A Study of Territoriality: The Role of Critical Mass in Adaptive Task Division

Miguel Schneider Fontán and Maja J Matarić

Instituto de Automática Industrial (IAI)
Consejo Superior de Investigaciones Científicas (CSIC)
La Poveda, Arganda del Rey
Madrid 28500
tel: (34-1) 871-1900 fax: (34-1) 871-7050
schneider@iai.csic.es

Volen Center for Complex Systems
Computer Science Department
Brandeis University
Waltham, MA 02254
tel: (617) 736-2708 fax: 736-2741
maja@cs.brandeis.edu

Abstract

This work demonstrates the application of the behavior–based approach to generating ethologically–inspired adaptive foraging using a division of labor into exclusive spatial territories. First, we use fixed group sizes to evaluate and compare the performance of the two types of adaptive solutions. Second, using a collection of experimental robot data, we empirically derive and demonstrate the critical mass for most effective foraging in our domain, and show the decline of performance of the space division strategy with increased group size.

1 Introduction

This paper describes work that applies the behavior–based approach for autonomous agent control to generating ethologically–inspired adaptive foraging. In contrast to foraging methods explored by various researchers to date (see section 3 for an overview), we employ a territorial principle that implements a division of labor into exclusive spatial areas. First, we use fixed group sizes of two, three, and four robots to evaluate and compare the performance of foraging. Second, using a collection of experimental robot data, we empirically derive and demonstrate the critical mass for most effective foraging in our domain. We also show how the performance of the group declines when the described task division strategy is applied to an increased group size, in a fixed–size global workspace.

2 Motivation

Designing and understanding group behavior are complementary and complex problems in artificial intelligence, robotics, and ethology (Brooks 1990*b*, Matarić 1995). Our previous work introduced a methodology for synthesizing a *basis behavior substrate* for generating various behaviors commonly found in nature, including aggregation, dispersion, following, flocking, and foraging (Matarić 1995). This paper extends our work on homogeneous agent groups executing identical control strategies over the entire environment to a somewhat more complex case of employing a spatial division of labor based on an ethologically common organizational principle of *territoriality*.

As we have argued in Matarić (1992*a*) and Matarić (1994*a*), adaptive group behavior is a balance between minimizing interference and maximizing synergy, and interference is the key stumbling block in the way of efficient group interactions. It is correlated with the spatial density of the agents over the lifetime of a task, so various approaches to resource division can be applied to counter its effects. Evolution has produced territoriality as a stable and recurring behavioral pattern across social species. Territoriality produces a physical division of space and all associated resources such as food and shelter (Gould 1982, McFarland 1987).

In this paper, we explore the effects of territoriality on foraging, the prototypical group behavior we have been using for studying social interaction and learning (Matarić 1994*b*). We apply a synthetic approach that consists of implementing ethologically–inspired behaviors on a collection of mobile robots, evaluating their performance on repeated trials, and looking both for 1) stable, robust, and generally useful behaviors we can derive that help synthesis for various robotics applications, and for 2) analogies and similarities to biological behaviors that may help inform analysis of natural phenomena.

We focus on a particular type of territoriality: one existing in a society with equitable spatial territories assigned *a priori*. In this paper, we address the following questions: 1) how does the size of the group affect the effectiveness of the territorial solution, and 2) how can territories be dynamically re–assigned if members of the group become temporarily or permanently unable to forage?

The rest of the paper overviews related work, then describes our experimental setup, the robots, the spatial assignment of the territories, and the specific foraging experiments. It then presents experimental results and implications on critical mass in this and other types of tasks featuring spatial territorial division of labor.

3 Related Work

The dynamics of group interaction in physical robots have only recently begun to be studied. The review in this section focuses on work on foraging–style collection tasks using either physical robots or realistic simulations implemented with the goal of studying issues of critical mass and control of group behavior.

Matarić (1992*b*) describes early work on minimizing complexity in controlling a collection of robots, and Matarić (1992*a*) outlines the first empirical results with the basis behaviors for control. These served as the foundation for the subsequent demonstrated group behaviors, including following, aggregation, dispersion, homing, flocking, and foraging (Matarić 1994*a*, Matarić 1995). The work described here used the same behavior–based methodology, constructing the individual agent controllers out of collections of distributed behavior networks. Unlike our previous work, however, which focused on fully homogeneous systems, this paper addresses issues of task division and thus specialization as an approach to interference minimization.

Arkin (1992) describes a simulated foraging task with communication–free robots. In a paper more related to the work described here, Arkin, Balch & Nitz (1993) present simulation work with the purpose of studying the issues of critical mass in a multi–agent retrieval task. Unlike our work, the robots are fully homogeneous, and no strict or dynamic territorial division is implemented. However, complementary results regarding critical numbers of agents for the given task are derived. Both their and our pursuit are motivated at least in part by the search for interactive, social strategies that demonstrate linear and superlinear performance improvements through collective strategies. Arkin & Hobbs (1993) describe the general schema–based control architecture, which bears some fundamental similarities to behavior–based control, and give the critical mass experiments. Finally, Arkin & Ali (1994) present a series of simulation results on related spatial tasks such as foraging, grazing, and herding.

Parker (1992) and Parker (1994) demonstrate work related to ours, on the same set of R2 robots with *a priori* hard–wired heterogeneous capabilities. A toxic waste cleanup task used in the work is equivalent to foraging. The Alliance architecture is proposed as an approach to dynamically assigning tasks to members of a robot groups, and is demonstrated on a group of robots dividing the cleanup task. Unlike the spatial division we employed, Parker (1994) describes a temporal division that sends one robot to survey and measure the environment, then return and report to the rest of the group, which uses the information to then clean up the spill. The approach is complementary to ours and demonstrates a clean tradeoff between spatial and temporal task division, both of which are ubiquitous in nature. The same work also describes a simulated office garbage–collection task in which the division of labor is performed based on a first–come first–served basis using a simple and elegant conflict–resolution scheme. This work shares a common philosophy with ours regarding dynamic task assignment; the spatial territories we employed can also be dynamically reassigned according to the adapting needs of the group.

Beckers, Holland & Deneubourg (1994) describe a fully stigmergic approach to the foraging task. Their group of five robots uses no external sensing or communication to collect the pucks. Instead, through a careful combination of the mechanical design of the robots' puck scoops and the simple controller that moves them forward and in reverse, the robots probabilistically move all of the pucks into a single cluster after a certain period of time. The final location of the cluster cannot be determined *a priori* but the collective behavior is highly repeatable and has minimal sensing and computational overhead. The authors also show critical mass effects by comparing task performance on group sizes ranging from one to five robots. These results are complementary to most other work in the field, in that they demonstrate an extreme near–sensorless and totally communication–free approach to foraging. Our approach uses minimal communication in order to ensure the activity of all other robots and thus adapt to any changes in territories. Even this communication could be eliminated and the information could be obtained through direct sensing, but at a relatively high interference cost. Similarly, Parker (1992) employs communication for temporal division of labor in order to solve the task and minimize interference.

Much work has been done in the field of Adaptive Behavior and Artificial Life on simulating insect colonies and studying their dynamics. This work has served as inspiration for robot experiments, and includes Deneubourg, Goss, Pasteels, Fresneau & Lachaud (1987), Deneubourg & Goss (1989), Deneubourg, Goss, Franks, Sendova-Franks, Detrain & Chretien (1990), Deneubourg, Theraulaz & Beckers (1992), Corbara, Drogoul, Fresneau & Lalande (1993), Colorni, Dorigo & Maniezzo (1992), Drogoul, Ferber, Corbara & Fresneau (1992), and many others.

4 The Experimental Setup

4.1 The Robots

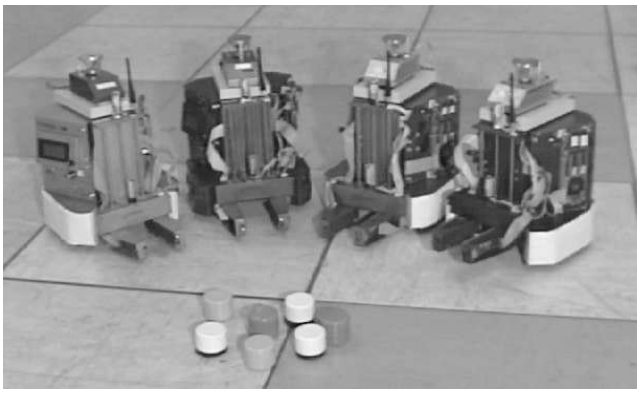

Figure 1: The R2e robot family: the robots are equipped with a differentially–steerable base, a gripper, piezo–electric bump and gripper sensors used to detect collisions and to grasp pucks, infra–red sensors for collision avoidance, and a radio transmitter for absolute positioning and message passing.

The experiments were conducted with a group of four IS Robotics R2e robots programmed in the Behavior Language, based on the Subsumption Architecture (Brooks 1990*a*, Brooks 1986). The robots are fully autonomous and equipped with with on–board power and processing. They consist of a differentially steerable wheeled base and a gripper for grasping and lifting objects. Their sensory capabilities include piezo–electric bump sensors for detecting contact–collisions and monitoring the grasping force on the gripper, and a set of infra–red (IR) sensors for obstacle avoidance and grasping (Figure 1).

The robots are also equipped with radio transceivers, used for determining absolute position and for inter–robot communication. Position information is obtained by triangulating the distance computed from synchronized ultrasound pulses from two fixed beacons, and updated at an approximate rate of 1 Hz. Inter–robot communication consists of broadcasting 6–byte messages at the rate of 1/2 Hz. Once per second, each robot broadcasts a diagnostic "I am alive" message along with its ID number to the whole group. If a robot fails to broadcast for a fixed period of time (in our experiments, 10 seconds), it is considered "dead" by the rest, who consequently adapt their behavior to the new group size and distribution. Hence, each of the robots is given the largest possible group size and can use it to determine how many others are cooperating on the task at each moment.

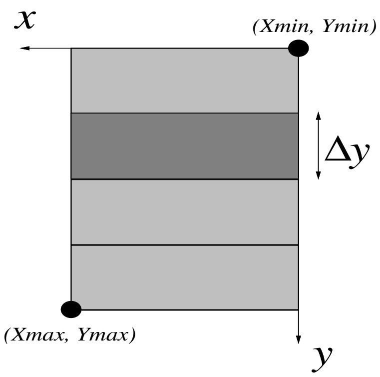

Figure 2: Division of space.

4.2 Definitions

The space ($\Re$) where all the robots work is constrained to a rectangular area defined by the coordinates (X_{min}, Y_{min}) and (X_{max}, Y_{max}) (see Figure 2). All the robots have different working spaces assigned *a priori*, and $\Re$ is divided in rectangular areas with equal height and width. The width of these regions is fixed to $\mid X_{max} - X_{min} \mid$, and independent of the number of working robots. The height (Δy) is dependent on the number of working robots and is defined as:

$$\Delta y = \frac{\mid Y_{max} - Y_{min} \mid}{Working\ Robots}$$

In order to adapt to the dynamically changing group size, each of the robots continually recomputes its adaptive Logical ID, denoted as i. Initially, each robot is given a pre–assigned unique hard–coded ID from the $[0..n]$ interval. During the lifetime of the task, this ID is used to compute the logical ID dynamically, based on the changing group size. Each robot computes its logical ID by determining how many other robots are not sending diagnostic messages, and how many of those have IDs lower than the robot's own ID ($\sigma Dead\ Robots$). Hence, the logical ID i is defined as:

$$i = ID - \sigma Dead\ Robots$$

The logical ID is used to dynamically compute the concepts of the working area, deposit area and deposit point:

- The Working Area (WA) for a robot (R_i) whose logical ID is i, is defined as the region where it looks for pucks, picks them up, and delivers them to the deposit area:

$$WA(R_i) = \{(X_{min},\ (i)\Delta y),\ (X_{max},\ (i+1)\Delta y)\}$$

- The Deposit Area (DA) is defined as the region to which the robot (R_i) delivers the pucks:

$$DA(R_i)=\{(X_{min},\ (i-1)\Delta y),\ (X_{max},\ (i)\Delta y)\};\ i > 0$$

$$DA(R_i) = \{(X_{min}, Y_{min}), (X_{min}+\delta, Y_{min}+\delta)\}; i = 0$$

where δ is the size of the "home" region.

- The Deposit Point (DP) is defined as the point towards which the robot will "home" to deliver the puck:

$$DP(R_i) = (\frac{X_{max}}{2}, (i-1)\Delta y + \frac{\Delta y}{2}); \quad \text{i} > 0$$

$$DP(R_i) = (X_{min}, Y_{min}); \quad \text{i} = 0$$

As it can be observed from the above definitions, the behavior of the robot whose logical ID is zero ($i = 0$) will be slightly different than that of the rest, as it will be in charge of placing all the pucks it grabs into the "home" region $DA(R_0)$, located in the corner of its work area (see Figure 3).

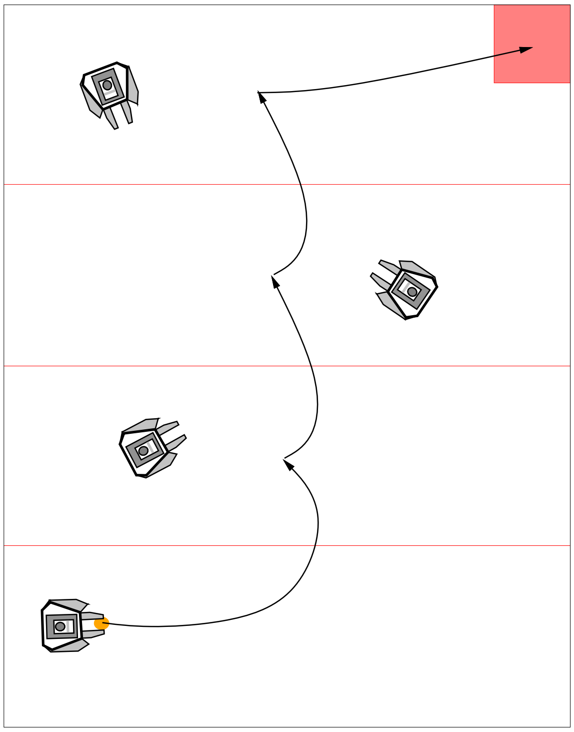

Figure 3: A puck's path from a distant region to the "home" region (upper right corner).

5 Behaviors

The main goal of the group is to collect all the pucks that are distributed over the playground, and take them to the "home" region. In order to reduce interference between robots, each robot is given a working area and a deposit area. Robots look for pucks while in their working area and deliver them once they reach the deposit area. While in the working area, robots actively search for pucks using their finger infra–red sensors, approaching, and picking them up. Once a robot grabs a puck in its working area, it homes to its deposit point and delivers the puck there. Note that each robot has a different deposit point, determined by its logical ID. When the robot crosses the border between its working area and the deposit area, it leaves the puck, and as the robot is now without a puck and outside its working area, it homes back to its working area. While the robot is outside its working area, it does not try to pick up pucks and considers them obstacles. Therefore, the behaviors that use the sensor inputs from the finger IR sensors do not try to approach the pucks, and simply avoid them and any other obstacles that are in the way of the robot on its way back to its own working area.

The robot society utilized in this experiment is a homogeneous group in that all of the members have identical controllers and thus exhibit the same behavioral capabilities. The difference between individuals is only displayed in territoriality, since each confines its behavior to a fixed territory, and can adapt that territory dynamically, depending on the size of the active group.

6 Sources of Interference

As in any multi–agent system, the interaction of a collection of robots produces interference, resulting from a competition for shared resources in the environment, in this case physical space and pucks (Matarić 1994*a*). In the forthcoming sections we outline those aspects that affect the behavior of the system, and their effect on the overall performance of the foraging task.

6.1 Heading Module

Most of the interference between robots arises when they leave their working area and "invade" other areas, either due to sensor and/or effector errors, or through the process of dropping off pucks. In order to minimize the interference while the robots are looking for pucks, they are equipped with a wandering and searching behavior whose goal is to cover the entire working area without invading the neighbors. Since the search area in our environment is rectangular, the wandering behavior always tries to turn in the direction parallel to the longest side of the working area. Consequently, the robots perform a sweep of the area in the direction parallel with the neighbor workarea boundaries, trying to minimize the possibility of invading the neighbor's working area.

The R2e robot family is not equipped with odometric sensors that could provide an estimate of the robot's current position and heading. However, the radio system provides absolute (x,y) position data to each of the robots once per second that can be integrated over time to compute a rough heading estimate. Given two consecutive positions $P_0 = (x_0, y_0)$ and $P_1 = (x_1, y_1)$, the

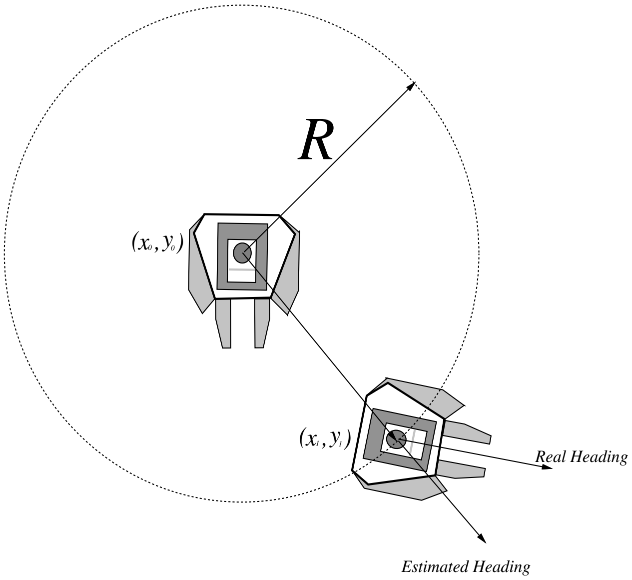

Figure 4: Heading Estimation.

heading of the robot is simply computed as:

$$heading = \arctan\left(\frac{y_1 - y_0}{x_1 - x_0}\right)$$

However, two sources of errors affect the performance of the heading module:

- The robot must move straight and without turns at least by a fixed distance (R) to compute a new heading. However, during the period of time it takes the robot to move from P_0 to P_1, unexpected events, like obstacle avoidance, may occur, that may alter the heading estimate (see Figure 4).

- Errors in the sonar positioning system also affect the heading computation. Over the lifetime of the task, insignificant errors are filtered away, but in small spaces even such errors can dramatically affect the overall achievement of the task. For example, false heading estimation might make the robot "invade" other areas more frequently, and thus increase overall interference.

6.2 Real World Dynamics

Figure 5 illustrates the situation in which a robot leaves a puck in its deposit area and interferes with the robot that is looking for pucks in its own working area. In this case, robot **a** has to home back to its working area, and may interfere with robot **b**.

The size of the working area effects the probability of interference between robots: the smaller the size of the working area the more probable it is that two robots may interfere (see quantitative results in section 7.3). In this

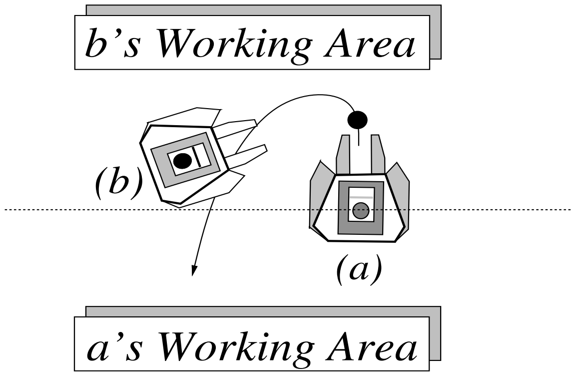

Figure 5: Invasion.

case, interference has side effects in the computation of the heading of both robots: as they are avoiding each other they cannot cover a straight distance (R).

7 Experimental Results

7.1 Experimental Layout

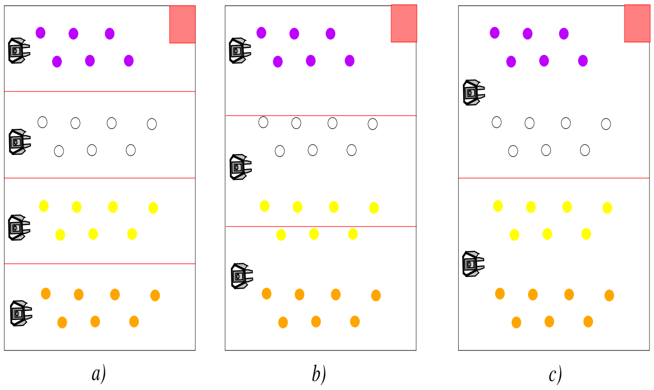

Figure 6: The experimental layout used for three different sets of experiments.

Three different experiments were done in order to quantitatively analyze the performance of the robots in the territorial foraging task. Figure 6 gives an overview of the different scenarios. In situation a), four robots were cooperating to perform the task, and the space was appropriately divided into four equally–sized regions. Robot "0", which is nearest to the home region, had six pucks in its working area, while the rest of the robots had seven. Scenarios b) and c) tested three and two robots, respectively. Initial puck distribution is shown, and differently–colored pucks are used in each of the regions in order to track puck movement over the duration of each trial, using video data gathering, in addition to position data. For each of the different layouts, experiments were repeated five times; all tabulated data show mean values for each experimental setup. The relative error in the worst case was 8%, measured using standard deviation.

7.2 Data Gathering and Analysis Methods

The following approach was used to compute and analyze the robot data. For each each robot we monitored how long every one of its behaviors was active, and how much time the robot spent in each of the relevant areas around the workspace:

- in the working area $T_{working-area}$,
- outside the working area $T_{outside-working-area}$,
- delivering pucks $T_{delivering}$.

We also gathered two other data points:

1. the number of pucks that had reached the home region 25 minutes after the beginning of the task,
2. the amount of time it took for the robots to place the 80% of the pucks (22 pucks) in the home region.

The total time the robot was working T_{total} could be simply computed as the sum of the times spent in each of the areas:

$$T_{total} = T_{working-area} + T_{outside-working-area} + T_{delivering}$$

Hence, the relevant data point, the percentage of time spent outside the working area (φ) is computed as follows:

$$\varphi = \frac{T_{outside-working-area} \times 100}{T_{total}}$$

This percentage was computed for each of the trials and the final results, shown below, are based on rounded mean values.

7.3 Performance

Number of Working Robots	**% of Delivered Pucks**
2	60%
3	80%
4	60%

Table 1: Percentage of delivered pucks in 25 minutes.

Time performance in the three different scenarios is shown in Tables 1 and 2. Table 1 indicates the percentage of the total pucks that were successfully delivered to the home region in 25 minutes. Table 2 shows the time (in minutes), the robots needed to deliver the 80% of the total pucks to the goal.

Number of Working Robots	**80 % of the Pucks Delivered in**
2	32 minutes
3	25 minutes
4	32 minutes

Table 2: Time spent in delivering 80% of the total pucks.

From the observation of these results, it may seem surprising that it took the equally long for two robots, as did four robots, to deliver the same percentage of pucks home. This effect results from the tradeoffs between interference, a bigger search space, and an increased work–load per robot. The above described uncertainty in the "heading module" leads to an inaccuracy in the "wandering" behavior, which results in the robot leaving its working area and interfering with the others. The smaller the working area the more dramatically errors in the "heading module" affect the "wandering" behavior, and therefore increasing the probability of a robot leaving its working area and interfering with its neighbors.

A clear relation between the time spent by the robots outside their working area and the time performance can be deduced from the data shown in Table 3. In this table the percentage of the time spent by the robots outside their working area is presented. The results indicate that with narrower working areas robots tend to "invade" other areas more frequently.

4 Robots		**3 Robots**		**2 Robots**	
ID	Time	ID	Time	ID	Time
0	26 %	0	20 %	0	8 %
1	29 %	1	24 %	1	8 %
2	29 %	2	18 %		
3	25 %				

Table 3: Percentage of the time spent by the robots outside the working area.

The robots are programmed to avoid any kind of object detected with their lateral IR sensors and their finger–IR sensors while they are outside their working area. However, when obstacles are too close, or difficult to detect (like other moving robots), the bumper–based avoid behavior takes control. Activation of this behavior is a good measurement of interference, because bumper hits are mostly due to inter–robot interference rather than interaction with other objects and boundaries of the environment, which are more likely to be detected with the IRs.

Results shown in Table 4, combined with those shown

Number of Working Robots	Average of Bumper Hits
2	4
3	7
4	20

Table 4: Bumper Hits.

in Tables 1, 2 and 3, highlight the fact that with increased group size the performance of the task division strategy declines due to inter–robot interference, explicitly expressed in terms of bumper hits. As demonstrated, the number of bumper hits grows steeply with increased group size, reflecting inter–robot interference. For example, three robots accrue seven hits while four robots accrue twenty. Three robots perform the task better than two robots (as can be seen in Tables 1 and 2), but interference increases, as is clearly demonstrated in Table 4. Overall, of the two, tree, or four robot sets we tested, three robots are the most efficient choice given the tradeoff between interference and work–load in the particular territorial division.

8 Discussion and Conclusions

Our experimental setup was designed to minimize inter–robot interference, and thus to achieve high task efficiency. This efficiency is directly dependent on the spatial density of the agents, since the most fundamental type of resource competition the robots encounter is that for space. This is a direct result of embodiment, and the underlying cause of basic interactions and behaviors in embodied robots and animals (Matarić 1994*a*). In this particular experiment, and based on the examination of the quantitative data recorded during repeated trials, we have found the sources of uncertainty, inherent to embodied agents, that demonstrate the critical mass for most effective foraging. Furthermore, we postulate that robot data was critical in locating these sources, since simulation results alone would have most likely failed to accurately reproduce the relevant effects, as detailed in section 6.

We have demonstrated that increased group sizes can, in embodied agents, negatively impact the effectiveness of the territorial solution. Intuitively, in a constrained environment, small groups can perform their task better than larger groups simply as a result of the direct relationship between robot density and interference. In future experiments we plan to explore the effects of much lower density on the effectiveness of the group, by significantly increasing the workspace and holding the group size constant.

Matarić (1994*a*) describes a methodology for estimating interference through computing the spatial density of the particular environment–task combination using the robot's physical size, kinematics of movement, and sensory range. This computation must take into account realistic sensory models with appropriate error and uncertainty. The computed value provides a fixed approximation of an efficient group size for the given workspace, assuming no drastic changes in either. However, the computation must be performed every time the size of the environment changes or one or more robots fail. Thus, the density value is best used as a rough approximation.

A robust, ethologically–inspired solution can be applied to optimize task achievement with or without the use of an estimated optimal density. We have demonstrated an approach in which the individual agent controllers are designed to be independent of group size, and furthermore to be adaptive to changes in group size. The current implementation allows for dynamically expanding and reassigning territorial boundaries among the agents. We are also considering an extension that allows superfluous robots to be removed from the workspace. As shown, given the specific parameters of our physical robots and the size of their workspace, the ideal number of robots for the foraging task is smaller than the complete set of available robots. If this fact cannot be computed before the robots are assigned the tasks, then it would be useful to be able to establish it dynamically.

This work focuses on one approach to minimizing interference: the use of spatial division of the task. Inter–agent interference is minimized as a consequence of spatial isolation of the agents' territories. Note that the agents themselves are not further specialized, but are homogeneous across the group. This approach is neatly complementary to the alternatives of using heterogeneous agents (i.e., employing different types of agents that may or may not be spatially isolated) and temporal isolation (i.e., employing division of labor in time rather than space). Other work by Goldberg & Matarić (1996) demonstrates the heterogeneous agent alternative using an implementation of the foraging task on the same robot family.

We plan to compare and tie our territoriality and critical mass results to task division behavior in animal societies in order to find common principles of group organization. We hope that our results can be informative and useful toward the goal of synthesizing group behavior in robots and that they can be used to inspire analysis of group behavior in nature.

Acknowledgements

Miguel Schneider Fontán's work is partially supported by the Spanish Ministry of Science under project I.Ares: CICYT, TAP 816193-C03-2. Maja Matarić's work is supported by the Office of Naval Research Grant N00014-

95-1-0759 and the National Science Foundation Infrastructure Grant CDA-9512448.

The authors wish to thank Dani Goldberg for his tireless help with the misbehaving robots, Lourdes Agapito for her useful comments on earlier versions of the paper, and the insightful reviewers for constructive suggestions.

References

Arkin, R. C. (1992), 'Cooperation without Communication: Multiagent Schema Based Robot Navigation', *Journal of Robotic Systems*.

Arkin, R. C. & Ali, K. S. (1994), Reactive and Telerobotic Control in Multi–Agent Systems, *in* 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior', MIT Press, pp. 473–478.

Arkin, R. C. & Hobbs, J. D. (1993), Communication and Social Organization in Multi–Agent Systems, *in* 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior', MIT Press, pp. 486–493.

Arkin, R. C., Balch, T. & Nitz, E. (1993), Communication of Behavioral State in Multi-agent Retrieval Tasks, *in* 'IEEE International Conference on Robotics and Automation', IEEE Computer Society Press, Los Alamitos, CA, pp. 588–594.

Beckers, R., Holland, O. E. & Deneubourg, J. L. (1994), From Local Actions to Global Tasks: Stigmergy and Collective Robotics, *in* R. Brooks & P. Maes, eds, 'Artificial Life IV, Proceedings of the Fourth International Workshop on the Synthesis and Simulation of Living Systems', MIT Press.

Brooks, R. A. (1986), 'A Robust Layered Control System for a Mobile Robot', *IEEE Journal of Robotics and Automation* **RA-2**, 14–23.

Brooks, R. A. (1990*a*), The Behavior Language; User's Guide, Technical Report AIM-1227, MIT Artificial Intelligence Lab.

Brooks, R. A. (1990*b*), Challenges for Complete Creature Architectures, *in* J. A. Meyer & S. Wilson, eds, 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior', MIT Press.

Colorni, A., Dorigo, M. & Maniezzo, V. (1992), Distributed Optimization by Ant Colonies, *in* F. Varela & P. Bourgine, eds, 'Toward A Practice of Autonomous Systems: Proceedings of the First European Conference on Artificial Life', MIT Press, pp. 134–142.

Corbara, B., Drogoul, A., Fresneau, D. & Lalande, S. (1993), Simulating the Sociogenesis Process in Ant Colonies with MANTA, *in* 'Toward A Practice of Autonomous Systems: Proceedings of the First European Conference on Artificial Life', pp. 224–235.

Deneubourg, J.-L. & Goss, S. (1989), Collective Patterns and Decision-Making, *in* 'Ethology, Ecology and Evolution 1', pp. 295–311.

Deneubourg, J. L., Goss, S., Franks, N., Sendova-Franks, A., Detrain, C. & Chretien, L. (1990), The Dynamics of Collective Sorting, *in* 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior', MIT Press, pp. 356–363.

Deneubourg, J. L., Goss, S., Pasteels, J. M., Fresneau, D. & Lachaud, J. P. (1987), 'Self-Organization Mechanisms in Ant Societies, II: Learning in Foraging and Division of Labor', *From Individual to Collective Behavior in Social Insects* **54**, 177–196.

Deneubourg, J. L., Theraulaz, G. & Beckers, R. (1992), Swarm-Made Architectures, *in* F. Varela & P. Bourgine, eds, 'Toward A Practice of Autonomous Systems: Proceedings of the First European Conference on Artificial Life', MIT Press, pp. 123–133.

Drogoul, A., Ferber, J., Corbara, B. & Fresneau, D. (1992), A Behavioral Simulation Model for the Study of Emergent Social Structures, *in* F. Varela & P. Bourgine, eds, 'Toward A Practice of Autonomous Systems: Proceedings of the First European Conference on Artificial Life', MIT Press, pp. 161–170.

Goldberg, D. & Matarić, M. J. (1996), Interference as a Guide for Designing Efficient Group Behaviors, Technical Report Computer Science CS-96-186, Brandeis University.

Gould, J. L. (1982), *Ethology; The Mechanisms and Evolution of Behavior*, W. W. Norton & Co., NY.

Matarić, M. J. (1992*a*), Designing Emergent Behaviors: From Local Interactions to Collective Intelligence, *in* J.-A. Meyer, H. Roitblat & S. Wilson, eds, 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior'.

Matarić, M. J. (1992*b*), Minimizing Complexity in Controlling a Collection of Mobile Robots, *in* 'IEEE International Conference on Robotics and Automation', Nice, France, pp. 830–835.

Matarić, M. J. (1994*a*), Interaction and Intelligent Behavior, Technical Report AI-TR-1495, MIT Artificial Intelligence Lab.

Matarić, M. J. (1994*b*), Learning to Behave Socially, *in* D. Cliff, P. Husbands, J.-A. Meyer & S. Wilson, eds, 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior', pp. 453–462.

Matarić, M. J. (1995), 'Designing and Understanding Adaptive Group Behavior', *Adaptive Behavior* **4**(1), 50–81.

McFarland, D. (1987), The Oxford Companion to Animal Behavior, *in* 'Oxford, University Press'.

Parker, L. E. (1992), Adaptive Action Selection for Cooperative Agent Teams, *in* 'From Animals to Animats: International Conference on Simulation of Adaptive Behavior', pp. 442–450.

Parker, L. E. (1994), Heterogeneous Multi–Robot Cooperation, PhD thesis, MIT.