Designing and Understanding Adaptive Group Behavior

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This article proposes the concept of basis behaviors *as ubiquitous general building blocks for synthesizing artificial group behavior in multiagent systems and for analyzing group behavior in nature. We demonstrate the concept through examples implemented both in simulation and on a group of physical mobile robots. The basis behavior set we propose, consisting of* avoidance, safe-wandering, following, aggregation, dispersion, *and* homing, *is constructed from behaviors commonly observed in a variety of species in nature. The proposed behaviors are manifested spatially but have an effect on more abstract modes of interaction, including the exchange of information and cooperation. We demonstrate how basis behaviors can be combined into higher-level group behaviors commonly observed across species. The combination mechanisms we propose are useful for synthesizing a variety of new group behaviors, as well as for analyzing naturally occurring ones.*

Key Words: group behavior; robotics; ethology; social interaction; collective intelligence; foraging

Introduction and Motivation

Intelligence is a social phenomenon. Most intelligent animals live in a society of kin, obey that society's rules, and reap the benefits. Social interactions can compensate for individual limitations, in terms of both physical and cognitive capabilities. Herds and packs allow animals to attack larger prey and increase their chances for survival and mating (McFarland, 1985), and organizations and teams facilitate information sharing and problem solving.

The complexity of any society is the product of the local interactions among its members. Synthesizing and analyzing coherent collective behavior from individual interactions is one of the great challenges in both ethology and artificial intelligence. In this article, we introduce and demonstrate a methodology for principled synthesis of group behavior, focusing on the most fundamental spatial and physical interactions among situated, embodied agents.

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Inspired by behaviors ubiquitous in nature, we propose basis behaviors as building blocks of adaptive agent control, social interaction, and learning. Basis behaviors are intended to be a substrate for generating analyzable adaptive behavior in complex environments such as animal and robot societies.

In section 2 we define basis behaviors, describe how they are selected for a given domain, and illustrate them with a specific basis behavior set for mobile, situated, spatially interacting embodied agents. In section 3 we describe our experimental environment and procedures used to test empirically the proposed basis behaviors. Section 4 gives the algorithms and examples of the robot data for each of the basis behaviors. Section 5 describes the control experiments we used to test heterogeneous alternatives for some of the basis behaviors. Section 6 introduces the methods for composing basis behaviors into higher-level aggregates, while Section 7 describes the algorithms and the data for two examples of composite behaviors, flocking and foraging. Section 8 discusses related work, and Section 9 concludes the paper.

2 Basis Behaviors

Our research is aimed at finding common properties across various domains of multiagent interaction for the purpose of classifying group behavior. Toward that end, we propose basis behaviors as a common property useful as a tool for structuring and thus simplifying behavior synthesis.

We define *behaviors* as control laws that take advantage of the dynamics of the given system to achieve and maintain its goals effectively, and *basis behaviors* as members of a minimal set of such behaviors, with appropriate compositional properties. Basis behaviors are stable, prototypical interactions between agents and the environment that evolve from the interaction dynamics and serve as a substrate for more complex interactions.

Biology provides evidence to support basis behaviors at a variety of levels. A particularly clean and compelling case can be found in motor control. Controlling a multijoint manipulator such as a frog leg or a human arm is a complex task, especially if performed at a low level. Mussa-Ivaldi and Giszter (1992) show a simplification in the form of a relatively small set of basis vector fields, found in the spine, that generate the frog's entire motor behavior repertoire from appropriate combinations of the basis vectors. Bizzi, Mussa-Ivaldi, and Giszter (1991) and Bizzi and Mussa-Ivaldi (1990) discuss control of the human arm with a similar approach. The described motor basis behaviors are a result of two types of constraint optimization: the dynamics of the manipulator and the dynamics of the motor tasks. In the case of motor control, the behaviors constitute prototypical reaches, grasps, throws, strides, and so on, most likely evolved to minimize energy through constraints such as minimal jerk, straight-line trajectories, and bell-shaped velocity profiles (Atkeson, 1989).

We believe that the concept of basis behaviors, or stable prototypical interactions, can be generalized all the way up the levels of adaptive control, from low-level motor actions to social interactions. In this article, we will focus on basis behaviors for group interaction used as a tool for describing, specifying, and predicting group behavior. By properly selecting such behaviors, one can generate repeatable and predictable interactions at the group level. Furthermore, one can apply simple compositional operators to generate a large repertoire of higher-level group behaviors from the basis set.

2.1 Selecting basis behaviors

It is difficult to imagine any fixed metric for selecting an "optimal" set of behaviors, as the choice of the basis behavior set depends on the domain and goals to which it will be applied. We make no attempt to devise optimality criteria or formal proofs of correctness. Although such proofs may be computable for simple models of the agents and the environment, they become prohibitively complex for increasingly realistic models of sensors, effectors, and dynamics.

We propose the following desirable criteria for selecting and evaluating basis behaviors. A basis behavior set should contain only behaviors that are necessary in the sense that each either achieves or helps to achieve a relevant goal that cannot be achieved with other behaviors in the set and cannot be reduced to them. Furthermore, a basis behavior set should be sufficient for accomplishing the goals in a given domain so no other basis behaviors are necessary. Finally, basis behaviors should be simple, local, stable, robust, and scalable (Matarić, 1994a).

To evaluate our selected behaviors, we applied these criteria to implementations on physical robots interacting in the real world, with all of the present error, noise, and uncertainty. To make the evaluation more complete, we tested various initial conditions and group sizes and based the analysis on a large amount of experimental data.

2.2 Basis behaviors for locomotion

Group behaviors in the spatial domain are goal-driven spatiotemporal patterns of agent activity. Certain purely spatial fixed organizations of agents correspond to achievement goals, whereas many spatiotemporal patterns correspond to maintenance goals. In all cases, the behaviors have optimized interaction dynamics based on conserving energy and maximizing interaction or synergy within the group.

We modeled energy conservation at the group level by minimizing interference between individuals. In any embodied agents, this translates directly into the achievement goal of *avoidance* and the maintenance goal of moving about without collisions—that is, *safe-wandering*. Avoidance in groups can be achieved by *dispersion*,

Table 1 A basis behavior set for the spatial domain, intended to cover a variety of spatial interactions and tasks for a group of mobile agents

Behavior	Definition
Safe-wandering	The ability of a group of agents to move about while avoiding collisions with obstacles and one another
Following	The ability of an agent to move behind another, retracing its path and maintaining a line or queue
Dispersion	The ability of a group of agents to spread out in order to establish and maintain some minimum interagent distance
Aggregation	The ability of a group of agents to gather in order to establish and maintain some maximum interagent distance
Homing	The ability of an agent to find a particular region or location

a behavior that reduces interference locally. It also can serve to minimize interference in classes of tasks that require even space coverage, such as those involving searching and exploration.

In contrast to various goals that minimize interaction by decreasing physical proximity, many others involve the exchange of resources through proximity, achieved through *aggregation*. Aggregating with other agents or moving to any specific location or region involves some form of *homing*. Any collective movement of a group requires coordinated motion in order to minimize interference. *Following* and *flocking* are two common forms of such structured group motion.

We will show that the behaviors we have listed so far, enumerated in Table 1, constitute a basis set for a flexible repertoire of spatial group interactions. Not surprisingly, they are all found in numerous species. Avoidance and wandering are survival instincts present in all mobile creatures. Following, often innate, also is ubiquitous (McFarland, 1985). Various forms of dispersion are observed in species ranging from simple insects to people (Waterman, 1989). For example, DeShutter and Nuyts (1993) show elegant evidence of gulls aggregating by dynamically rearranging their positions in a field to maintain a fixed distance from one another. Camazine (1993) observes analogous behavior in gulls on ledges and rooftops. Well-known studies in psychology illustrate that people maintain similar, predictable arrangements in confined spaces (Gleitman, 1981). In a simulated domain, Floreano (1993) demonstrates that evolved ants use dispersion consistently.

The complement of dispersion, aggregation, is found in species ranging from slime molds (Kessin & Campagne, 1992) to social animals (McFarland, 1987). Aggregation is used for increased protection, resource pooling, and sharing the bases of social interaction and culture. The combination of dispersion and aggregation is an effective tool for density regulation, a basis for a variety of social behaviors. For instance, army ants regulate the temperature of their bivouac by aggregating and dispersing according to the local temperature gradient (Franks, 1989).

Homing is a basis of navigation and is manifested by all mobile species. Extensive biological data on pigeons, bees, rats, ants, salmon, and many others can be found in Gould (1987), Schone (1984), Waterman (1989), Foster, Castro, and McNaughton (1989), and Matarić (1990).

In addition to the described behavior set, various other frequently occurring group behaviors exist, such as flocking, surrounding, and herding, related to prey capture and migration (McFarland, 1987). In a later section, we describe how these and many other behaviors can be generated from combinations within the basis set.

Experimental Environments and Procedure

To isolate the specific dynamics of the test environment from the resulting behavior of the system, two different experimental environments were used, an interaction modeler and a collection of physical robots. The results from the two were compared, and only the behaviors that met the described criteria in both domains were considered.

The Interaction Modeler (IM) is a simulator that allows for modeling a simplified version of the physics of the world and the agent sensors and dynamics. The main purpose of the IM was to observe and compare phenomena to those obtained on physical robots, to test vastly larger numbers of agents than were physically available, and to vary parameter values more easily.

Most of the data presented in this article come from the robots, a collection of 20 physically identical vehicles dubbed "The Nerd Herd" (Fig. 1). The robots are run fully autonomously, with all of the processing and power on board. The control systems are programmed in the Behavior Language, a parallel programming language based on the Subsumption Architecture (Brooks, 1986, 1990). Each robot is 12 inches long and is equipped with four wheels, piezoelectric bump sensors around the body, and a two-pronged gripper for carrying pucks. The gripper contains contact switches at each tip and six infrared (IR) sensors: two pointing forward for detecting objects, two on the inside for detecting "grabbed" pucks, and two pointing down for aligning.

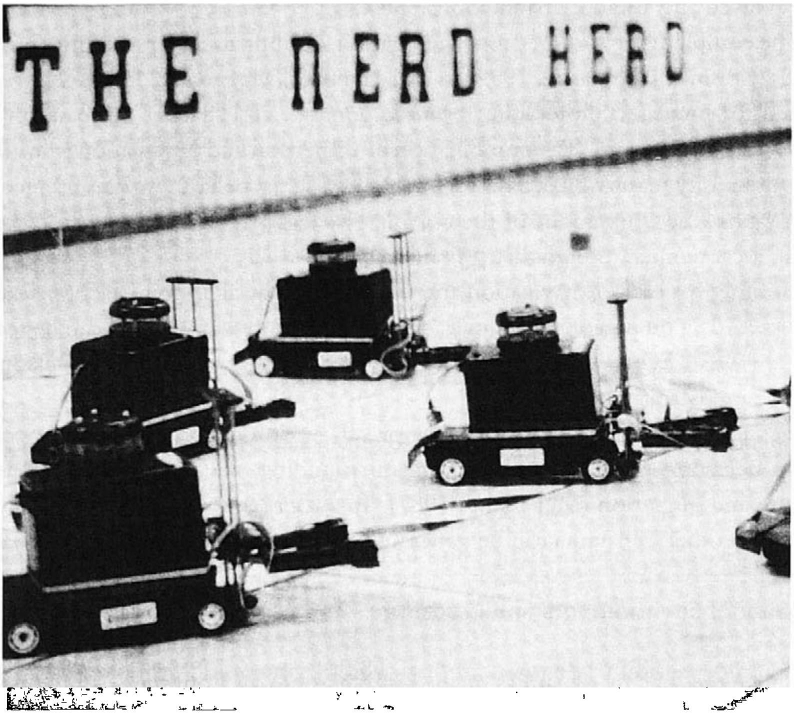


Figure 1
Some of the 20 mobile robots used to validate the group behavior methodologies we describe. These robots demonstrated group safe-wandering, following, aggregation, dispersion, flocking, and foraging.

The robots also are equipped with a radio system used for localization (based on triangulation with data from two fixed base stations), communication (at a rate of approximately one byte per robot per second), and data gathering. Communication is used to compensate for limited sensing. In particular, radios are used to distinguish robots from other objects in the environment, an ability that cannot be implemented with the on-board IR sensors.

Working with physical hardware requires dealing with control uncertainty and sensor and effector variability, which is reflected in the group behavior: Even when programmed with identical software, the robots behave differently owing to their varied sensory and actuator properties, and variability between individuals becomes amplified as many robots interact over extended periods. As in nature, this variability creates a demand for more robust and adaptive behavior and provides stringent tests for our proposed basis sets.

We tested all behaviors in both experimental domains and in at least 20 trials. Some of the experiments were conducted with random initial conditions (i.e., random robot positions), whereas in others identical initial positions were used to measure the repeatability of the behaviors. Modeler data were gathered by recording relevant state (such as position, orientation, and gripper state) over time. The same data were gathered in robot experiments by using the radio system. For each robot experiment, the robots' identification numbers, initial positions, and movement histories were recorded from the radio data, as well as on videotape, for validation and cross-referencing. Different strategies for the same group behaviors were tested and compared across the two experimental domains (Matarić, 1994a).

The robot data are plotted with the Real-Time Viewer (RTV),[1] a special-purpose software package that uses the radio data to perform real-time display, as well as replay, of the robots' positions, their movement trails, the positions of the previously manipulated pucks, and the home region. In RTV plots, the robots are shown as black rectangles, with white arrows indicating the front and identification numbers in the back. In some experiments, robot state also is indicated with a symbol or a bounding box. The size of the rectangles representing the robots is scaled to maintain the correct robot-environment ratio of the surface area, in order to demonstrate the relative proximity of all active robots. The bottom of each plot shows which of the 20 robots are being run. The corner display shows elapsed time, in seconds, for each snapshot of the experiment.

Basis Behavior Algorithms

In this section, we present the algorithms used to implement each of the proposed basis behaviors in the IM and on the robots. The algorithms are given in algorithmic pseudocode. Their formal definitions can be found in Matarić (1994a).

4.1 Safe-wandering

```
Safe-Wander:

Avoid-Kin:
Whenever an agent is within d_avoid
   If the nearest agent is on the left, turn right.
      otherwise turn left.
```

1 RTV was implemented by Matthew Marjanović of the MIT Artificial Intelligence Laboratory.

```
Avoid-Everything-Else:
Whenever an obstacle is within d_avoid
   If an obstacle is on the right only, turn left.

   If an obstacle is on the left only, turn right.
   After 3 consecutive identical turns, backup and
   turn.

   If an obstacle is on both sides, stop and wait.
   If an obstacle persists on both sides,
      turn randomly and back up.

Move-Around:
Otherwise move forward by d_forward, turn randomly.
```

Inspired by animal navigation routines (Wehner, 1987), we implemented safe-wandering as a combination of two drives: one that prevents the agent from colliding with obstacles and another that keeps it moving. The avoidance component consisted of two complementary behaviors, one for avoiding kin and another for avoiding everything else. The `Avoid-Kin` behavior takes advantage of group homogeneity; because all agents execute the same strategy, the algorithm can take advantage of the resulting spatial symmetry. If an agent fails to recognize another with its other-agent sensors (radios), it subsequently will detect it with its collision-avoidance sensors (IR) and treat it as a generic obstacle, using the `Avoid-Everything-Else` behavior. We experimented with variations of this avoidance algorithm and found no significant performance differences. The strategy for safe-wandering is the combination of the two avoidance strategies, with a default drive for moving and occasional random turns.

4.2 Following

```
Follow:
Whenever an agent is within d_follow
   If an agent is on the right only, turn right.
   If an agent is on the left only, turn left.
```

Following is achieved with a simple rule that steers the follower to the position of the leader and can be implemented as a complement of the `Avoid-Everything-Else` behavior, as illustrated with three robots in Figure 2.

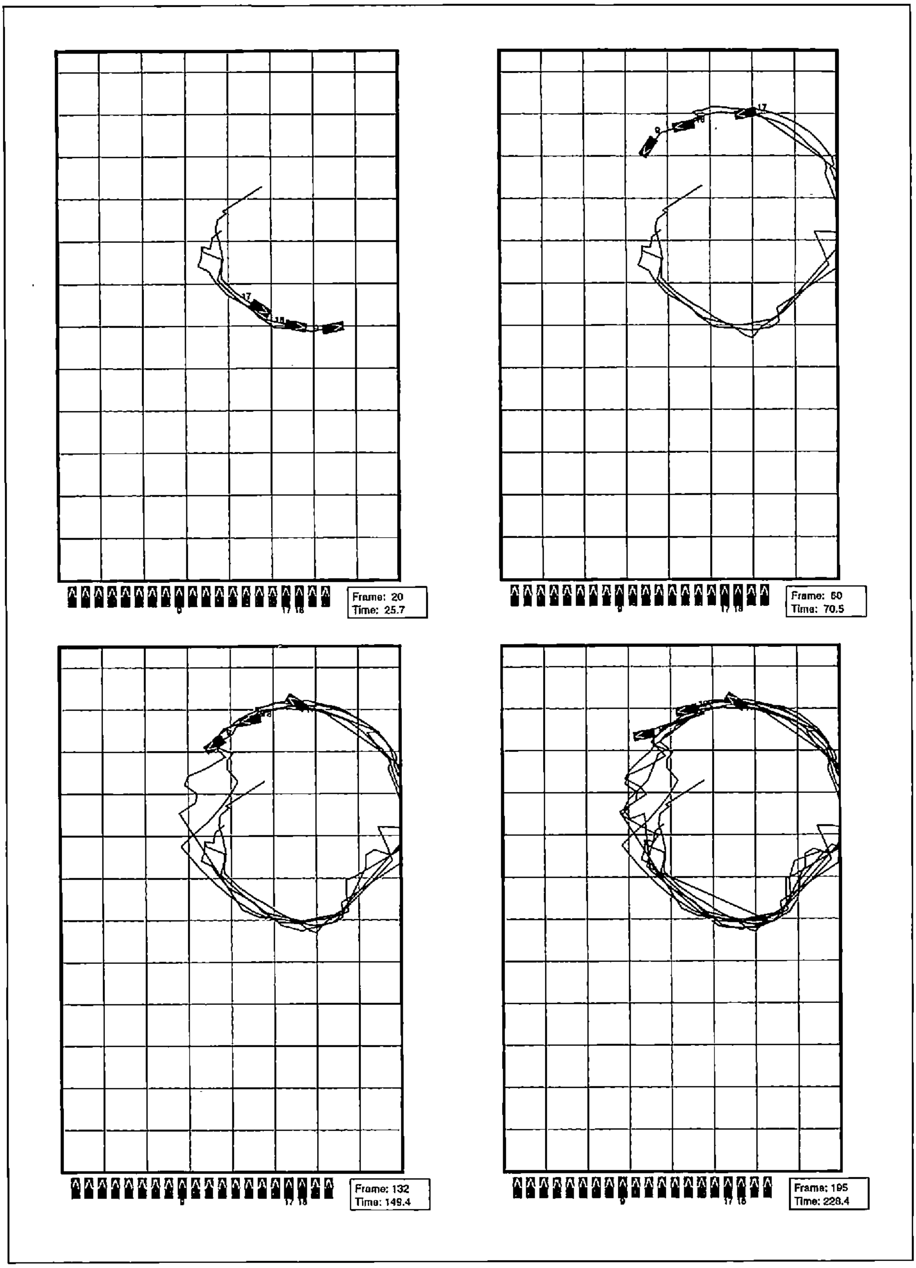


Figure 2
Continuous following behavior of three robots over 4.8 minutes. In the initial conditions, the wheels of the front robot are turned sideways, resulting in a circular trajectory. The robots reliably maintain a stable queue despite individual variations in control.

Our approach models tropotaxic behavior in insects, in which movement is based on the stimulus gradient across two (or more) sensors (McFarland, 1987). Ant osmotropotaxis is based on the differential in pheromone intensity perceived by the left and right antennae (Calenbuhr & Deneubourg, 1991), whereas the agents described here use the binary state of the two IR sensors on the gripper.

Under conditions of sufficient density, safe-wandering and following can produce more complex global behaviors. For instance, osmotropotaxic behavior of ants exhibits emergence of unidirectional lanes (i.e., regions in which all ants move in the same direction). The same lane-forming effect could be demonstrated with robots executing following and safe-wandering behaviors. However, more complex sensors must be used to determine which direction to follow. Using only IR sensors, the agents cannot distinguish between other agents heading toward and away from them and thus are unable to select whom to follow.

4.3 Dispersion

```
Disperse:
Whenever one or more agents are within d_disperse
    move away from Centroid_disperse.
```

A robust dispersion behavior can be designed as an extension of the existing safe-wandering. While avoidance in safe-wandering reacts to the presence of a single agent, dispersion uses the local distribution of all the nearby agents (i.e., the locations of other agents within the range of the robot's sensors) to decide in which direction to move. The algorithm computes the local centroid to determine the density distribution of nearby agents and moves away from the area of highest density. As illustrated in Figure 3, initially crowded in one part of the available free space, the agents apply the dispersion rule to establish `d_disperse` or the maximum available interagent distance.

Under conditions of high density, the system can be slow in achieving a dispersed state, as local interactions propagate far and the motion of an individual can disturb the state of many others. Thus, dispersion is best viewed as an ongoing process that maintains a desired distance between the agents while they are performing other tasks.

4.4 Aggregation

```
Aggregate:
Whenever nearest agent is outside d_aggregate
   turn toward the local Centroid_aggregate, go.
Otherwise, stop.
```

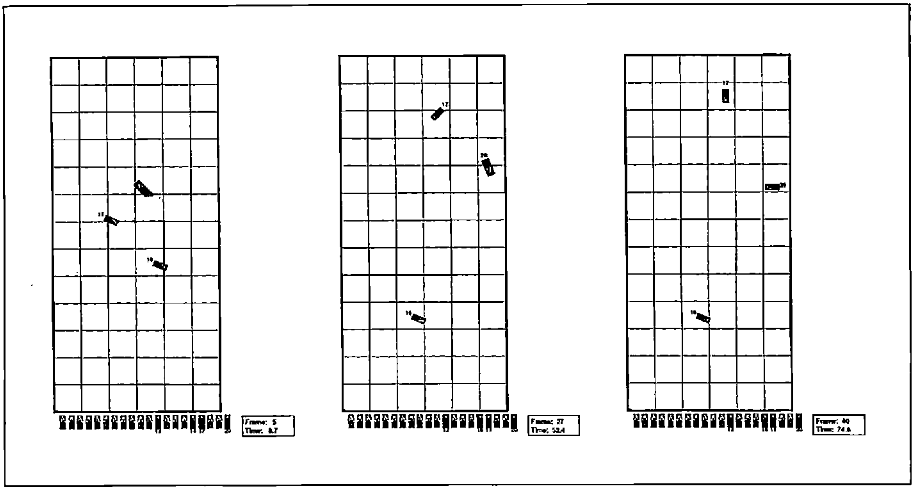


Figure 3
Dispersion with three robots, initiated close to one another. The robots found a static dispersed equilibrium state after 74 seconds.

Aggregation is the inverse of dispersion. We used the centroid operator with a maximum instead of a minimum distance and evaluated the performance using the same criteria used for dispersion.

4.5 Homing

The simplest homing strategy, observable across species, is greedy local pursuit. Figure 4 illustrates homing by five robots using this strategy. The data illustrate that the actual trajectories are far from optimal, due to mechanical and sensory limitations, in particular the error in sensed position. The same algorithm, when tested on the IM, produces more direct homing trajectories.

```
Home:
Whenever at home
  stop.
  otherwise turn toward home, go.
```

Owing to interference, homing became increasingly inefficient as the group size grew in our experiments. The data clearly indicated the need for some form of coordinated group navigation, such as flocking, which will be introduced later.

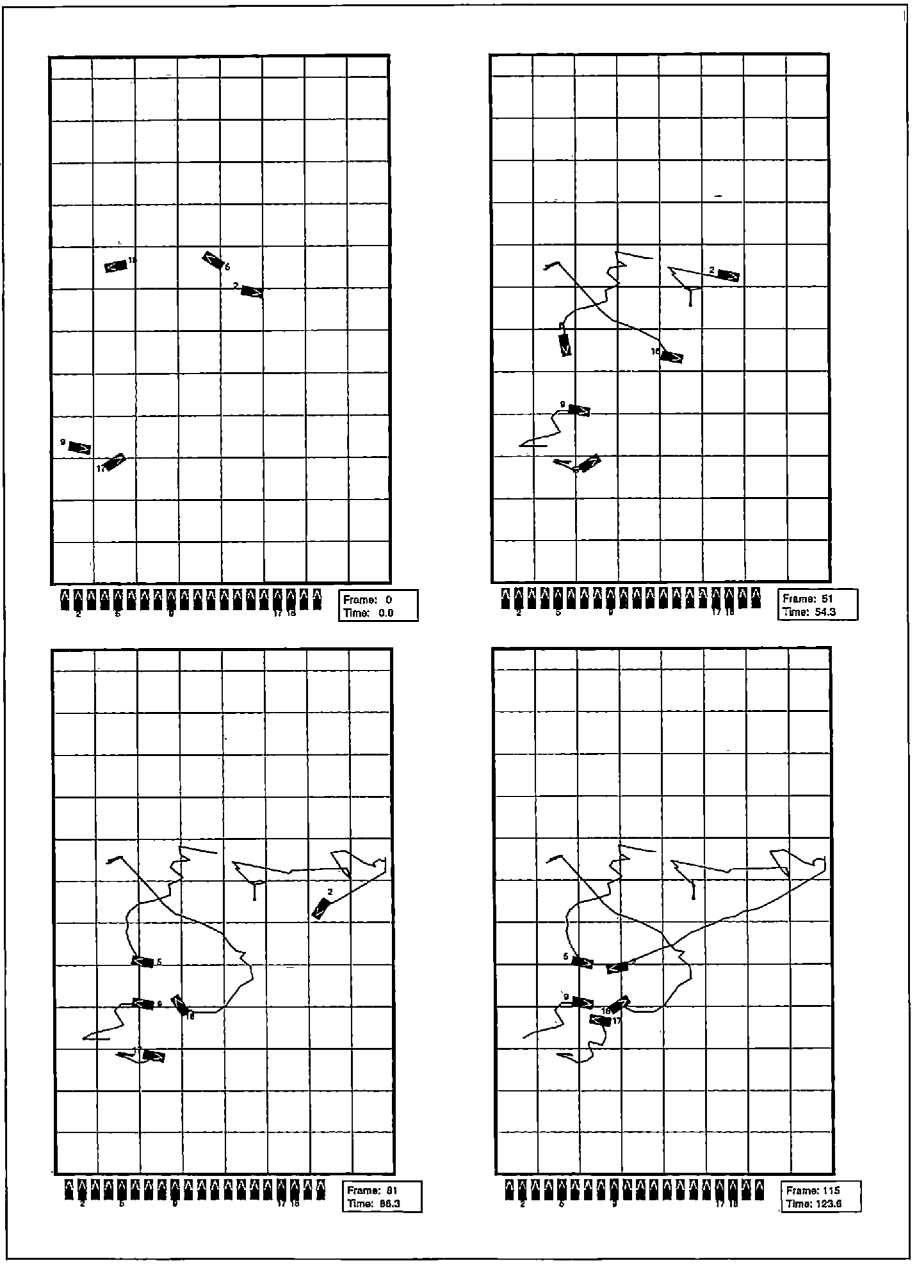


Figure 4
Homing behavior of five robots. Started in an arbitrary initial configuration, four of the robots reached the home region within 100 seconds, and the fifth joined them 30 seconds later. The trails reflect errors in position sensing, as well as interference between the robots as they approach the home region.

ehavior of Heterogeneous Groups

In addition to evaluating all the basis behaviors according to the prespecified criteria (see Matarić, 1994a, for details), we also compared two of the previously described distributed algorithms with heterogeneous, hierarchical alternatives. The two behaviors, aggregation and dispersion, were chosen because they can be stated in terms of achievement goals and, given sufficient space, can reach a static state. The algorithms were evaluated based on the number of steps required to reach that state.

We loosely modeled a society with an established pecking order (Chase, Bartolomeo, and Dugatkin, in press; Chase, 1982, 1993; Chase and Rohwer, 1987) by implementing a hierarchy based on randomly assigned unique identification numbers. Whereas in homogeneous algorithms all agents moved simultaneously according to identical local rules, in the hierarchical cases the agents with the locally higher identification numbers moved while others waited for their turn. In all cases, a simple precedence order of movement emerged.

The experiments were conducted in the IM, performing 20 trials with each group size (3, 5, 10, 15, and 20 agents) and each of the algorithms. Additionally, the algorithms were tested on two different degrees of task difficulty. Aggregation was tested on two terminating conditions: a single aggregate containing all of the agents, and a small number of stable aggregates. The former terminating condition is more difficult. Similarly, dispersion was tested on two initial conditions: a random distribution of initial positions, and a packed distribution in which all the agents start out in one half of the available space. The latter condition is more difficult.

We found that, in the case of aggregation, hierarchical strategies performed somewhat better than our homogeneous approaches. Figure 5 plots the average number of moves an agent takes in the aggregation task against the different group sizes and the two different terminating conditions: a single aggregate and a few stable groups. Both hierarchical and homogeneous algorithms behaved as expected, performing better on the simpler of the two terminating conditions. Their performance declined consistently with the growing group size.

Unlike aggregation, in the case of dispersion, homogeneous strategies outperformed hierarchical ones. Figure 6 plots the average number of moves an agent makes in the dispersion task for the different group sizes on two different initial conditions: a random distribution and a packed initial state. Again, both hierarchical and homogeneous algorithms improved with the easier initial conditions. We got consistent results with multiple types of dispersion and aggregation algorithms using such hierarchies.

Although the performance difference between the homogeneous and hierarchical algorithms was repeatable and consistent, it was small, and its magnitude barely

Figure 5
The performance of two different aggregation algorithms based on the number of steps required to reach static aggregated state. Two termination conditions were tested: a single group (data points shown with boxes) and a few stable groups (data points shown with dots). Hierarchical algorithm performance is interpolated with solid lines; homogeneous algorithm performance is interpolated with dots.

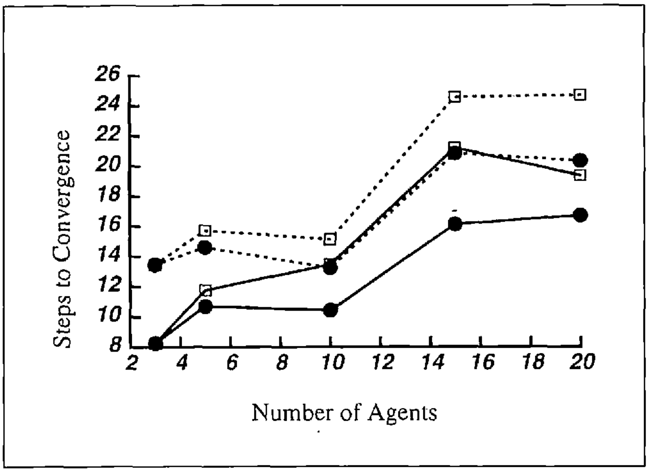
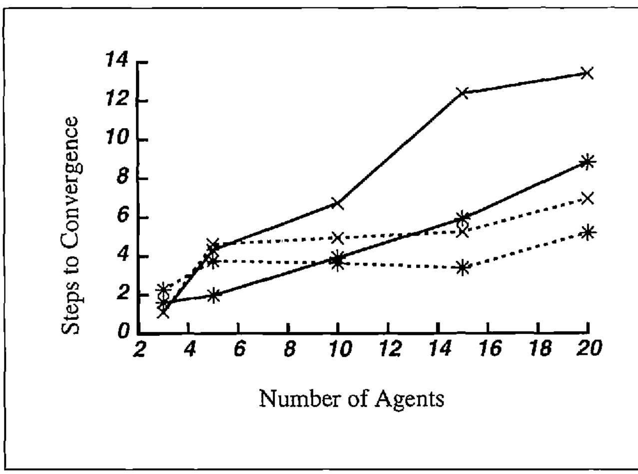


Figure 6
The performance of two different dispersion algorithms based on the number of steps required to reach static dispersed state. Two initial states were tested: a random distribution (data points shown with stars) and a packed distribution (data points shown with crosses). Hierarchical algorithm performance is interpolated with solid lines; homogeneous algorithm performance is interpolated with dots.



surpassed the standard deviation among individual trials for each of the algorithms and group sizes. The standard deviation was particularly significant in the case of small group sizes (three and five agents). Thus, no statistically significant difference was found in global performance of hierarchical and homogeneous algorithms for aggregation and dispersion. Furthermore, the slight differences that were detected between the two strategies would most likely be negligible on physical agents, owing to sensor uncertainty and effector errors.

We believe that the similarity in performance between the homogeneous and simple heterogeneous algorithms is caused by the following:

- *Functionally homogeneous agents*: Despite the linear priority ordering, the agents are fundamentally homogeneous as they are functionally indistinguishable. Thus, the hierarchical relationships between agents are spatially and temporally independent, because the agents keep no history of their past encounters with one another.
- *Simplicity of behavior*: Because all agent interactions are spatially and temporally local, the identification-based agent heterogeneity has no time-extended consequences. We hypothesize that more abstract interactions, involving strategies that keep history, would show significantly different results.
- *Large group sizes*: In sufficiently large groups of functionally identical agents, temporary effects are averaged out as fluctuations and noise. This property is crucial for producing reliable global behavior in the presence of local perturbations and is observable in the shown data: The general trends in global performance are consistent, even though the standard deviation among trials is fairly large.

The experiments comparing simple hierarchical and homogeneous algorithms demonstrate that, in the described domain, simple hierarchical strategies do not affect the global performance because their impact on the global behavior is negligible. More complex hierarchical strategies could be devised to ensure their influence on the global behavior but would require an increased perceptual and cognitive overhead, such as keeping a history of past encounters and models of previously encountered agents. These data permit us to hypothesize the following: For simple spatial domains, simple homogeneous solutions can work well, and more complex strategies requiring individual agents to perform recognition, classification, and representation might be required to improve group performance significantly. These more complex strategies are found commonly in nature, where societies across species establish and maintain dynamically changing pecking orders whose exact purpose is not yet known (Chase et al., in press; Chase, 1993).

omposing Higher-Level Behaviors

Basis behaviors serve as a substrate for a variety of more complex interactions. We developed an architecture for combining basis behaviors that allows for generating an unbounded number of higher-level behaviors by using two types of combinations. As with complementary and contradictory drives, our architecture allows for complementary behaviors, whose outputs are executed concurrently, and for contradictory

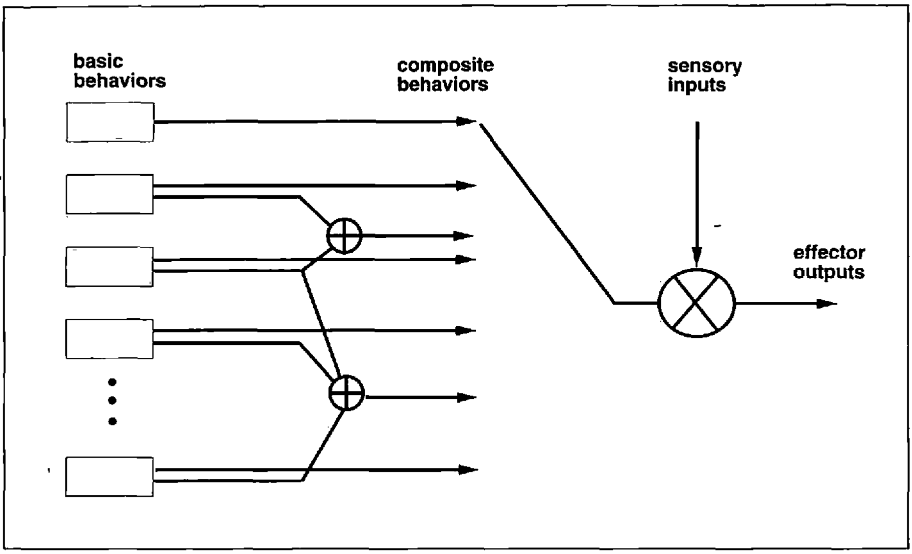


Figure 7
The control architecture for generating group behaviors consists of complementary and contradictory combinations of subsets from a fixed basis behavior set. Complementary combinations are marked with ⊕, contradictory combinations with ⊗.

behaviors, whose outputs are mutually exclusive and can be executed only one at a time. The two types of combination operators, applied to the fixed set of basis behaviors, can generate an unbounded repertoire of collective behaviors (Fig. 7).

6.1 Combining complementary basis behaviors

In the spatial domain, the outputs of all basis behaviors are in the form of direction and velocity vectors, so appropriately weighted sums of such vectors directly produce coherent higher-level behaviors. To illustrate this method, we implemented a *flocking* behavior by combining the outputs of safe-wandering, aggregation, dispersion, and homing, such that the specified constraints are satisfied, as shown in Figure 8. Intuitively, aggregation keeps the robots from getting too far from one another, dispersion keeps them from getting too close, homing moves the flock toward some goal, and safe-wandering prevents collisions for each agent individually (and thus the flock as a whole).

The choice of weights on the behavior outputs depends on the dynamics and mechanics of the agents and the ranges of their sensors. In our experiments, the weights were derived empirically. The conditions for triggering the constituent basis behaviors can overlap or be mutually exclusive. The latter was the case in flocking, where the constituent basis behaviors were complementary (i.e., their conditions

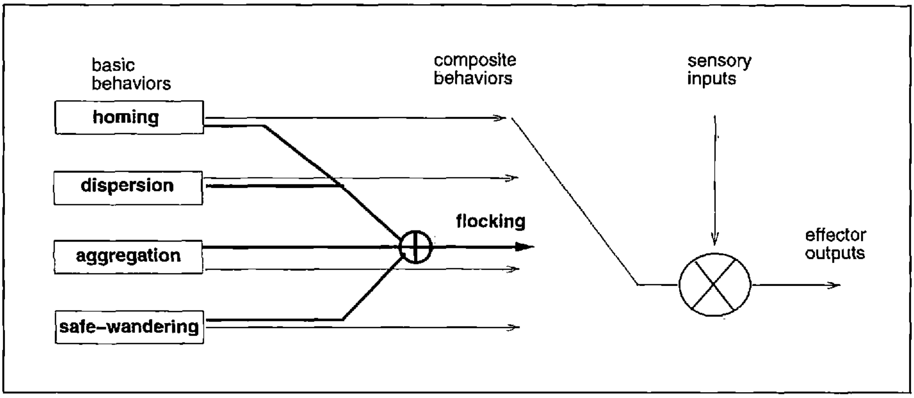


Figure 8
The implementation of flocking as a combination of safe-wandering, dispersion, aggregation, and homing. The first three behaviors produce robust flocking; homing gives the flock a goal location and direction in which to move.

did not interfere):

```
d_avoid < d_disperse < d_aggregate
```

Aggregation contained a special condition: The robots at the front slowed down but did not turn around, thus preventing the flock from collapsing inward. This allowed for adding homing with very simple triggering conditions: Whenever a robot had no others in the front, it moved in the direction of home. Consequently, the robots that happened to be at the front of the flock "pulled along" the rest. If any of them moved incorrectly, failed, or were removed,[2] others would take over and "lead" the flock. Consequently, flocking was very robust and did not degrade with decreased group sizes (Matarić, 1994a).

The described basis behavior set allows for generating many other composite behaviors, including *surrounding*, from a combination of aggregation and following, and *herding*, from a combination of surrounding and flocking, as shown in Figure 9. Because behavior combinations are based on continuous function (weighted sums) of the input parameters, the same behaviors can be used in multiple combinations. As an alternative to designing the conditions by hand, we also have explored methods for generating them automatically through reinforcement learning (Matarić, 1994c).

6.2 Combining contradictory basis behaviors

Temporal sequences of basis behaviors allow for producing higher-level collective behaviors whose subcomponents are mutually exclusive and are triggered by different

2 All the cases were tested.

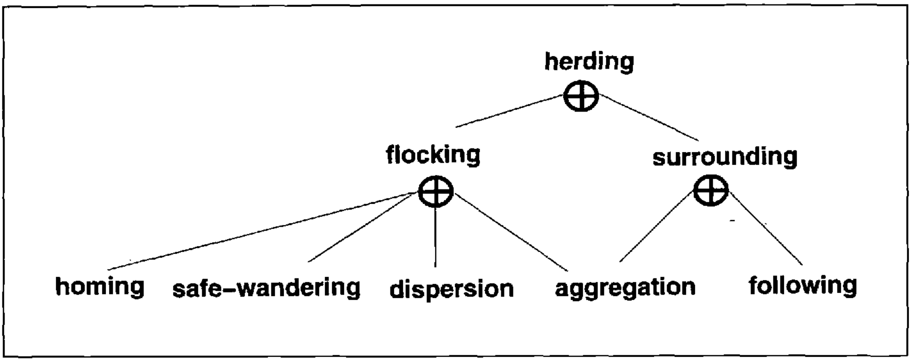


Figure 9
An example of complementary basis behavior combinations within a higher-level task.

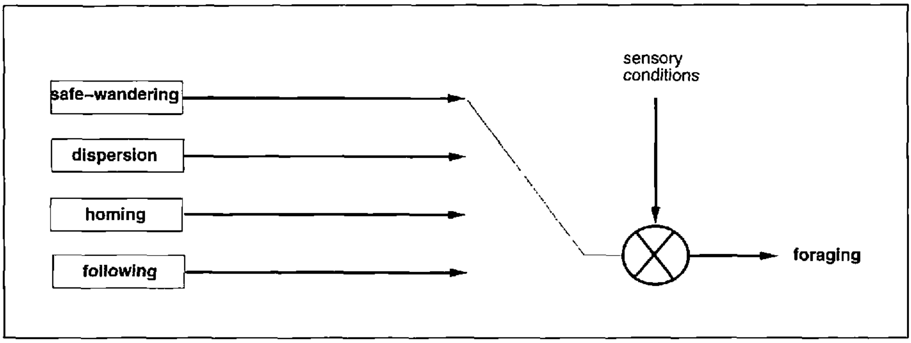


Figure 10
The implementation of foraging using a combination of safe-wandering, dispersion, homing, and following. Each triggered by different sensory conditions, the behaviors collectively result in foraging.

sensory and internal conditions. We used this method to implement *foraging*, the prototypical and ubiquitous gathering-hoarding behavior (Fig. 10).

Foraging demonstrates how mutually exclusive basis behaviors can be combined into a higher-level compound behavior. The combination is simple in that conflicts between two or more interacting agents, each potentially executing a different behavior, are resolved uniformly owing to agent homogeneity. Because all agents share the same goal structure, they will all respond consistently to environmental conditions. For example, if a group of agents is following toward home and encounters a few agents (another group) dispersing, the difference in the agents' external state will either induce all the agents to follow toward home, if they are of the same kind, or will result in the groups' avoidance of each other, thus dividing them again.

Foraging is just one example of a variety of spatial and object manipulation tasks observed in nature that can be implemented with the described architecture and the given basis behaviors. Other such behaviors include sorting objects, building structures, surveying, and mapping.

Compound Behavior Algorithms

The algorithms for two compound behaviors, flocking and foraging; are described here, with some examples of the data.

7.1 Flocking

```
Flock:
Sum outputs from Safe--Wander, Disperse, Aggregate,
and Home.
```

As described earlier, flocking is a ubiquitous form of structured group movement that minimizes interference, protects individuals, and enables efficient information exchange. We implemented flocking with the simple algorithm shown here. The weights on the behavior outputs were determined experimentally, from the dynamics and mechanics of the agents, the ranges of the sensors, the agents' turning radii, and their velocity. In the robot implementation, flocking consisted of a combination of safe-wandering and aggregation only, with an appropriate threshold.

Like following, flocking is a coordinated-motion behavior that is best evaluated by testing its duration, repeatability, and robustness. The performance of flocking depended on the size of the flock: Small flocks, consisting of four or fewer agents, were less stable, whereas larger flocks remained stable even if several agents failed owing to mechanical problems. Figure 11 demonstrates such a case, in which one of the agents' position sensors failed, causing it to diverge from the rest.

Typical flocking behavior is shown in Figure 12. Flocking was also tested in more challenging environments. For example, a barrier roughly the size of two robots was presented in front of the flock as the flock was moving. As expected, the flock split into two groups around the obstacle and rejoined on the other side.

Various forms of flocking, schooling, and herding are found in numerous species. Evolution has produced remarkably similar behaviors in vastly different domains for creatures moving collectively on the ground, in the air, or under water. Our implementation of flocking, generated from the basis behaviors, is similarly generic and domain-independent. The idea that flocking can be generated by simple rules has been popular among many researchers. For example, DeShutter and Nuyts (1993) and Goss, Deneubourg, Beckers, and Henrotte (1993) show a similar approach by demonstrating how simple rules can result in gull flock formation in simulation. Even more directly, Reynolds (1987) presents an elegant graphical simulation of bird

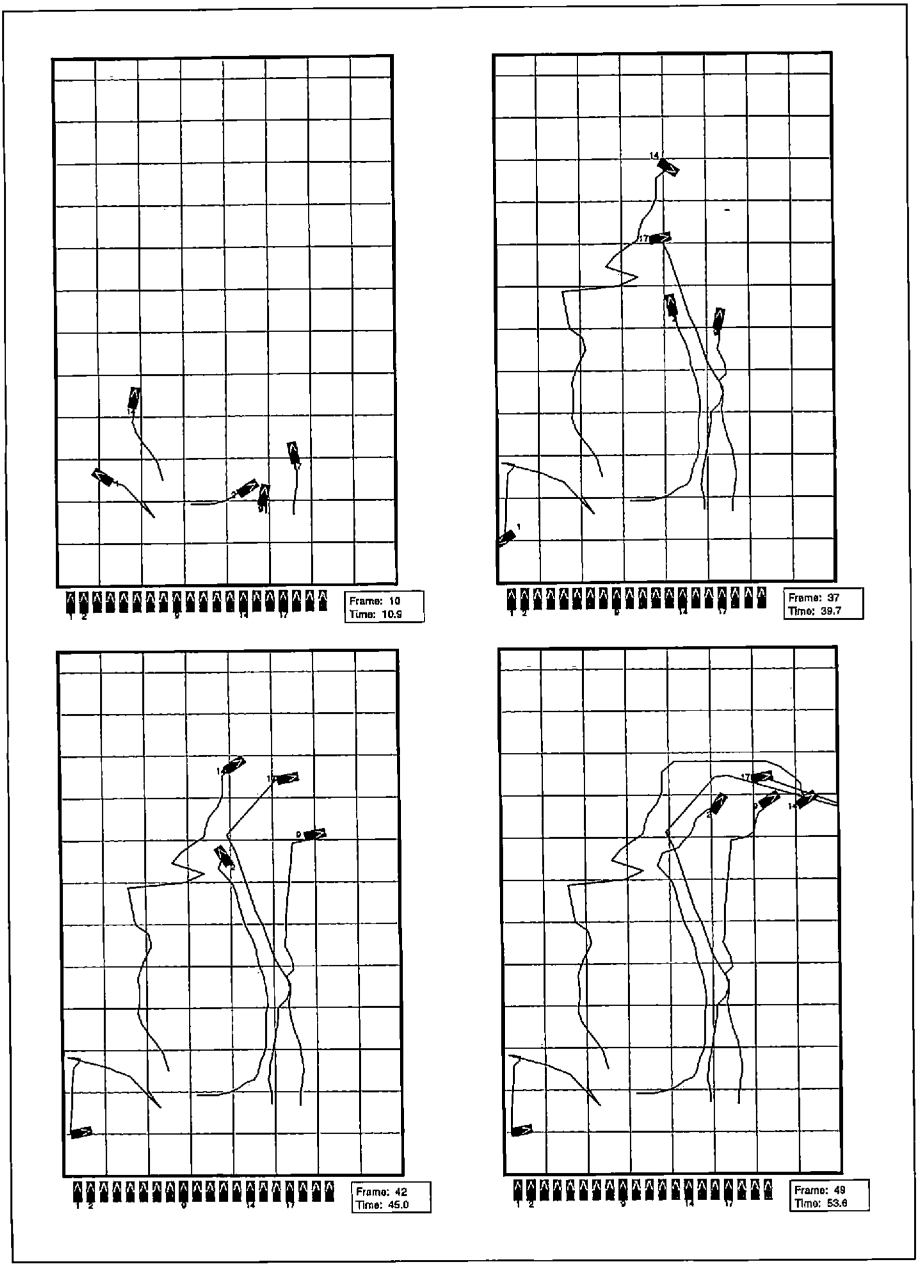


Figure 11
Flocking behavior of five robots. One of the robots separates, without affecting the behavior of the others. Owing to a failure of the position sensors, the robot falls behind the group. The rest of the robots reorganize and maintain the global structure.

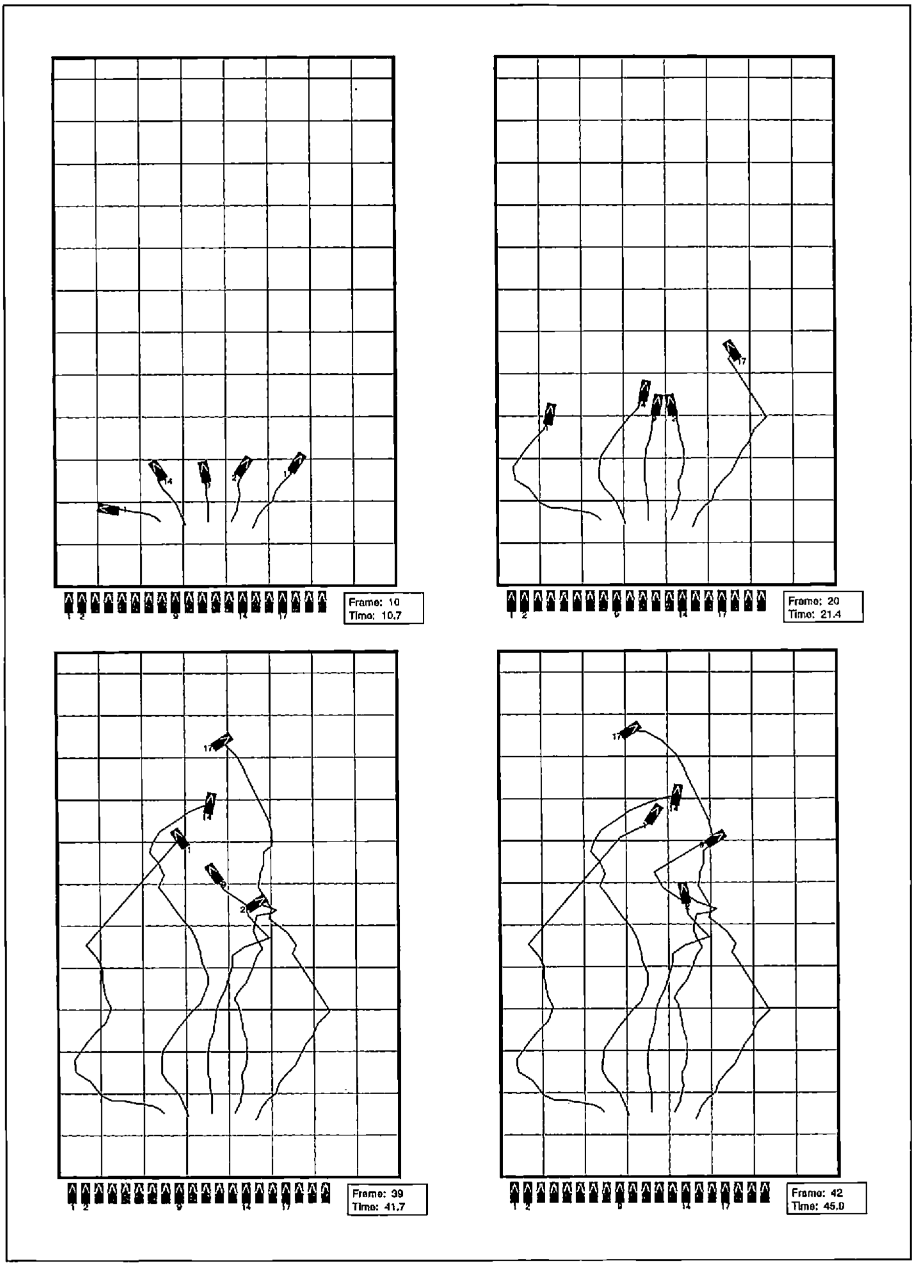


Figure 12
Flocking behavior of the same five robots as in Figure 11 in another trial. The robots maintain a coherent flock, despite the often large position errors sensed by individuals. These errors are manifested in the variability in the spacing between the robots as the flock moves.

flocking. The robot implementation required more rules owing to the more complex dynamics.

7.2 Foraging

```
Forage:
Whenever crowded? disperse.
Whenever at-home
   If have-puck, drop-puck.
   Otherwise disperse.
Whenever sense-puck
   If not have-puck, pickup-puck.
Whenever behind-kin, follow.
```

In foraging, the high-level achievement goal of the group is to collect objects from the environment and deliver them home. In our scenario, in addition to the basis behavior repertoire, individual agents also are equipped with the facilities for picking up and dropping pucks. Foraging uses a restricted notion of kinship defined by the agents' puck state: Any two robots without pucks are "kin," as are any two that are carrying pucks. Because, unlike animals, the robots cannot directly sense one another's external state, the robots used radios to broadcast their puck state within a limited radius.

Floreano (1993) shows that evolved systems of ants favor dispersion as the first step in foraging. Similarly, in our system foraging is initiated by dispersion, then safe-wandering. Finding an object triggers homing. Encountering another agent with a different immediate goal, as manifested by its puck state, induces avoiding. Conversely, encountering kin triggers flocking. Reaching home and depositing the object triggers dispersion if multiple robots are at home or safe-wandering if the robot is alone. The shown pseudocode algorithm demonstrates the precedence hierarchy of the different relevant conditions and their associated behaviors.

Figure 13 demonstrates typical robot performance by showing snapshots at different stages during the foraging process. Most foraging runs were terminated after 15 minutes, at which time approximately two-thirds of the pucks were collected. The long duration of the runs was largely due to the inefficient search strategy: The robots did not remember where the pucks were. An improved strategy, in which the robots stored the location of the pucks and returned to it repeatedly until all of the pucks were transported, was used as a part of the group learning algorithm we subsequently implemented (Matarić, 1994c).

Not taking advantage of exact puck location was at least partially justified because, over the course of an experimental run, the pucks outside the home region were

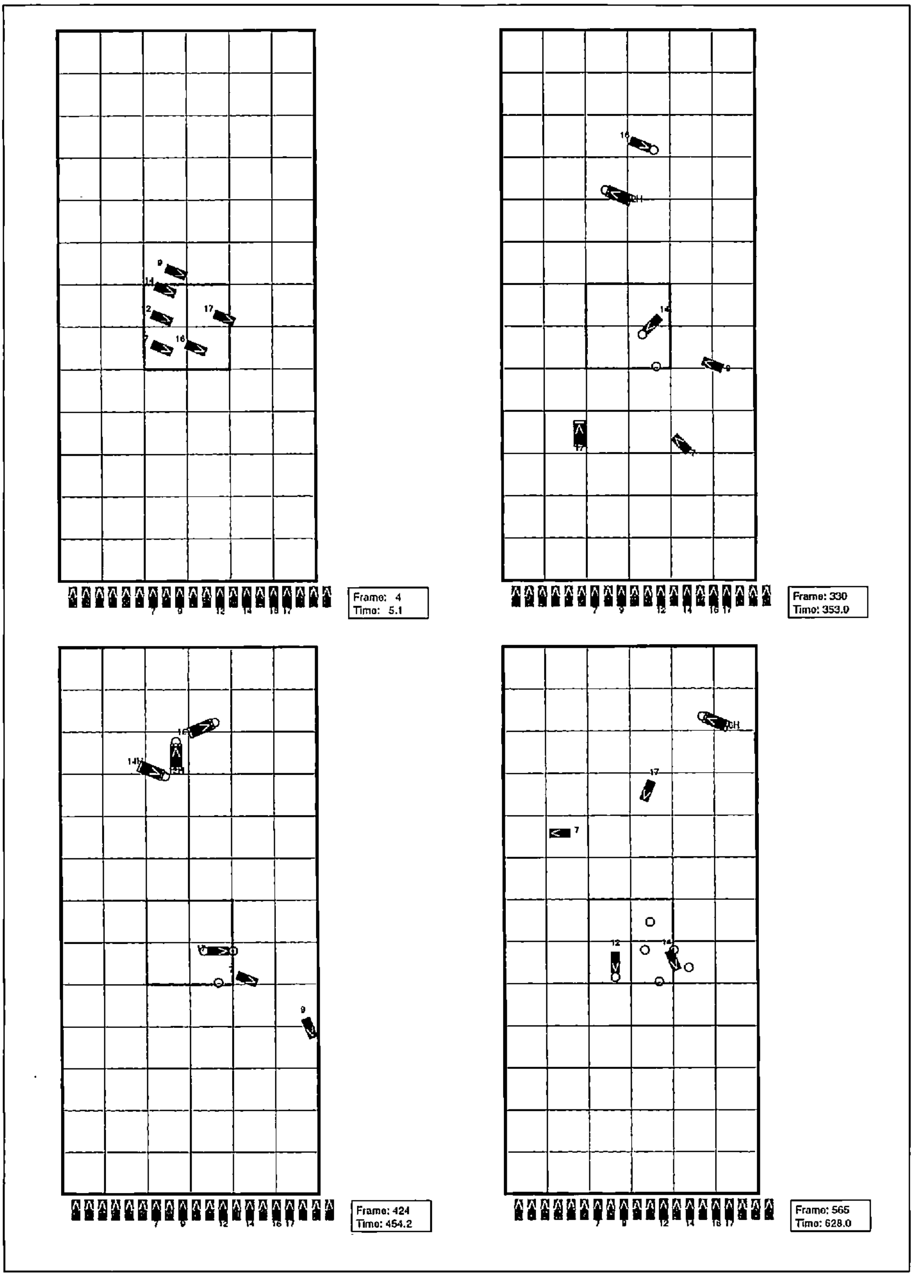


Figure 13
Foraging behavior of six robots. The robots are initiated in the home region. The pucks are clustered initially at the bottom center of the workspace. After dispersing, they safe-wander and search for pucks, pick them up, and take them home. If they encounter another robot with a puck while they are carrying one, they follow, as shown in the third frame of the data. After some time, the pucks accumulate in the home region.

pushed around and gradually dispersed over an expanding area. This, in turn, affected the global behavior of the system; the more dispersed the pucks became, the more likely the robots were to stumble onto one of them by random search.

In our system, foraging could be accomplished by a single agent, so the task itself does not require cooperation, and the goal of the collective solution is to accelerate convergence with the growing size of the group. Arkin, Balch, and Nitz (1993) describe simulation results of a similar task with varying amounts of agents and interagent communication. Complementary to our results, they find that performance improves with simple communication and with increased group size, up to a point. As shown here, in confined spaces, interference overwhelms the benefit of parallelism in large and thus higher-density groups. In our environment, the collective solution always outperformed a single agent but, as the group size grew, so did the role of interference-minimizing behaviors such as dispersion, following, and flocking.

Related Work

Group behavior has been studied by a variety of disciplines ranging from biology and ethology to sociology and artificial intelligence (AI). In its attempt to contribute to group behavior synthesis, our approach spans a number of disciplines, most notably AI, robotics, artificial life, and ethology.

Within classical AI, distributed AI (DAI) addresses group behavior but typically deals with highly cognitive agents that are very different from those we studied in that they are neither embodied nor situated in a simulated or natural physical world (for an overview, see Gasser & Huhns, 1989). Other branches of DAI deal with simpler distributed systems, focusing on the role of cooperation and competition in the multiagent environment (Huberman, 1990). In robotics, the last decade has witnessed a shift in the emphasis of research away from purely theoretical and simulated work toward physical implementations akin to ours. Most of the work in robotics is focused on control of a single agent, but several groups have obtained and experimented with multiple physical robots. For example, Fukuda, Nadagawa, Kawauchi, and Buss (1989) deal with coordinating multiple interlocking robotic units; Caloud, Choi, Latombe, LePape, and Yim (1990) and Noreils (1993) apply a planner-based controller to a pair of box-pushing robots in a master-slave configuration; Kube and Zhang (1992) work on simulations of simple behaviors that are being incrementally transferred to physical systems; Parker (1994) applies a behavior-based task-sharing architecture in a collection and box-pushing tasks with three wheeled and one legged robots; and Matarić, Nilsson, and Simsarian (1995) use the described basis behaviors in a box-pushing task with a pair of legged robots. Unlike our work, most of the multirobot research is not directly inspired by biology nor does it attempt to analyze natural behavior. Robotics work closest to ours in terms of overall philosophy as well as choice of behaviors and goals is that of Altenburg (1994) on a variant of foraging using a group of LEGO robots controlled in reactive, distributed style, and work by Beckers, Holland, and Deneubourg (1994) demonstrating clustering of initially randomly distributed pucks into a single cluster through purely stigmergic communication among four robots.

Simulations of group behavior in situated systems are becoming more common. A number of simulations of behavior-style controlled systems such as ours have been implemented, including those of Steels (1989), who describes simple agents using self-organization to perform a gathering task; Brooks, Maes, Matarić, and Moore (1990), who show a fully decentralized collection of noncommunicating collecting agents; and Arkin et al. (1993), who demonstrate a schema-based approach on a retrieval task. More complex simulations are being introduced, using realistic physical models of the agents, such as in the work of Hodgins and Brogan (1994), which describes herds of hopping robots.

Artificial life work most relevant to ours features simulations of colonies of antlike agents, as described by Corbara, Drogoul, Fresneau, and Lalande (1993); Colorni, Dorigo, and Maniezzo (1992); Drogoul, Ferber, Corbara, and Fresneau (1992); and many others. Similar to our approach, many such artificial life systems strive to exploit the dynamics of local interactions between agents and the world in order to create complex global behaviors.

Few projects directly bridge the gap between natural and artificial group behavior. Work with both physical and simulated ant colonies is an exception: Deneubourg, Goss, Pasteels, Fresneau, and Lachaud (1987); Deneubourg and Goss (1989); Deneubourg, Goss, Franks, Sendova-Franks, Detrain, and Chretien (1990); and others have examined the role of simple control rules and limited communication in producing trail formation and task sharing. Deneubourg, Theraulaz, and Beckers (1992) define some key terms in swarm intelligence and discuss issues of relating local and global behavior of a distributed system. More recently, this work is also being transferred successfully to physical robots.

Conclusions and Future Work

With the goal of contributing to more principled synthesis of group behavior by using inspiration and examples from biological systems, we have described basis behaviors as a method for structuring agent interactions. We demonstrated how these behaviors can be implemented on simulated agents and physical mobile robots. Our basis behavior set—consisting of avoidance, safe-wandering, aggregation, dispersion, following, and homing—is general and serves as an effective substrate for producing higher-level composite behaviors for achieving a variety of individual and collective goals including flocking and foraging.

It is unlikely that any particular basis set can be proven to be optimal for a complex domain. However, given the natural prevalence of the types of behaviors we implemented, we believe that the basis set we chose effectively utilizes the interaction dynamics and results in simple, robust, and general behaviors. We demonstrated the effectiveness of the behaviors in our basis set by showing necessity (they are not reducible to each other) and sufficiency (they can generate a large repertoire of more complex agent interactions).

For basis behaviors to be a truly effective substrate of adaptive behavior, they must serve as a substrate for efficient and general learning. We have evaluated the described basis behaviors in a series of subsequent experiments demonstrating a group of four mobile robots learning to forage (i.e., adaptively discovering an efficient foraging strategy comparable to the one described earlier). The robots were able to acquire foraging automatically within 15 minutes. Details of the experiments and results can be found in Matarić (1994a,c). We also tested the agents' ability to learn social rules such as yielding and communicating. The results of those experiments are described in Matarić (1994b).

Our continuing work is aimed at applying the basis behavior idea to more social and cooperative tasks with multiple agents, again tested in simulation and on physical robots. We currently are comparing homogeneous and heterogeneous groups in composite behaviors that involve sharing tasks and information. Furthermore, we are exploring the viability of using genetic programming (Koza, 1992) for automatic generation of basis behavior sets for specific domains.

Basis behaviors represent a level of description of individual and group behavior that is both general and parsimonious. They allow for principled and efficient synthesis of adaptive behaviors in complex group environments such as the one exemplified by the robot colony we used in our experiments. The approaches and results we demonstrated are meant as stepping stones toward studying increasingly complex natural and artificial social agents.

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