will successfully use that trail. Where there are multiple food sources, or multiple trails of different lengths to the same food source, the non-linear dependence of the probability of successful trail-following on pheromone concentration sharply favours the rate of increase in strength of trails which are already strong, or short, or lead to rich food sources; as a strong trail recruits and retains ants, it reduces the number of ants available to strengthen other trails; evaporation and breakdown of the pheromone continually reduce the strength of all trails; the net result is that a single trail becomes dominant, and it is usually the 'best' choice from the point of view of length and richness of food source. The important factor is that very small fluctuations in the pheromone concentrations of different trails, occurring at the beginning of the recruitment, are amplified and determine the eventual outcome of the collective decision making process (Beckers *et al.* 1989; Deneubourg and Goss, 1989).

The stigmergic principle also appears to organise corpse-gathering behaviour in ant colonies. Observations show that these insects tend to put the corpses of dead nestmates together in cemeteries which occur in certain places far from the nest and which grow in size with time. If a large number of ant corpses are scattered outside a nest, the ants from the nest will pick them up, carry them about for a while, and drop them; within a short time it will be seen that the corpses are being put into small clusters, and as time goes on the number of clusters will decrease and their size will grow until eventually all the corpses will be in one or two large clusters. The emergence of these clusters has been studied by Deneubourg *et al*. (1990), who showed that a simple mechanism involving the modulation of the probability of dropping corpses as a function of the local density of corpses was sufficient to generate the observed sequence of the clustering of corpses.

These examples from social insects show how global problems can be solved by exploiting the interactions between workers, and between workers and the environment. These processes give rise to self-organized structures which are not represented explicitly in each or any agent, but which guide and influence the actions of individual agents. The work described in this paper explores the possibility of extending these principles to robotics.

How would it be best to put stigmergy to work in robots? The traditional computational paradigm of robotics typically involves sensing the environment, then detecting features, then constructing or modifying a world model, then reasoning about the task and the world model in order to find some sequence of actions which might lead to success, then executing that action sequence one step at a time while updating the world model and replanning if necessary at any stage. Doing any of these is intractable in at least some domains; doing all of them in an unstructured dynamic environment fast enough to survive in that environment has turned out to be a practical impossibility regardless of the hardware resources available. Behaviour-based architectures, inspired by biology and epitomised by Brooks' subsumption architecture, have changed all that (Brooks 1986). A behaviour-based robot essentially consists of a small number of simple modules, each of which is capable on its own of sensing some limited aspect of the environment, and of controlling part or all of the robot's effector system to achieve some limited task; these modules are embedded in a simple architecture which uses low bandwidth communication between the modules to select which module or modules actually has access to the effectors at any time. The overall simplicity means that such systems have excellent real time performance even with modest resources. The subsumption architecture uses a hard-wired priority scheme for the selection process; the highest priority behaviour active at any time gains control of the output of the whole robot. By a careful choice of modules, and ingenious exploitation of the interactions between behaviours, environment, and tasks, Brooks and others have shown that robots can be constructed which can carry out sophisticated and complex tasks reliably in unstructured dynamic environments (Flynn & Brooks 1989; Connell 1990).

The fit between stigmergy and behaviour-based robotics is excellent. It is the essence of stigmergy that the consequences of behaviour affect subsequent behaviour. Behaviour-based systems deal directly in behaviour. Conventional robots are too slow to cope with an environment containing other moving robots, and too expensive for anyone to be able to experiment with large numbers of them; behaviour-based robots cope well with unstructured dynamic environments and are cheap. We might expect the biological principle of stigmergy to fit better with the biologically inspired architectures of behaviour-based robots than with the alien computational paradigm of conventional robotics. Finally, in 'synthesising phenomena normally associated with natural living systems' and getting them to do something useful in the real world, combining stigmergy with behaviour-based robotics might help to make artificial life look a little less remote than is sometimes the case.

Behaviour-based robotics has given new force to the branch of AI concerned with situated agents and embedded systems. As well as effective slogans ('the world is its own best model' - Flynn & Brooks 1989) and important new ideas ('emergent functionality' - Steels 1991) the field has generated a deep conviction that systems for the real world must be developed in the real world, because the complexity of interactions available for exploitation in the real world cannot be matched by any practical simulation environment. It is for this reason that we have chosen to implement stigmergic mechanisms directly on behaviour-based robots rather than undertaking any preliminary simulation studies; we do however recognise that simulation may be a valid and useful method for investigating stigmergic phenomena in general.

2. Materials and Methods

We decided to develop a system using multiple robots to gather together a dispersed set of objects into a single cluster, much like the corpse-gathering behaviour of ants. As a first step towards achieving this task using stigmergy, a robot was designed which could move small numbers of objects and which was more likely to leave them in locations where other objects had previously been left. This was accomplished by effectively sensing a very local density via a simple threshold mechanism. The plan was to evaluate the performance of the robots with this mechanism and to develop the mechanism and the behaviours as necessary until the task could be performed reliably.

The battery-powered robots (Figure 1) are built on a 21x17cm platform. A 12v motor powered wheel is positioned at the mid-point of each long side, with a castor wheel at the mid-point of one of the shorter sides; this allows the robot to move forwards or backwards in a straight or curved trajectory, and to turn on the spot. Each robot carries a 17cm wide aluminium forward-facing C-shaped gripper with which it can push objects. The objects used are circular pucks, 4cm in diameter and 2.5cm in height. The robots are run in a square arena 250x250cm; before the start of each run, 81 pucks are placed on a regular 25cm grid in the arena (Figure 2).

The robots are equipped with two IR sensors for obstacle avoidance, and a microswitch which is activated by the gripper when a certain number of pucks

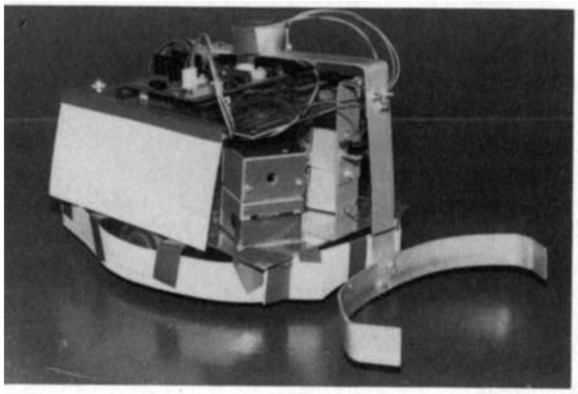

Figure 1: Robot equipped with a gripper for object Gathering. Experiments were carried out with from 1 to 5 robots of the same type,

are pushed. For the experiments reported here, this number is set to three. The robots have only three behaviours, and only one is active at any time. When no sensor is activated, a robot executes the default behaviour of moving in a straight line until an obstacle is detected or until the microswitch is activated (pucks are not detected as obstacles). On detecting an obstacle, the robot executes the obstacle avoidance behaviour of turning on the spot away from the obstacle and through a random angle; the default behaviour then takes over again, and the robot moves in a straight line in the new direction. If the robot is pushing pucks when it encounters the obstacle, the pucks will be retained by the gripper throughout the turn. When the gripper pushes three or more pucks, the microswitch is activated; this triggers the puck-dropping behaviour, which consists of backing up by reversing both motors for 1 second (releasing the pucks from the gripper), and then executing a turn through a random angle, after which the robot returns to its default behaviour and moves forwards in a straight line. The obstacle avoidance behaviour has priority over the puck-dropping behaviour.

The robots operate completely autonomously and independently; all sensory, motor, and control circuitry is on board, and there is no explicit communication (IR or radio link) with other robots or with the experimenters. The robots only react to the local configuration of the environment.

At the start of each experiment, the robots are placed in the centre of the arena, each pointing in a different direction. Every 10 minutes of runtime, the robots are stopped manually, the sizes and positions of clusters of pucks are recorded, and the robots are restarted. A cluster is defined as a group of pucks separated by no more than one puck diameter. The experiment continues until all 81 pucks are in a single

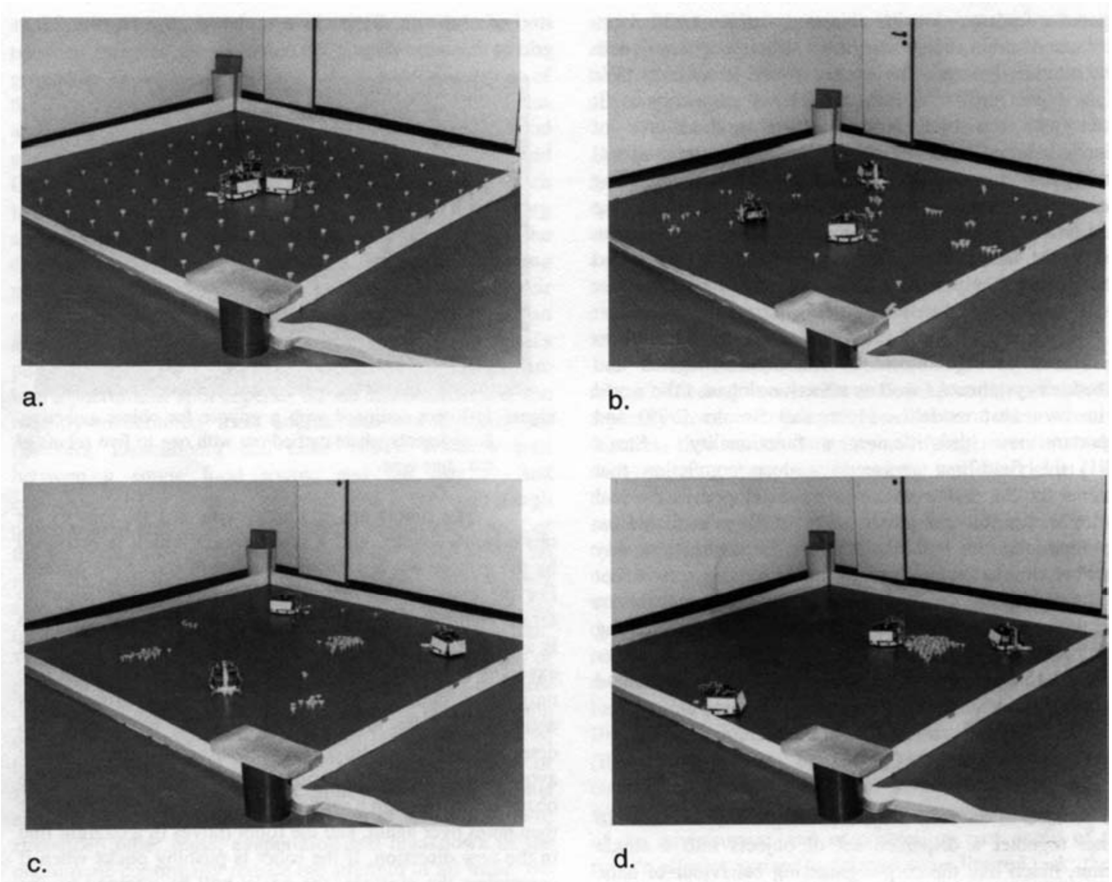

Figure 2. The initial setup (a) and time evolution of a typical experiment involving a group of three robots. Phase 1 (b), occurring after approximately 10 min, is characterised by a large number of small clusters containing from 1 to 10 pucks. In Phase 2 (c), some clusters grow rapidly and the environment becomes more heterogeneous. Finally, Phase 3 (d) is characterised by the competition between a small number (2 – 3) of large clusters and evolves towards the clustering of all objects in one pile.

cluster. Experiments reported here have used one to five robots working simultaneously.

3. Results and analysis

From a qualitative point of view, experiments have three more or less distinct phases, regardless of the number of robots. At the start, the arena contains only single pucks (Figure 2a). In the first phase, a robot typically moves forwards scooping pucks into the gripper one at a time; when three have been gathered, the robot drops them, leaving them as a cluster of three, and moves off in another direction. Within a short time, most pucks are in small clusters which cannot be pushed (Figure 2b). In the second phase, the robot removes one or two pucks from clusters by striking the clusters at an angle with the gripper; the pucks removed in this way are added to other clusters when the robot collides with them. Some clusters grow rapidly in this phase. After a time, there will be a small number of relatively large clusters (Figure 2c). The third and most protracted phase consists of the occasional removal of a puck or two from one of the large clusters, and the addition of these pucks to one of the clusters, often to the one they were taken from in the first place. To our initial surprise, the process eventually results in the formation of a single cluster (Figure 2d).

If the experiment is allowed to run on, a puck or two will occasionally be removed from this single cluster, but they are inevitably returned to it as there is no other structure within the arena which can trigger the puck-dropping behaviour. As the number of robots increases, the number of pucks likely to be in transit from the cluster back to the cluster tends to increase, and the stable state is a dynamic equilibrium. Because the robots have no means of detecting that the task has been completed, they carry on working just the same (interestingly enough, so do ants.)

Figures 3 and 4 show the results, in terms of number of clusters and maximum cluster size respectively, from five representative experiments run under identical circumstances and using one, two, three,

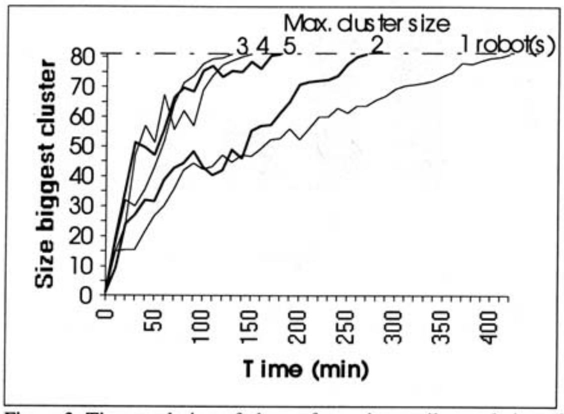

Figure 3: Time evolution of cluster formation until completion of the task (81 pucks in one cluster) for experiments involving one to five robots.

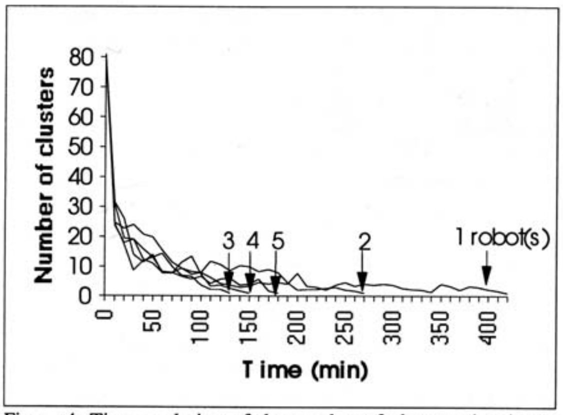

Figure 4: Time evolution of the number of clusters showing an exponential decrease from 81 to 1 cluster for experiments involving one to five robots.

four and five robots. Phase 1 is clearly seen in all five experiments in the steep fall in the number of clusters by the time the first observations were taken after 10 minutes. Phase 2 is where cluster size and number of clusters are both most variable, because the largest cluster is still relatively small and vulnerable to being broken up, and there are still plenty of clusters of one and two pucks which can rapidly be added to any of the existing clusters. Phase 3 can be seen in the steady and surprisingly regular rise in the size of the largest cluster, which is always the 'same' cluster once its size rises above about 25.

Phases 2 and 3 require some explanation. The puck-dropping behaviour cannot differentiate between a local concentration of three pucks, and one of more than three pucks. What process is organising the net transfer of pucks from smaller to larger clusters when the robots are unable to discriminate between them with their sensors? And what role is played by stigmergy? The answer is surprisingly subtle.

Because the robots turn through random angles whenever they meet a wall, meet another robot, or drop pucks, they may be regarded as following a succession of random straight-line paths through the environment. For a given cluster in a given location, a straight-line path may or may not lead to a collision. The outcome of any collision in terms of whether any pucks are added to or taken away from the cluster depends of the number of pucks carried by the robot at the time of the collision, and on the relationship between the course of the robot and the point of contact with the cluster. It is only possible to remove pucks if the collision is almost tangential to the cluster; a more 'frontal' collision will trigger the puck-dropping behaviour.

The probability that a random path produces a frontal or tangential collision with a cluster is a function of the size, shape and position of the cluster. The stigmergic coupling operates as follows: if a robot adds pucks to a cluster, or removes pucks from it, the consequent change in size and shape alters the probability that a subsequent random path taken by that (or any other) robot will strike the cluster frontally or tangentially, thereby affecting the probability of adding or removing further pucks in the future.

We can now consider the dynamics of this process in a little more detail. Assume for convenience that all clusters are roughly circular, and that the spatial distribution of random paths in the arena is approximately uniform. Consider the five possible combinations of situation (number of pucks being carried by a robot on a random path) and outcomes affecting a given cluster (number of pucks added to or removed from the cluster; there is no need to consider outcomes that leave the cluster unchanged):

Situation A: the robot is not carrying a puck
Outcome (i): 1 puck removed from the cluster
(ii): 2 pucks removed from the cluster
Situation B: the robot is carrying 1 puck
Outcome (i): 1 puck added to the cluster
(ii): 1 puck removed from the cluster
Situation C: the robot is carrying 2 pucks
Outcome (i): 2 pucks added to the cluster

In order to remove a single puck, a robot needs to strike a cluster almost tangentially, describing a chord only a small distance inside the circumference; to remove two pucks, it must describe a chord an additional distance inside the circumference. The probability that a random path will produce one of these outcomes will be simply proportional to the relevant distances. Since these distances will both reduce slightly with increasing cluster size, the probabilities of the associated outcomes will also reduce slightly with cluster size. In order to add a single puck, a robot carrying one puck must strike the cluster so that its original course describes a chord further in from the circumference than the distance for removing one puck; the probability of this outcome is proportional to the radius of the cluster minus the distance allowing the removal of one puck. This probability is therefore much greater than the probability of removing one puck, and increases with cluster size slightly faster than the radius increases. (The radius will of course increase as the square root of the number of pucks in the cluster.) A robot carrying two pucks will add them to a cluster wherever it strikes the cluster, and so the probability of this outcome is proportional to the radius of the cluster and increases as the square root of the number of pucks in the cluster.

We can now summarise the expected effects of each situation on a cluster as a function of the size of the cluster. Situation A can only remove pucks from the cluster, and the probability of doing so decreases with increasing cluster size. Situation B will tend to add pucks to the cluster because the probability of B(i) is greater than that of B(ii), and the probability of doing so increases with increasing cluster size. Situation C can only add pucks to the cluster, and the probability of doing so again increases with increasing cluster size. Whatever the situation, it will therefore always be the case that larger clusters will be more likely to gain pucks and less likely to lose pucks than smaller clusters. Stigmergy is therefore active in controlling both the rate of gaining and of losing pucks; either outcome (gaining or losing) alters the size of a cluster and therefore increases the probability of a robot producing the same outcome in that location in the future. Since the total number of pucks in the environment is constant, the inevitable result will be the eventual formation of a single cluster containing all the pucks.

The stigmergic principle allows a single agent to interact with the effects of its own previous actions; this is how a single robot achieves the task. From the standpoint of conventional robotics, it is in many ways remarkable that adding one, two, three or four more identical agents still allows the task to be completed, especially since the agents cannot communicate with one another, have no information about position, and there is no explicit specification of where the single large cluster is to be built. It is even more remarkable that the time to completion of the task decreases progressively with the addition of one and two agents (Fig. 8). This may be understood as follows: for most of the time, the robots operate in parallel unaffected by direct interactions with the others, but their behaviour is influenced by the previous behaviour of the others via stigmergy, mediated through the configuration of pucks and clusters. When they do meet, they will lose some 'working' time in avoiding each other, but since they arrive on random courses and leave on random courses, the basis of the stigmergic action will not be disturbed;

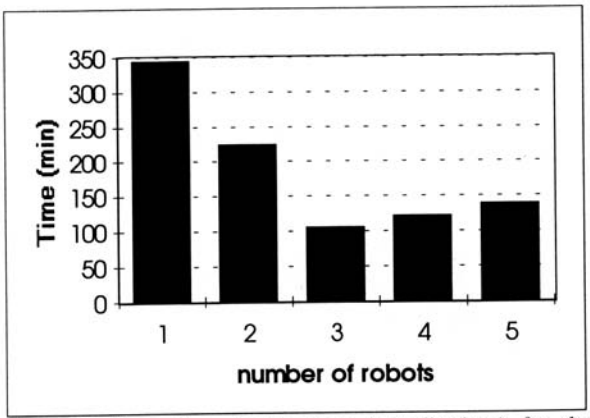

Figure 5: Mean time (averaged on 3 replications) for the clustering of 81 pucks in one pile for one to five robots working simultaneously. For these experiments the optimal group size appears to be three.

if they meet when carrying pucks, the interaction may result in pucks being abandoned or transferred; again, they will lose some working time but the stigmergic process will not be affected. Finally, due to the priority of the obstacle avoidance behaviour, two robots meeting near a cluster may destroy it while turning away from each other. If the frequency of interaction of n robots is sufficiently low, the task might be expected to be completed almost n times faster than with a single robot; on the other hand, if it is sufficiently high, clusters might be destroyed so often that the task duration is extended, possibly indefinitely. The results accord with this analysis. Figure 5 shows the mean time to completion for three replications of each condition. We felt that a strict interpretation of 'completion' was appropriate because the curves in Figure 4 all approach the state of completion reasonably smoothly, even though the stable end state is a dynamic equilibrium. The gains from parallel working appear to be maximised by three

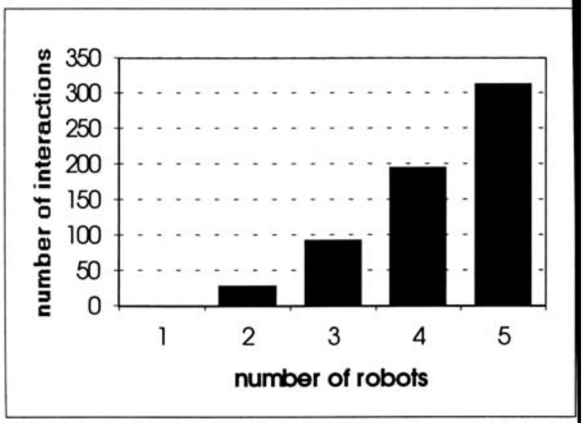

Figure 6: Number of interactions occuring during 20 min in typical experiment involving 1 to five robots. A interactions are counted only avoiding behaviour between two robots.

robots.

In order to evaluate the hypothesis that robot-robot interactions might be responsible for this degradation of performance, further experiments were carried out. Pucks were distributed in five equal clusters in the arena, and the interactions between robots were counted for a twenty minute period for each number of robots. The results are plotted in Figure 6, and show a positively accelerated increase with number of robots. A typical interaction between two robots lasts 4 seconds, so 100 interactions consume over 13 robot-minutes; since the difference in number of interactions between three and four robots is just over 100, the potential gain in total working time supplied by the fourth robot of 20 robot-minutes would be reduced to under 7 robot minutes by the increase in interactions.

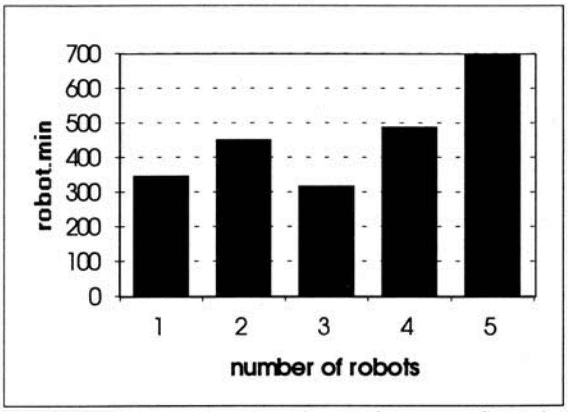

Figure 7: Efficiency (in robot.minutes) for one to five robots working simultaneously. The optimal group size is three, after which the efficiency, in terms of time and energy consumtion, decreases.

Figure 7 shows the average effort required for completion in robot-minutes. The interest here is to look for signs of synergy, which would be indicated by a decrease in the total effort accompanying an increase in the number of robots. This appears to occur with three robots in relation to one and two, but because of the small difference and the small number of samples, further replications will be required to resolve this. It would not be surprising if synergy occurred; we have noticed that the spatial distributions look noisier with more robots, and a certain amount of noise may break up smaller clusters faster than large clusters (which are more robust) which could well speed the task. In the rapid loss of efficiency following the addition of a fourth and fifth robot it becomes obvious that there must be an optimal group size above which the gain of adding a supplementary robot is more than offset by the loss of time due to the increased number of interactions.

Our target was to get the robots to do something useful. Whilst it would certainly be useful to put a team of cleaning robots into a dirty environment on evening and to come back next morning to find all the dirt in a single pile, it would be even more useful to find the dirt in a pile in a designated place. We reasoned that the rapid positive feedback from a 'seed cluster' might induce the formation of the final pile in that location. However, in order to prevent the seed cluster being broken up by accident in the early stages, we used a large saucer instead of a cluster of pucks (anything low enough not to trigger obstacle avoidance would have done). Three robots formed the final cluster round the saucer in 126 minutes - slightly longer than the average finishing time without a seed cluster, but proof that the robots could be induced to form a single cluster in a designated place.

We then wondered what would happen if we provided two seed clusters of different sizes, and so a competition between a large plate and the saucer was organised, again with three robots. The results emphasised the importance of developing real-world systems in the real world. When the experiment was stopped after 300 minutes, the plate was on top of a cluster containing most of the pucks, and the saucer was being moved gradually towards the plate. Neither of these would have happened during a simulation; either might be exploitable by a subsequent development of the system to achieve some relevant task in the real world.

4. Discussion

In this instance, stigmergy has been shown to be able to control and coordinate a number of robots so that a potentially useful task can be performed. It is worth noting that it seems to be a robust technique, able to cope with occasional robot failure (a stopped robot simply becomes a static obstacle; other robots avoid it and any pucks it was carrying are soon scavenged). Another less frequently considered advantage of multiple robotics is that, if speed gains can be made by adding additional robots without reconfiguring any of the robots already working on the task, then the speed of the task can be controlled by changing the number of robots; with a single robot, the only way to speed up is to make the robot work faster.

Some studies of multiple robots attempt to achieve coordination by explicit and direct communication between robots (Arkin 1993). It is possible to view stigmergy as an indirect method of communication - assuming that the object of direct communication is to affect the behaviour of the other robot, we could say that a robot which causes another to produce a certain behaviour through stigmergy has had an implicit communication with that robot through the environment (Mataric 1993). But stigmergy is by no means an inferior form of communication when the object of the communication is to cause a particular behaviour to be produced in a particular location. Consider what a direct communication requires: the sending robot must encode and transmit a message about what is to be done, and where it is to be done (implying a knowledge of location, unless this is coded by the site of origin of the message); this message is local in time and space, and so only those robots close enough and not otherwise engaged will be free to receive the message; they must then decode the message, and either remember it for long enough to get to the place and carry out the action, or remember it for even longer while they carry out some other more important task. A stigmergic communication requires no encoding or decoding, no knowledge of place, no memory, and it is not transient; all it requires is that a robot passes near enough to the location where the communication was placed to be affected by it. As we saw above, random wandering is an effective way of achieving this, though of course it may not be efficient. In fact, the environment can be regarded as a sort of external memory, accessible to all. Pursuing this analogy, the use of volatile pheromones in the environment may represent a type of short-term memory. Perhaps stigmergy is best regarded as the general exploitation of the environment as an external memory resource; it is certainly possible to investigate computational schemes which take this approach (Bull and Holland, 1994).

Acknowledgments

This work has been realised as a contribution to the research group on ‘Prerational Intelligence’ held in 1993-’94 at the ‘Center for Interdisciplinary Research’, University of Bielefeld. We would like to thank the Center for Interdisciplinary Research for the financial support of this project. We are also grateful to Richard King and ‘Lionheart Electronics’ for technical help and discussions.

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