Stay Outta My Way: Interference as a Guide for Designing Efficient Group Behavior

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Abstract

In this paper we present an ethologically inspired methodology for the incremental improvement of collective group behaviors. The goal is to aid in the implementation of *efficient* group behaviors, where efficiency is measured in terms of *time*, *interference*, and *robustness*. Among these, it is interference that can provide the best indication of how to modify a collective group behavior in order to accomplish a given task more efficiently. Interference may be reduced by employing one of the three canonical spatio-temporal arbitration schemes presented: *pack arbitration*, *caste arbitration*, or *territorial arbitration*. The choice of an arbitration scheme for a given task is based on which provides the most improved efficiency. As an example of this methodology we implement a collective *hoarding* behavior with four robots, and show how this group behavior may be improved by using the interference present in the system to help in the selection of the best arbitration scheme.

Topic areas: collective and social behavior, autonomous robots, applied adaptive behavior.

1 Introduction and Motivation

Designing and implementing cooperative group behaviors for robots is considered something of a black art. It generally involves an extensive amount of programming and reprogramming with a lot of parameter adjustment in between. At a more fundamental level, it is often not clear how to implement, or even approach implementing, a task for a group of robots (Matarić 1995*b*). What seems to be lacking is a general methodology which is both practical, and applicable to a large domain of tasks. In this paper, we propose one possible methodology.

Implementing efficient group behaviors in robots is challenging for several reasons. There is the ever-present issue of noisy and unreliable sensors, and the fact that any one robot is limited to a certain perceptual and action space defined by its sensors and physical characteristics. Working within those constraints presents a challenge for developing efficient group behaviors. One must decide how to resolve a number of issues when planning the implementation of a given task for a group of robots, including *individuality*, *cooperation*, *communication*, *interference* and *density dependence* (Brooks 1990*b*).

Individuality deals with how the behaviors of the various *classes* of robots (or agents) differ and how many classes of robots there are, while *cooperation* deals the interaction of those classes. In implementations with specialized sub-classes, if no single sub-class can complete the entire task, by definition there must be a point where the task of one class ends and the task of another begins, i.e., the output of one class becomes the input of another. This interface between different classes is where cooperation occurs.

Any time more than one robot is present in a system there is the possibility that one will *interfere* with the actions of another. Thus, increasing numbers of robots may speed up the completion of a task until a key point at which interference becomes too great. This issue of critical mass is a critical aspect of any multi-agent system, and is closely related to the issue of *density* of robots. In locally-controlled, distributed systems, such as those we focus on, mass (i.e., group size) is typically perceived through local density. *Communication* may be used to get a broader view in such a system and help coordinate the actions of individual robots or the classes they belong to, thus impacting all of the previous issues.

How can a designer resolve these issues? How does one decide upon or derive the "correct" number of classes, and the behavioral repertoire that each will possess, along with how many robots will belong to each class? Will there be any explicit communication, and if so, what form will this communication take? What information will be passed and how often?

Ethology provides examples that hint at a general methodology for constructing efficient group behaviors. Consider inter– and intraspecific competition as an example. In all cases, such competition is for a resource that is limited, whether it be food, space (territory), mates or any essential requirement. When competition is intraspecific, the result is direct interference between individuals, which may lead to aggression. When competition is interspecifics, the result is often the exploitation of the resource by one species to the exclusion of the other (McFarland 1987).

In both cases, competition places evolutionary pressure on the individuals. There are several mechanisms by which this pressure is "eased". Over the short-term, the individuals most successful at acquiring the scarce resource will survive and breed. In the frame of evolutionarily significant time, the result of interspecific competition will be the extinction of the species less successful in acquiring the resource, or its adaptation to a niche where competition is lesser and the prospects of survival are greater.

In the case of intraspecific competition, the evolutionary result may be more subtle. Consider the example of three species of North American warbler which inhabit the same community, and are genetically related. Members of all three species are insectivorous, of similar size, and to casual observation, exhibit the same foraging behavior when searching for food. Upon closer inspection, it is observed that, although all three species forage in the same trees, they do so in different parts. One species prefers to forage in the upper branches, the second in the middle, and the third in the lower branches of the same trees. These observations, and similar ones for other sets of closely related species, suggest a compelling property: *evolution works to reduce competition (interference) among species and between individuals of the same species* (McFarland 1987).

This last observation provided the inspiration and initial motivation for our methodology. If evolution through natural selection works to minimize interference, can some artificial form of evolution be employed to reduce interference within groups of robots? Since the goal of such a process would be to minimize the interference in the system, it makes sense to use the interference already present as a guide for reduction. It may be relatively easy to determine where interference exists in the system – is it due to competition for food, territory, etc. The location of the interference, however, does not solve the fundamental problem of determining how to modify the group behavior in order to best ameliorate it. The best modification may relate to one or more of the aforementioned issues – individuality, communication, density dependence – or some other issue such as morphology. We again look to ethology for guidance in the creation of the interference-reducing *spatio-temporal arbitration schemes* which constitute our methodology, described next.

2 The Methodology

Our methodology is based on a set of canonical ethologically-based spatio-temporal arbitration schemes. The goal of this methodology is to aid in the design and implementation of *efficient* goal-directed behaviors for groups of autonomous agents, more specifically robots. The efficiency criterion is captured in the values of three attributes of the system.

- *Time*: in order for an implementation to be considered efficient, the amount of time required for the robots to complete the task must be minimized. In nature, energy consumption rather than time is more relevant, but in the robot case time can be directly equated to energy consumption.
- *Interference*: the amount of interference among robots must also be minimized. It is a key measure of efficiency since any interference, as we define it, is counterproductive to the goal of the task, and since it has a direct impact on time.
- *Robustness*: the robustness of the system must be maximized. A group behavior that fails due to the loss of any one robot cannot be considered efficient, even if this failure is unlikely to occur.

These three efficiency criteria are important in the methodology and help the designer decide between the various arbitration schemes.

The methodology we present makes several key assumptions about the characteristics of the group task that is being implemented. It is assumed that the given task is *cooperative*. In other words, competition among individuals is not a required characteristic of the task. If it were, the effect could be that of maximizing instead of minimizing interference. A second, closely related, but stronger assumption is that the individual robots adhere to the practice of *altruism*, defined as sacrificing their individual interests whenever they impede the efficient completion of the task by the group.

Adherence to altruism has several interesting consequences. As with the assumption about cooperation, altruism ensures that there is no deliberate competition among individuals. It also limits the types of unintentional competition the system can manifest to *territorial* *competition* alone. Since there is no resource that the robots will deliberately compete for, all objects (which may be considered "food" or "mates") that the robots must manipulate during the task may be eliminated from competition. But since robots are physical embodied agents and lack perfect sensing, the only resource for which they cannot help but compete is space, or territory. We believe that these assumptions about competition hold for many classes of tasks involving embodied agents.

We now present our five–step methodology. The first step, implementation of a homogeneous solution, is the primer for the methodology. The remaining four steps constitute an iterative refinement model in which the interference of the systems is analyzed, an interference–reducing arbitration scheme is selected and implemented, and which is in turn analyzed for interference. We describe each of these steps in turn.

2.1 Step 1: The Homogeneous Implementation

The first step in our methodology is to devise a homogeneous implementation for the desired task. The robots which are assigned the task should be behaviorally identical. Each of the robots should be behaviorally capable of completing the entire task by itself. This homogeneous group implementation should not employ any manner of explicit communication, via radio or radio ethernet, for example. The reason for this initial proscription against communication is two–fold. First, since each robot must be capable of completing the entire task, if it were the only individual of the group, communication would be of no use. In addition, the goal of this first step is to help determine exactly what are the characteristics of interference in the system. It would be counterproductive to employ communication, which may improve efficiency by possibly skew the interference dynamics which we wish to observe from the onset, using a base–case scenario. It is important to note that this lack of communication means that without the ability to discover the short–term goals of other robots through direct sensing, no altruism can exist. We assume that altruism implies some ability for explicit communication or direct sensing of short–term goals, along with a means for individuals to communicate acquiescence.

This initial homogeneous implementation now becomes the primer for the iterative improvement model via the analysis of its interference patterns.

2.2 Step 2: Characteristic Interference

Once the group behavior has been implemented, several trials can be run in order to observe the interference patterns and analyze them, either qualitatively or quantitatively. Qualitative analysis may suffice since it is usually fairly obvious to a human observer where and in what manner robots are physically interfering with each other. A critical factor in the observability of the interference pattern characteristic to a system is the population density of the robot group. With one robot in the system, there will clearly be no observable robot interference patterns. Conversely, a system in which the robot density is so high that individuals can scarcely move produces no characteristic interference either.

Let us consider the *characteristic interference* of a system to be a function mapping two dimensional space to three dimensional space. Then the characteristic interference at each point would be the sum over some finite period of time of all the interference that occurs at that point. The result would be a surface with peaks indicating locations of characteristic interference, a sort of finger print for the system. With this finger print, it is now possible to select an arbitration scheme for lessening the interference.

2.3 Step 3: An Arbitration Scheme

Once a major source of interference is identified, some type of spatio–temporal arbitration scheme can be implemented to reduce the interference. We believe that there are three canonical arbitration schemes for tasks that fall in the domain defined by the constraints mentioned earlier. These are 1) *pack arbitration*, 2) *caste arbitration* and 3) *territorial arbitration*. The choice of arbitration scheme is based on the improvement each provides in the aforementioned three criteria of efficiency for the given task. There are some general statements that can be made about interference and robustness, but the time criterion is closely dependent on the specifics of the given task. The selection of an arbitration scheme also influences issues such as communication.

Because inter–robot interactions that we are considering are spatio-temporal in nature, there are four basic forms this interaction can take. Robots may either be in the *same place* (SP) or in *different places* (DP), and they may be in these places at the *same time* (ST) or at *different times* (DP). Combining these possibilities gives us four basic forms of interaction: SPST, SPDT, DPST, and DPDT.

SPST interactions are what we have, so far, been calling interference, i.e. when two robots try to occupy the same location at the same time. We have looked to the other three forms of interaction for possible solutions to SPST interference. We have associated arbitration schemes, as well as ethological examples, with each spatio–temporal solution to SPST interference. We now describe these in detail.

2.3.1 Pack Arbitration

Pack arbitration is modeled after the phenomenon of the pack observed in wolf and other animal societies. In these, any individual is physically and behaviorally capable of performing any function (excluding sexual functions) necessary to the group. In order to minimize aggressive behavior which, if not controlled, can jeopardize the pack, a form of dominance hierarchy exists among the individuals.

Similar to animal packs, in pack arbitration, all of the individuals of the robot group are physically and behaviorally capable of performing any of the functions necessary for the group to complete the task, as was also true for the initial homogeneous group. An alternate description of this scheme is that SPST interference is converted to SPDT arbitration. The main form of spatio–temporal arbitration is then a dominance hierarchy which may be based on the relative functionality of the robots (i.e. a robot with slightly better IR sensors is dominant); or it may be based on a relatively random scheme, such as robot ID. For example, Matarić (1994*a*) implemented an arbitrary ID–based dominance hierarchy as a total order of a group of robots, and used it to evaluate performance of homogeneous versus ordered aggregation and dispersion behaviors.

In pack arbitration, the main mechanism for interference reduction is altruism. When two individuals wish to claim the same resource, whether it be an object or space, the individual lower in the dominance hierarchy defers to the higher. As with the purely homogeneous solution, robustness is inherent in pack arbitration. Since all of the robots are capable of the same actions, the loss of any one individual will not make achieving the goal impossible, unless no robots remain. In addition, when one robot fails, the relative positions of the other robots in the dominance hierarchy remain intact. Because only relative dominance is important, recomputation of absolute positions is unnecessary.

This form of arbitration contains some implicit assumptions about communication. It is assumed that two or more individuals will be able to determine whether they share the same short–term resource goals and what their relative dominance positions are. Thus some of the information that must be communicated, either explicitly or via direct sensing, is: short-term goals, location, and position in the hierarchy.

2.3.2 Caste Arbitration

Caste arbitration is modeled after the structure apparent in many social insect societies. In these, individuals are behaviorally heterogeneous and are not capable of accomplishing all of the tasks that the group requires. Individuals may also be physically differentiated. As an example, consider many ant species whose colonies include worker, drone, possibly warrior castes, and at least one queen. Each individual is a member of one of these *castes* and has associated physical and behavioral characteristic. No one caste can maintain the colony without the others.

Spatio–temporal arbitration with castes is accomplished with several mechanisms. Interaction among individuals of different castes is limited, even if these share the same territory. Worker and warrior ants which are often found in proximity, do not interact to any great degree. In addition, if certain castes do interact it is usually only so that the output from one caste becomes the input to the other. Leaf–cutter ants are a good example of the caste system: the cutter ants continually bring pieces of foliage to the nest to be masticated and provide the substrate for the cultivation of the fungus that feeds the colony. These crops are tended by a different caste of worker ant which do no cutting (Holldobler & Wilson 1990). There may also be some small degree of territoriality in these societies. The queen, for example, seldom moves from one spot. Similar to pack, caste arbitration is also a form of SPDT arbitration.

Similar to what is observed among social insects, caste arbitration may be employed when working with groups of robots. For example, it may be possible to divide the global task into several sub–tasks in such a way as to lessen the interference. One such approach serializes the sub–goals, so that the output from one caste becomes the input to another.

Robustness in caste arbitration is achieved by allowing members to change castes when necessary. If, for example, all the members of one caste fail, a member of some other caste must be able to take over. Again, this type of robustness is found in nature. In honey-bee societies, young worker bees tend the larvae and feed them, at least in part, a special nutritive substance called royal jelly. As a bee gets older this gland becomes non-functional, and eventually the bee becomes a forager. If for some reason the population of nurse bees declines so that the larvae are underfed, an old forager bee may regenerate these glands and become a nurse bee again (McFarland 1987).

In caste arbitration, some critical information needs to be communicated among individuals. Either explicitly or through sensing, individuals must be aware of how many functional members each caste possesses so that it may be determined when an individual must switch castes.

2.3.3 Territorial Arbitration

The motivation for the third type of spatio–temporal arbitration, *territorial arbitration*, comes from the behavior of asocial animals, such as bears, orangutans, and non–social insects. In these species, interference among individuals is minimized by the fact that they interact as little as possible. They maintain some sort of private "space", so that, except for breeding, they are seldom close to another member individual.

In a similar manner, the territorial arbitration scheme gives each robot its own territory which no other robot may enter, thus minimizing interference. Territorial arbitration is both DPST and DPDT arbitration. Since robots are basically isolated (DP), it is irrelevant whether actions occur at the same time or not. The only physical interaction between the robots occurs at the boundaries of their territories where the robots may not necessarily come in contact with each other, but may manipulate some object that another robot has left, or, in turn, leave some object for another robot.

Robustness in this scheme, as in the others, must be maintained. If one robot fails, the remaining individuals may have to expand their territories in order to subsume that of the failed individual. If the task requires this sort of adaptive territorial division, then the robots need to know *a priori*, or be able to determine, their territorial positions dynamically with respect to other robots.

The constraint on communication is that there must be some signal, either explicitly communicated or sensed, that an individual sends out to inform others that either a) it is functioning, so that its absence marks a failure, or b) it has stopped functioning. The other robots must have this information in order to know when to expand their territories. If a failed robot suddenly becomes functional, the others must contract their territories to the previous size. Communication could also allow the robots to dynamically change the shape and/or size of their territories to better exploit the changing dynamics of the task. It is important to keep in mind that, according to our basic assumption, altruism holds whenever applicable, so any individual will "sacrifice" its territory if it helps the group achieve its goal more efficiently.

An implementation of just such an arbitration scheme was demonstrated by Fontán & Matarić (1995), who show a group of forager robots that collect pucks within their specific mutually–exclusive territories, and deliver them to the boundary of the next territory closer to the home region. Over time, all pucks are delivered to the home location with minimal interference between the agents. The territorial boundaries can be dynamically readjusted if one or more members of the group fails or returns. The failure is detected through the absence of otherwise periodic communication message "I'm alive."

2.4 Step 4: Evolution/Implementation

Once an appropriate arbitration scheme for reducing interference has been selected, evolution–through the modification of the group behaviors–will produce a new society in which, ideally, the location(s) of highest interference in the homogeneous group now show less interference. In nature, evolution produces the next, improved solution. In robotics, it is up to the designer to program one, or to attempt to automate the refinement process, perhaps through the use evolutionary techniques such as genetic algorithms and genetic programming (Matarić & Cliff 1996).

2.5 Step 5: Repeat the Process

At this stage, the resulting group behavior may be satisfactory. If it is not, the whole process, starting with the analysis of characteristic interference in Step 2, is iterated. The changes in the dynamics of the system might have led to the formation of new zones of high interference. Thus, perhaps a new arbitration scheme can be picked, or the current one modified slightly. It is not too difficult to imagine several of these arbitration schemes working in synchrony. Consider a system employing caste arbitration in which one of the castes, consisting of several robots, is responsible for the subgoal of collecting certain objects and moving them to another location. Two or more robots of this caste may try to acquire the same object at the same time, and interfere with each other. To avoid this, a pack arbitration scheme can be employed within this specific caste. Thus, it may be quite reasonable to go through several cycles of arbitration revision before being satisfied with the resulting group behavior.

We have applied the described the iterative refinement model to an ethologically-inspired robotics implementation, described next.

3 Hoarding: An Experimental Example

As an example of the use of this methodology, we implemented a *hoarding* behavior, a prototype for various collection and cleanup tasks. Hoarding consists of foraging, which is the searching for and acquisition of food, along with its storage in one or more locations (McFarland 1987). Many species, including some squirrels, birds, honey bees, and ants, display hoarding. In social insects, such as bees, hoarding is performed by many individuals collectively. The hoarding task that we implemented also requires the robots to search collectively for "food", in this case small metal cylinders, and bring them to a specific location.

3.1 The Experimental Setup

The group hoarding task is performed in an eleven by fourteen foot rectangular enclosure we call the Corrall. Twenty-seven of the small metal cylinders, or *pucks*, are placed evenly but randomly throughout the Corrall, except at the location where the robots will hoard the pucks. This location, called *Home*, is a ninety degree sector of a circle with a radius of two feet and its center at one corner of the Corrall. The robots, which are also initially distributed throughout the Corral, must find pucks and bring them Home (Figure 1).

3.2 The Robots

We use four IS Robotics R2e robots (alternately called the Don Group and the Socially Mobile) in the experi-

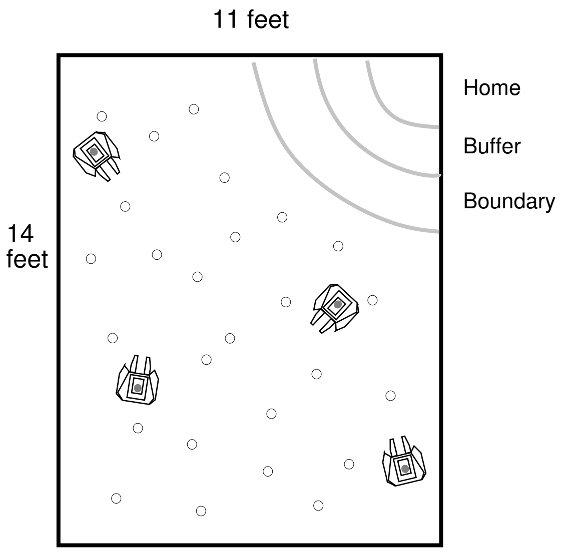

Figure 1: Experimental setup of Corrall for group hoarding behavior. Robots must search for pucks and bring the ones they find to Home.

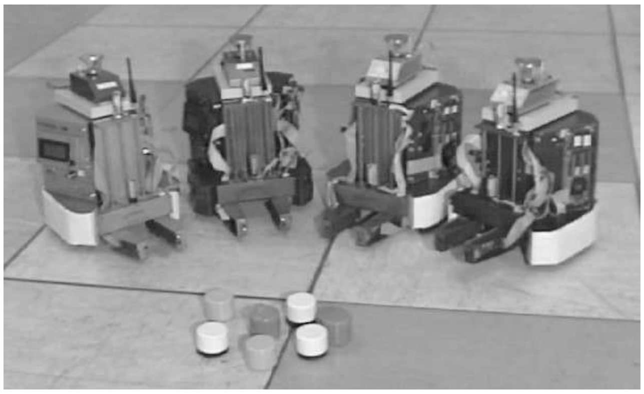

Figure 2: The Don Group: the four–robot family used in the hoarding experiments.

ments described in this section (Figure 2). Each robot is equipped with two drive motors and is holonomic, allowing it to make turns of arbitrary radii. Each robot also possess a gripper mechanism which can be raised and lowered with two fingers that open and close. The sensing capabilities of each robot consist of piezo–electric bump sensors on the inside panels and in the gripper, five infrared sensors around the body of the robot and one on each finger for proximity detection, a color sensor in the gripper, a radio transmitter/receiver for communication with other robots and a base station, and an ultrasound triangulation system for positioning.

The robots are programmed in the Behavior Language (Brooks 1990*a*), a real-time parallel programming language based on work from Brooks (1986), Connell (1990), and Maes (1989). Behavior Language programs are written in an extended subset of Lisp and are compiled into a collection of finite state machines. These FSM's are then compiled into working code and downloaded to the robots. The executable code that controls the robots forms a modified version of the *subsumption architecture* (Brooks 1986).

3.3 Homogeneous Hoarding

The first step of the methodology is to implement a homogeneous solution for the task (Figure 3). The robots are programmed to wander around the Corrall, using their IR and bump sensors to avoid obstacles. When the IR sensors at the tips of the fingers detect an object, a robot goes into a "puck detection" mode. It raises the fingers five or six inches to determine whether or not it can "see" over the object. If it cannot, then the object is either a wall or another robot. In such a case, the robot goes into an avoid mode and leaves the vicinity of that object. If the robot can see over the object, then it is considered to be a puck. The robot slowly approaches the puck and grabs it when it comes between the two fingers.

Once a robot has a puck, it raises its lift and starts a *homing* behavior, which brings the robot near Home. Raising the lift while homing serves two purposes. First, while the robot is homing it is also avoiding all obstacles. Any pucks lying in the robot's path are too small to be considered obstacles. Raising the lift and only using the finger IR's to sense objects that are taller than the pucks (like walls and other robots) is more efficient. Second, due to the shape of the robots, raising the lift allows the robots to collect and push any pucks in their path to Home.

When a robot that has a puck enters the Buffer, it slows down and performs a more refined version of the homing behavior to get close to the corner. Upon entering Home, the robot drops the puck, backs up, lowers its lift, closes the gripper, and leaves Home in search of more pucks. The closed gripper ensures that the robot does not mistakenly pick up pucks that are near Home.

The Boundary serves a repelling function. It does not make sense to allow a robot without any pucks to enter Home. When a robot that has no pucks enters the Boundary, it turns around, closes its gripper, and leaves. When safely out of the Boundary, the robot again resumes its puck collection behavior.

With the homogeneous hoarding behavior implemented we are ready to observe its characteristic interference pattern.

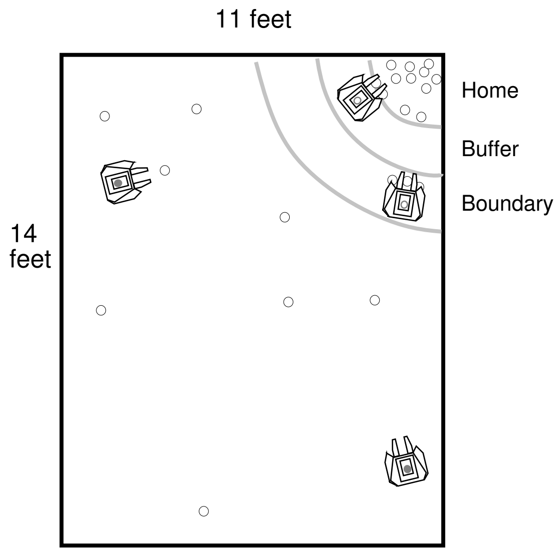

Figure 3: Homogeneous group hoarding behavior.

3.3.1 Interference Pattern

We performed trials using all four of the robots we have available. We did not believe that using fewer robots would illustrate the dynamics of the system as well. After only several trials of the homogeneous group hoarding behavior it became clear that there was a lot of interference created in the Home and Buffer zones when more than one robot attempted to deposit pucks at the same time. Upon reflection, this observation makes intuitive sense. The density of the robots in the region where they search for pucks is relatively low, resulting in relatively little interference. When several robots, however, acquire pucks they all attempt to enter Home, the scarcest spatial resource in the system. This interference at Home may be greatest at the beginning of the trial when, due to the presence of many uncollected pucks, the probability of all four robots acquiring pucks at the same time is relatively high. With the point of highest interference located, we can employ one of the arbitration schemes to reduce it.

Note that another method for changing interference properties is to alter the environment. We could, for example, move Home to the middle of the workspace, thus eliminating interference. As shown in foraging experiments in Matarić (1995*a*), interference in this case is higher around puck zones than it is around the home region. However, in this example we assumed that changing the environment is not an option, and that an efficient solution must be found through an alternative control/arbitration strategy.

3.4 Selection of an Arbitration Scheme

Following the methodology, we now have three arbitration schemes from which to chose, with the basis of selection being the maximization of efficiency.

3.4.1 Pack Arbitration

The first method of arbitration we consider for the collective hoarding task is pack arbitration. Since the R2e's are practically identical, we could use robot ID's as the basis for the dominance hierarchy. If two or more robots simultaneously approached Home carrying pucks, the one highest in the hierarchy would be allowed to deposit pucks first. The other robot(s) would have to wait for the dominant robot to leave the Buffer zone before being allowed to deposit pucks in turn.

In terms of efficiency, this scheme is robust and would lessen the interference around Home, but it may not be efficient in terms of time. Given the small size of the home region, one or more robots may often have to remain idle, waiting for a dominant robot to deliver pucks before they can. This idle time translates to wasted energy which could be used to search for more pucks.

3.4.2 Territorial Arbitration

One territorial arbitration scheme would be to construct a bucket brigade. The area of the Corral could be divided into rectangular strips with each robot assigned to a strip. Each robot would search its strip, finding pucks and depositing them in the next territorial strip closer to Home. The robot whose strip contained Home, would have the job of depositing the pucks at Home. As with the pack arbitration solution described above, this territorial scheme may be efficient in terms of lessening interference and possessing robustness by allowing robots to adapt their territories according to robot failures. ((Fontán & Matarić 1995) describe just such a territorial arbitration scheme.) But, just as before, this scheme will probably not be efficient in terms of time. As the distance of a robot's territory from Home increases, so does its amount of idle time during the task. The robot farthest from Home only has to move the pucks in its own territory. All of the other robots must move their own pucks and the pucks of at least one other robot. Thus, the farthest robot will finish moving its pucks first, and waste energy pointlessly looking for pucks, while the other robots still have a large part of their task remaining.

3.4.3 Caste Arbitration

The third possibility is a caste arbitration scheme. In this scheme, three of the robots would perform a hoarding behavior similar to the homogeneous one. The only difference is that they would not bring pucks all the way Home, but leave them at the line dividing the Boundary and Buffer. The fourth robot would remain exclusively in the Home and Buffer zones, collect the pucks left on the boundary line, and take them Home (Figure 4). This is analogous to forager ants and some sort queen or caretaker ant. This scheme would be efficient in terms of reducing interference by limiting access to the Home and Buffer regions. It could also be made efficient in robustness by allowing a member of the foraging caste to replace a failed robot in the Home/Buffer regions. Unlike the previous two schemes, this one would also be efficient in time, since no robot would ever be idle.

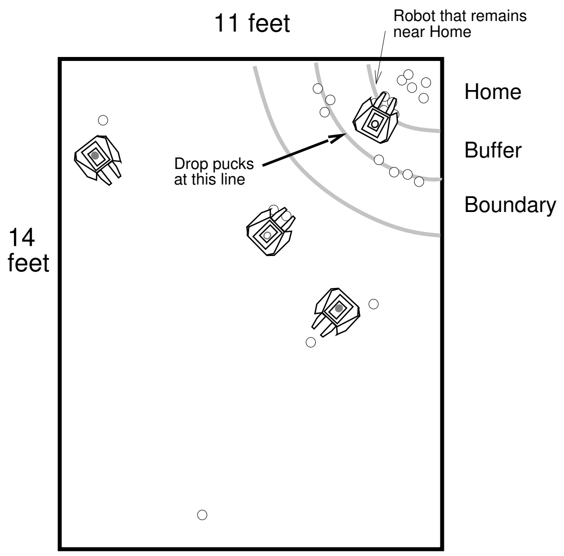

Figure 4: Group hoarding behavior with caste arbitration.

3.4.4 Implementation

Because of its high efficiency, it is the caste arbitration scheme that we implemented. In our actual implementation, due to the inaccuracies of sensing and position information, the "queen" robot that remains at Home is effectively blind. It does not search for pucks, but rather makes an arc scooping up any pucks that are left on the Boundary/Buffer line. In nature, also, some caste members are specialized functions to the exclusion of others. For example, in some species of ant, the queen who is a highly specialized in egg production, is blind, can hardly move, and requires constant care (McFarland 1987).

We are currently gathering data from the caste arbitration implementation of hoarding. The first set of preliminary trials we have already run already provide a comparison between our initial homogeneous and caste arbitration hoarding behaviors, and indicate that, as hypothesized, interference is indeed reduced with caste arbitration.

3.5 Continuing Work

The experiments described here are a work in progress. We are currently in the process of collecting data for both the homogeneous and caste arbitration hoarding groups, scheduled to be completed by the end of February. At that time we plan to perform a more rigorous quantitative analysis and comparison of the time of completion for the task, and the location and nature of the interference, scheduled to be completed by the middle of March. We are also monitoring and recording the temporal interaction of all the behaviors within the individual robot controllers, and plan to correlate those results with the externally manifested interference patterns. We plan to include all of those results in the final paper, as well as present a video illustrating and comparing robot performance using different arbitration strategies we introduced.

4 Related Work

Multi–robot systems are relatively rare so only a handful of papers have been written describing their properties. In contrast, a large body of literature exists describing simulations of simplified agents as well as insects. This section gives a partial review of some of the work that is most related to that described in the paper. Much of the directly related work has been already mentioned where appropriate throughout the paper. The reader is encouraged to see Matarić (1995*b*) for a more complete set of references from Artificial Intelligence, Distributed AI, Artificial Life, and Mathematical Biology.

Work in artificial life, focusing on simulating insect colonies, features various forms of group behaviors. Unlike the work described in this paper, which focuses on methods for principled synthesis of efficient group behavior, artificial life simulations tend to aim at modeling and analyzing natural social systems. A partial list of the most related work 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.

Robotics work, in contrast, focuses on synthesis. Matarić (1992) describes early work on minimizing complexity in controlling a collection of robots and outlines the first empirical results of using ethologically–inspired basis behaviors as a substrate for multi–agent control. The basis behaviors were used to demonstrate following, aggregation, dispersion, homing, flocking, foraging, as well as learning to forage, learning to cooperatively move objects, and learning social rules (Matarić 1994*a*, Matarić 1994*b*, Matarić 1995*a*, Simsarian & Matarić 1995).

Arkin (1992) describes a simulated foraging task with communication–free robots and Arkin, Balch & Nitz (1993) demonstrate simulation work with the purpose of studying the issues of density and critical mass in a hoarding–like task using fully homogeneous robots. 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. This work is equivalent to our fully homogeneous initial case.

Parker (1992) and Parker (1994) describe multi–robot experiments on the same set of R2 robots with *a priori* hard–wired heterogeneous capabilities using the Alliance architecture. A toxic waste cleanup task used in the work is equivalent to hoarding and our previous use of foraging. Parker (1994) describes a temporal division that sends one robot to survey and measure the environment, and then has the rest of the group use its information to clean up the spill. This approach is a form of the caste system with outputs of one caste servings as inputs to another.

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. This work is an instance of a complete homogeneous society in which the members do not even recognize each other, much else communicate or display altruism or explicit cooperation.

5 Conclusions

In this paper we have presented an ethologically based methodology for the iterative improvement of group behaviors. This methodology is applicable to task domains in which cooperation and altruism, if appropriate, are assumed to be the desired modes of interaction. In such domains, SPST interference can be lessened by the use of one or more spatio–temporal arbitration schemes–namely pack, caste, and territorial arbitration. The appropriate arbitration scheme to select is the one that provides the most improvement in efficiency, as measured by the decrease in time and interference, and the increase in robustness. Our presented methodology consists of the implementation of a homogeneous solution, the analysis of its characteristic interference, and the selection and implementation of one of above arbitration schemes based on the criterion of efficiency. This process of analysis and refinement can be iterated. We have shown how this methodology may be utilized to help implement and refine a group hoarding behavior.

In general it is very difficult to design and implement collective cooperative group behaviors. A structured methodical approach to the incremental improvement of group behaviors, alternating between analysis, implementation, and observation, such as we have presented here, is a step towards the facilitation of working with groups of robots.

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