

Designing and Understanding Adaptive Group Behavior

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Abstract

This paper proposes the concept of *basis behaviors* as ubiquitous general building blocks for synthesizing artificial group behavior in multi-agent 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.

Running head: Group Behavior

1 Introduction and Motivation

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

The complexity of any society results from the local interactions among its members. Synthesizing and analyzing coherent collective behavior from individual interactions is one of great challenges in both ethology and artificial intelligence. In this work 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.

Inspired by behaviors ubiquitous in nature, we propose *basis behaviors* as building blocks of adaptive agent control, social interaction, and learning. Basis behaviors are meant as 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 empirically test 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 described 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 multi-agent 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* to be control laws that take advantage of the dynamics of the given system to effectively achieve and maintain its goals, and *basis behaviors* to be 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 in support of basis behaviors at a variety of levels. A particularly clean and compelling case can be found in motor control. Controlling a multi-joint manipulator such as a frog leg or a human arm is a complex task, especially if performed at a low level. Mussa-Ivaldi & 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 & Giszter (1991) and Bizzi & 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 work, 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. The next section describes the selection process.

2.1 Selecting Basis Behaviors

It is difficult to imagine any fixed metric for selecting an “optimal” set of behaviors, since the choice of the basis behavior set depends on the domain and goals it will be applied to. We make no attempt at devising optimality criteria or formal proofs of correctness. While 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 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 (Mataric 1994a).

To evaluate our selected behaviors, we applied the above criteria to implementations on physical robots interacting in the real world, with all of the present error, noise, and uncertainty. In order 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 spatio-temporal patterns of agent activity. Certain purely spatial fixed organizations of agents correspond to achievement goals, while many spatio-temporal 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, i.e. *safe-wandering*. Avoidance in groups can be achieved by *dispersion*, a behavior that reduces interference

Safe–Wandering	the ability of a group of agents to move about while avoiding collisions with obstacles and each other.
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 inter–agent distance.
Aggregation	the ability of a group of agents to gather in order to establish and maintain some maximum inter–agent distance.
Homing	the ability to find a particular region or location.

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.

locally. It can also 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, is also ubiquitous (McFarland 1985). Various forms of dispersion are observed in species ranging from simple insects to people (Waterman 1989). For example, DeShutter & Nuyts (1993) show elegant evidence of gulls aggregating by dynamically rearranging their positions in a field to maintain a fixed distance from each other. 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



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*.

(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), Muller & Wehner (1988), Waterman (1989), Foster, Castro & McNaughton (1989), and Mataric (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 will describe how these and many other behaviors can be generated from combinations within the basis set. We begin by describing our implementation and evaluation of the proposed behavior set.

3 Experimental Environments and Procedure

In order 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 above 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 Modeler 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 more easily vary parameter values.

The majority of the data presented in this paper comes from the robots, a collection of 20 physically identical vehicles dubbed “The Nerd Herd” (Figure 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, Brooks 1990). Each robot is 12 inches long, equipped with four wheels, piezo–electric bump sensors around the body, and a two–pronged gripper for carrying pucks. The gripper contains contact switches at each tip and six infra–red sensors: two pointing forward for detecting objects, two on the inside for detecting “grabbed” pucks, and two pointing down for aligning. The robots are also equipped with a radio system used for localization (based on triangulation with data from two fixed base stations), communication (at a rate of about 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 due to their varied sensory and actuator properties, and variability between individuals become 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), while in others identical initial positions were used in order 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’ IDs, initial positions, and movement histories were recorded from the radio data, as well as on video tape, for validation and cross referencing. Different strategies for the same group behaviors were tested and compared across the two experimental domains (Mataric 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 of the home region. In RTV plots, the robots are shown as black rectangles with white arrows indicating the front and ID numbers in the back. In some experiments, robot state is also 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 twenty robots are being run. The corner display shows elapsed time, in seconds, for each snapshot of the experiment.

¹RTV was implemented Matthew Marjanović.

4 Basis Behavior Algorithms

In this section we present the algorithms used to implement each of the proposed basis behaviors in the Interaction Modeler and on the robots. The algorithms are given in algorithmic pseudo code. Their formal definitions can be found in Mataric (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.
```

```
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; since 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 will subsequently 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.

Our approach models tropotactic 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 1992), while 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, osmotropotactic 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 in order to determine which direction to follow. If using only IRs, the agents cannot distinguish between other agents heading toward and away from them, and are thus 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 of the nearby agents (i.e., the locations of other agents within the range of the robot's sensors) in order 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 in order to establish `d_disperse` or the maximum available inter-agent distance.

Under conditions of high density, the system can be slow in achieving a dispersed state since local interactions propagate far and the motion of an individual can disturb the state

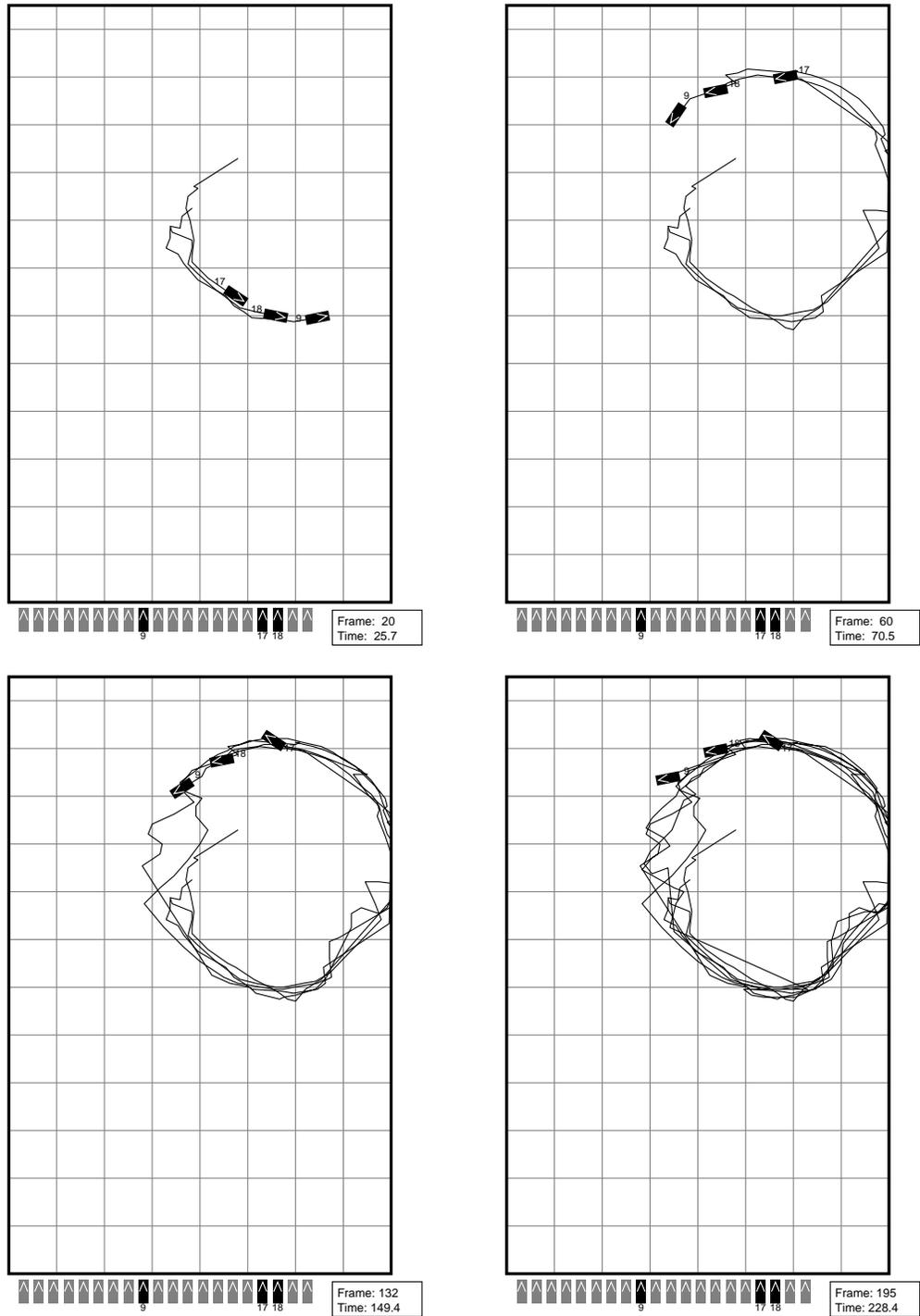


Figure 2: Continuous *following* behavior of 3 robots over 4.8 minutes. In the initial conditions, the wheels of the front robot are turned sideways, resulting in a circular trajectory. The robots reliably maintain a stable queue in spite of individual variations in control.

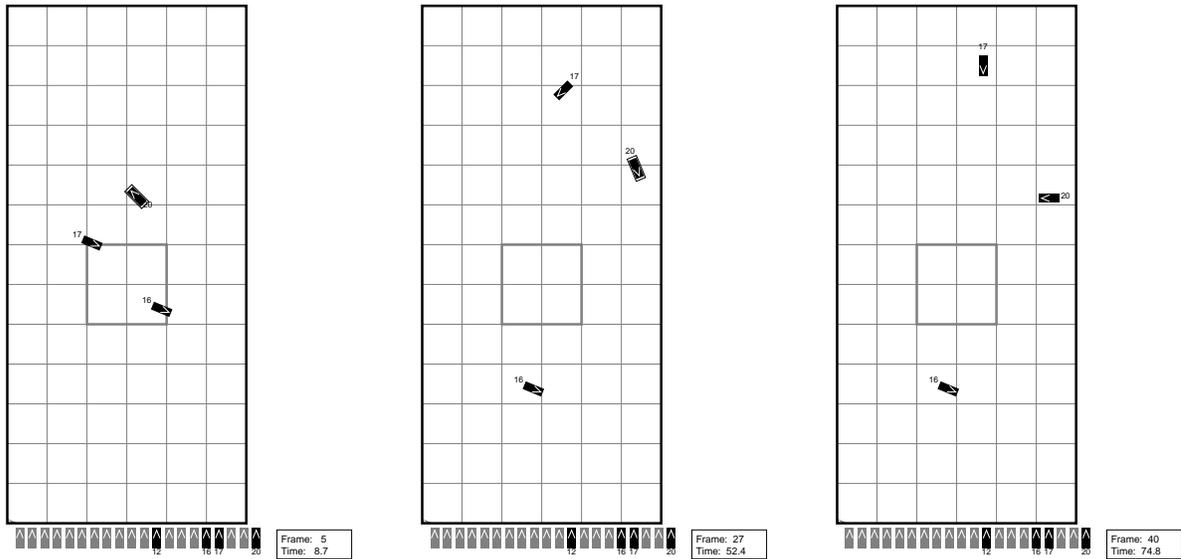


Figure 3: *Dispersion* with three robots, initiated close to each other. The robots found a static dispersed equilibrium state after 74 seconds.

of many others. Thus, *dispersion* is best viewed as an ongoing process which 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.
```

Aggregation is the inverse of *dispersion*. We used the centroid operator with a maximum instead of minimum distance, and evaluated the performance using the same criteria used in *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 Interaction Modeler, produces more direct homing trajectories.

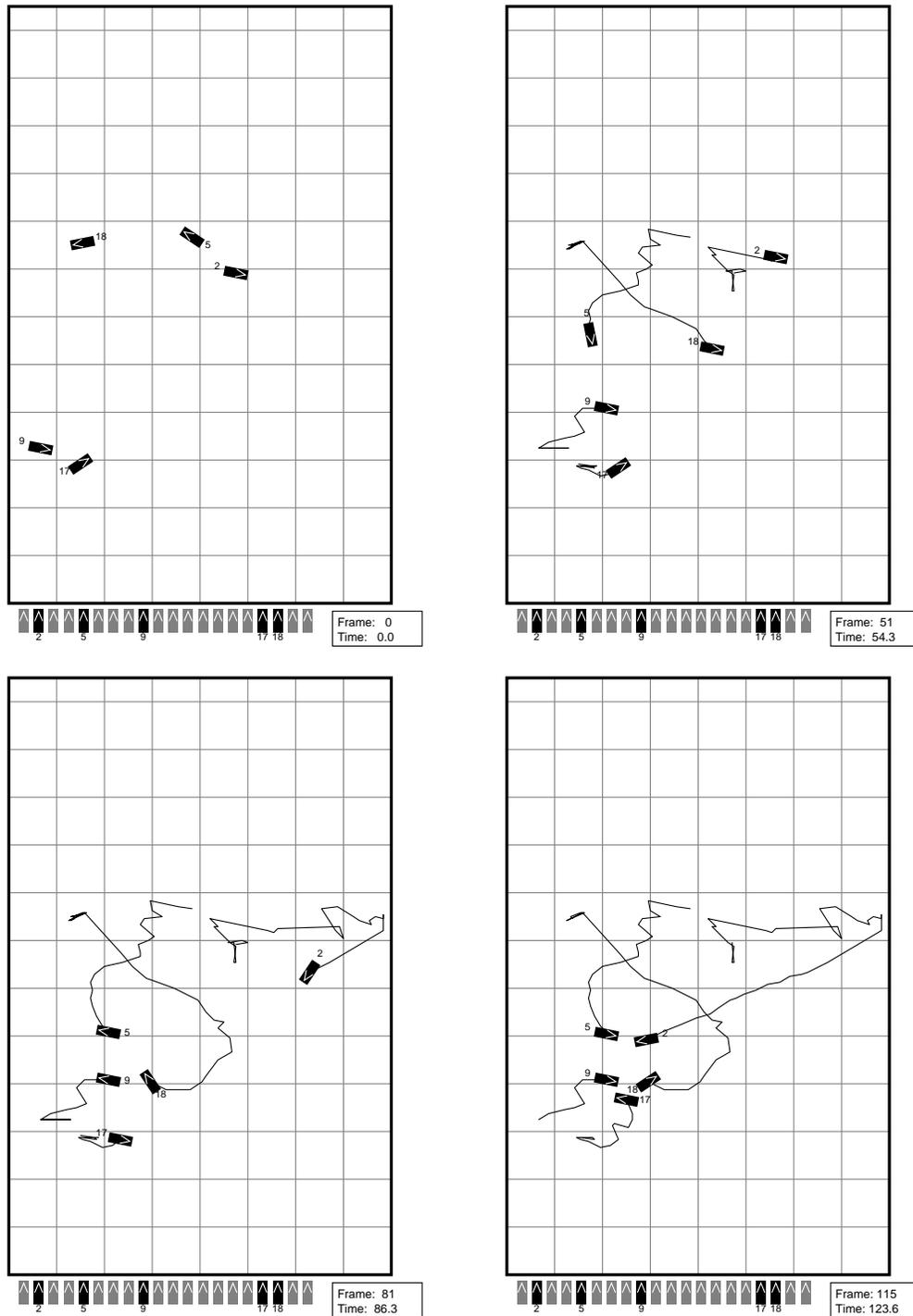


Figure 4: *Homing* behavior of five robots. Started in an arbitrary initial configuration, four of the robots reached the home region within 100 seconds, and the fifth joined them 30 seconds later. The trails reflect errors in position sensing, as well as interference between the robots as they approach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

```

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

```

Due 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.

5 Behavior of Heterogeneous Groups

In addition to evaluating all of the basis behaviors according to the prespecified criteria (see (Mataric 1994a) for details), we also compared two of the above 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.

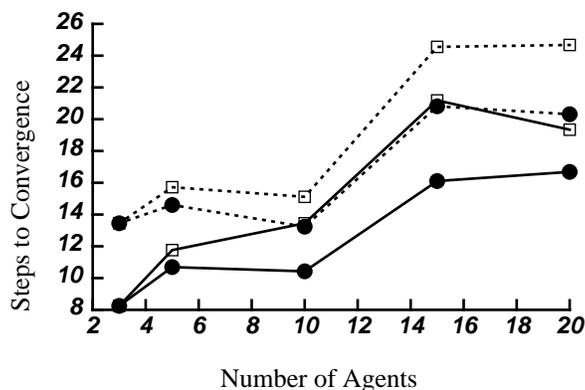


Figure 5: The performance of two different *aggregation* algorithms based on the number of steps required to reach static aggregated state. Two termination conditions were tested: a single group (data points shown with boxes) and a few stable groups (data points shown with dots). Hierarchical algorithm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

We loosely modeled a society with an established pecking order (Chase, Bartolomeo & Dugatkin 1994, Chase 1993, Chase 1982, Chase & Rohwer 1987) by implementing a hierarchy based on randomly assigned unique ID numbers. While in homogeneous algorithms all agents moved simultaneously according to identical local rules, in the hierarchical cases the agents

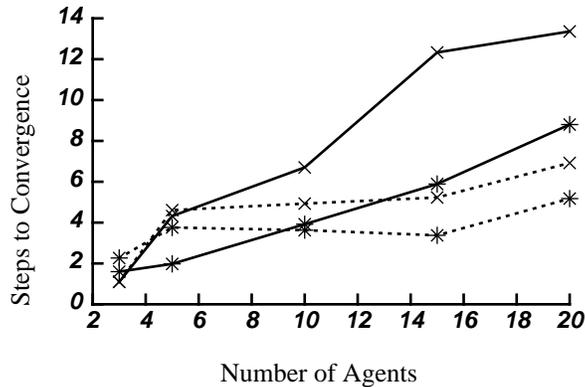


Figure 6: The performance of two different *dispersion* algorithms based on the number of steps required to reach static dispersed state. Two initial states were tested: a random distribution (data points shown with stars) and a packed distribution (data points shown with crosses). Hierarchical algorithm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

with the locally higher ID numbers moved while others waited for their turn. In all cases, a simple precedence order of movement emerged.

The experiments were conducted in the Interaction Modeler, 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 of 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 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 (3 and 5) group sizes. 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 mostly likely be negligible on physical agents, due 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*: In spite of the linear priority ordering, the agents are fundamentally homogeneous since they are functionally indistinguishable. Thus, the hierarchical relationships between agents are spatially and temporally independent, since the agents keep no history of their past encounters with each other.
- *Simplicity of behavior*: Since all agent interactions are spatially and temporally local, the ID-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 quite 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 in order to assure 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. This data permit us to hypothesize the following: for simple spatial domains 1) simple homogeneous solutions can work quite well, and 2) more complex strategies requiring individual agents to perform recognition, classification, and representation might be required to significantly improve group performance. These more complex strategies are commonly found in nature, where societies across species establish and maintain dynamically changing pecking orders whose exact purpose is as yet unknown (Chase et al. 1994, Chase 1993).

6 Composing 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 behaviors, whose outputs are mutually

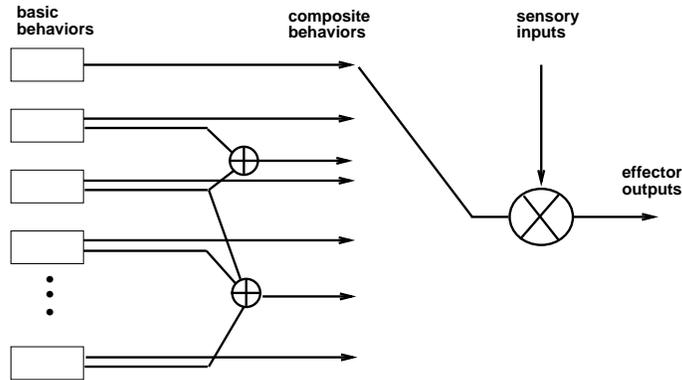


Figure 7: The control architecture for generating group behaviors consists of complementary and contradictory combinations of subsets from a fixed basis behavior set. Complementary combinations are marked with \oplus , contradictory combinations with \otimes .

exclusive and can only be executed 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 (Figure 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 each other, *dispersion* keeps them from getting too close, *homing* moves the flock toward some goal, and *safe-wandering* prevents each agent individually, and thus the flock as a whole, from collisions.

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 empirically derived. 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 did not interfere:

$$d_{\text{avoid}} < d_{\text{disperse}} < d_{\text{aggregate}}$$

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 as well; 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,

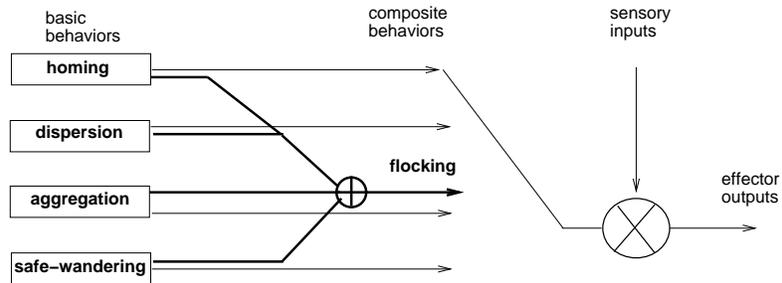


Figure 8: The implementation of *flocking* as a combination of *safe-wandering*, *dispersion*, *aggregation*, and *homing*. The first three behaviors produce robust *flocking*; *homing* gives the flock a goal location and direction to move in.

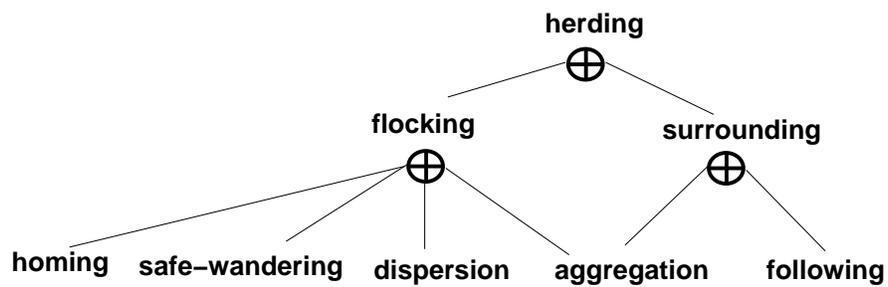


Figure 9: An example of complementary basis behavior combinations within a higher-level task.

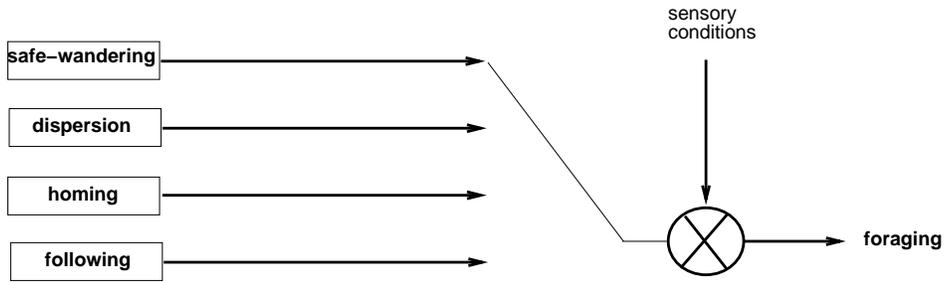


Figure 10: The implementation of foraging using a combination of *safe-wandering*, *dispersion*, *homing*, and *following*. Each triggered by different sensory conditions, the behaviors collectively result in foraging.

or were removed², others would take over and "lead" the flock. Consequently, *flocking* was very robust and did not degrade with decreased group sizes (Mataric 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. Since 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 have also explored methods for generating them automatically through reinforcement learning (Mataric 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 triggered by different sensory and internal conditions. We used this method to implement *foraging*, the prototypical and ubiquitous gathering/hoarding behavior (Figure 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 due to agent homogeneity. Since all of the 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 it encounters a few agents *dispersing*, the difference in the agents' external state will either induce all of the agents to follow toward home, if they are of the same kind, or will result in the groups avoiding each other, thus dividing the group 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

²We tested all of these cases.

mapping.

7 Compound Behavior Algorithms

This section gives the algorithms and shows examples of the data for two compound behaviors: *flocking* and *foraging*.

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 a simple algorithm shown above. 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 thresholds.

Like *following*, *flocking* is a coordinated-motion behavior which is best evaluated by testing its duration, repeatability, and robustness. The performance of *flocking* was dependent on the size of the flock; small flocks, consisting of four or fewer agents, were less stable, while larger flocks remained stable even if several agents failed due 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 & Nuyts (1993) and Goss, Deneubourg, Beckers & 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 flocking. The robot implementation required more rules due to the more complex dynamics.

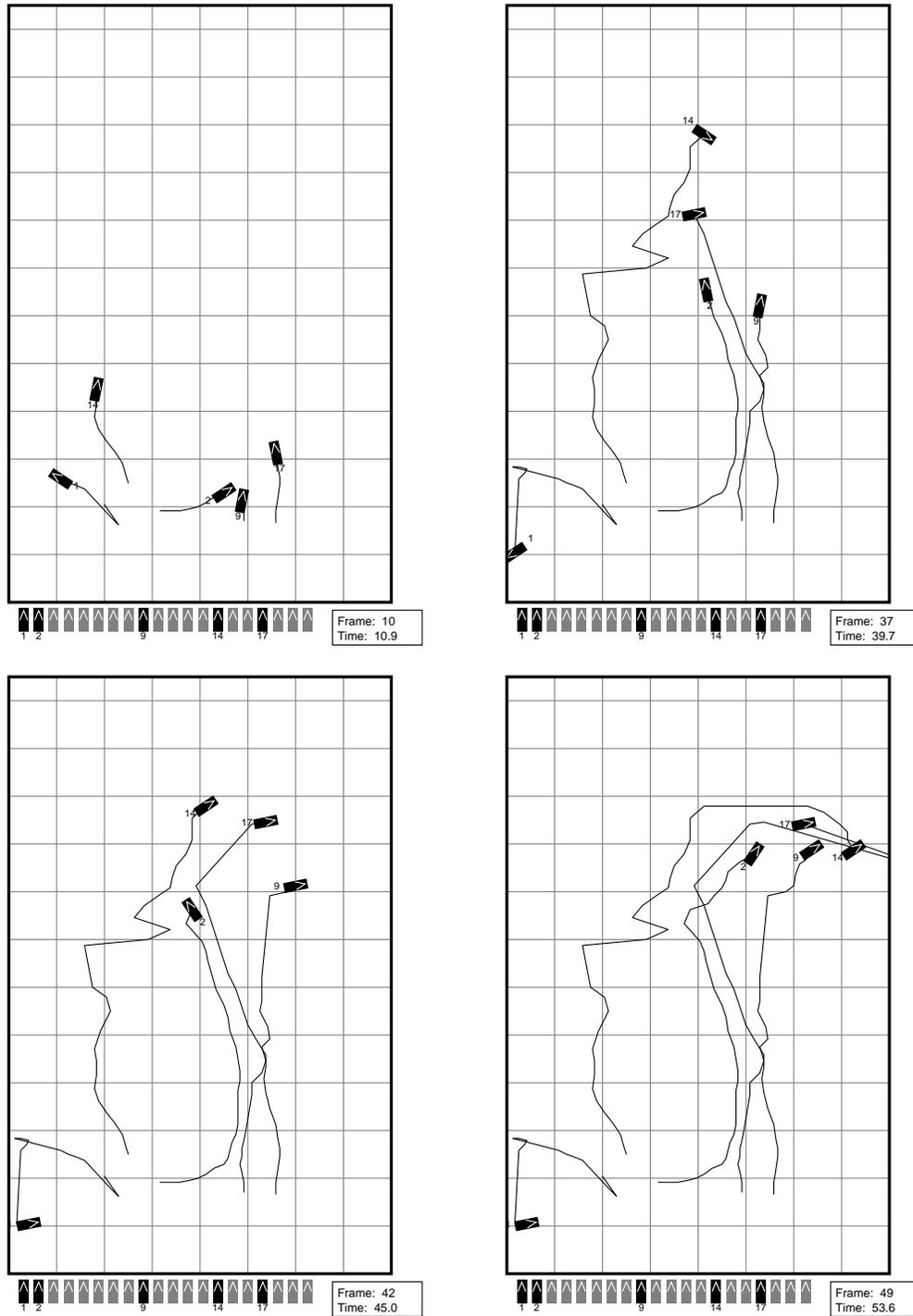


Figure 11: *Flocking* behavior of five robots. One of the robots separates, without affecting the behavior of the others. Due to a failure of the position sensors, the robot falls behind the group. The rest of the robots reorganize and maintain the global structure.

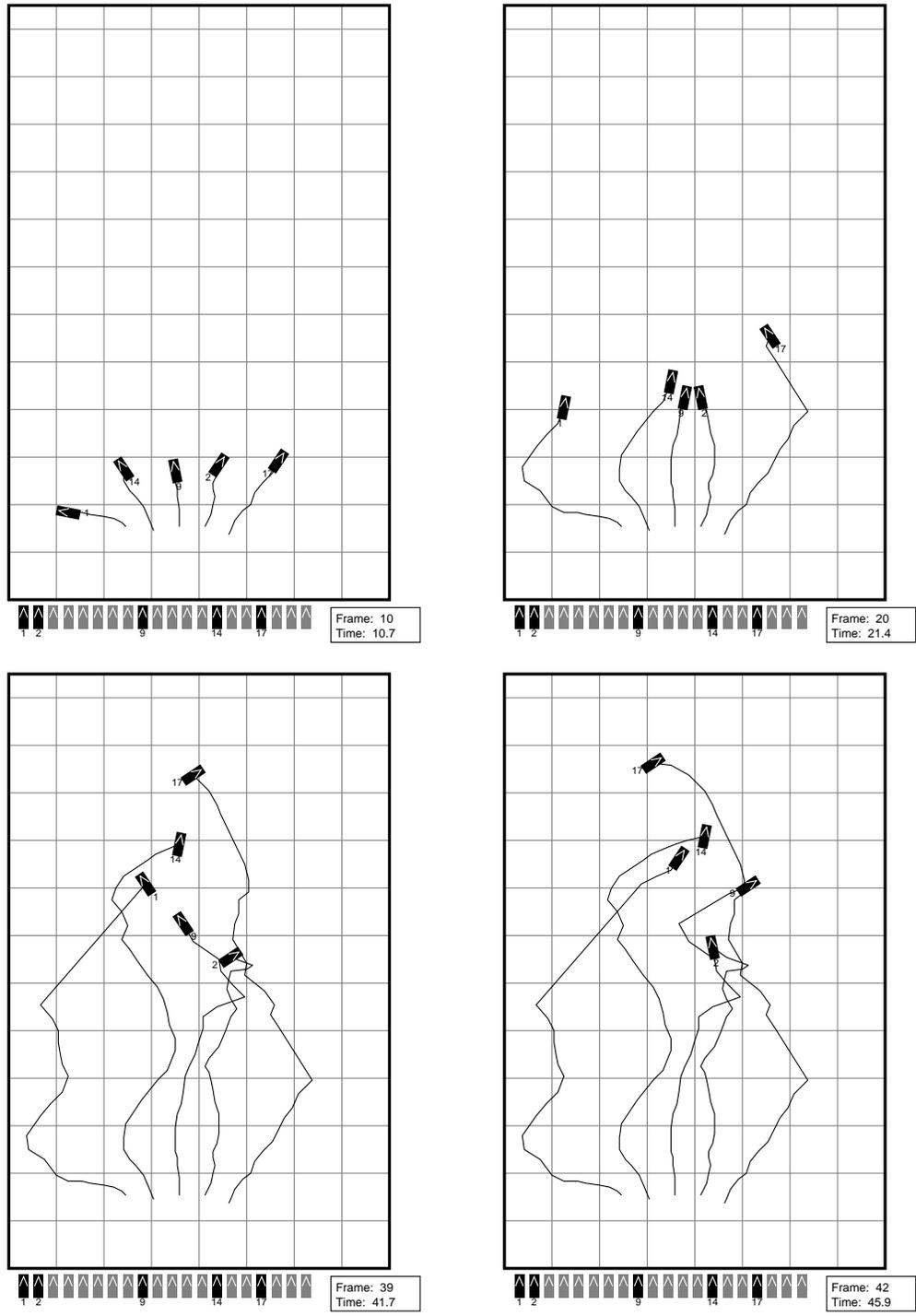


Figure 12: *Flocking* behavior of the same five robots in another trial. The robots maintain a coherent flock, in spite of the often large position errors sensed by individuals. These errors are manifested in the variability in the spacing between the robots as the flock moves.

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 are also 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. Since, unlike animals, the robots cannot directly sense each other'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 pseudo-code 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 about 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 since, over the course of an experimental run, the pucks outside the home region were 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 & Nitz (1993) describe simulation results of a similar task with varying amounts of agents and inter-agent communication. Comple-

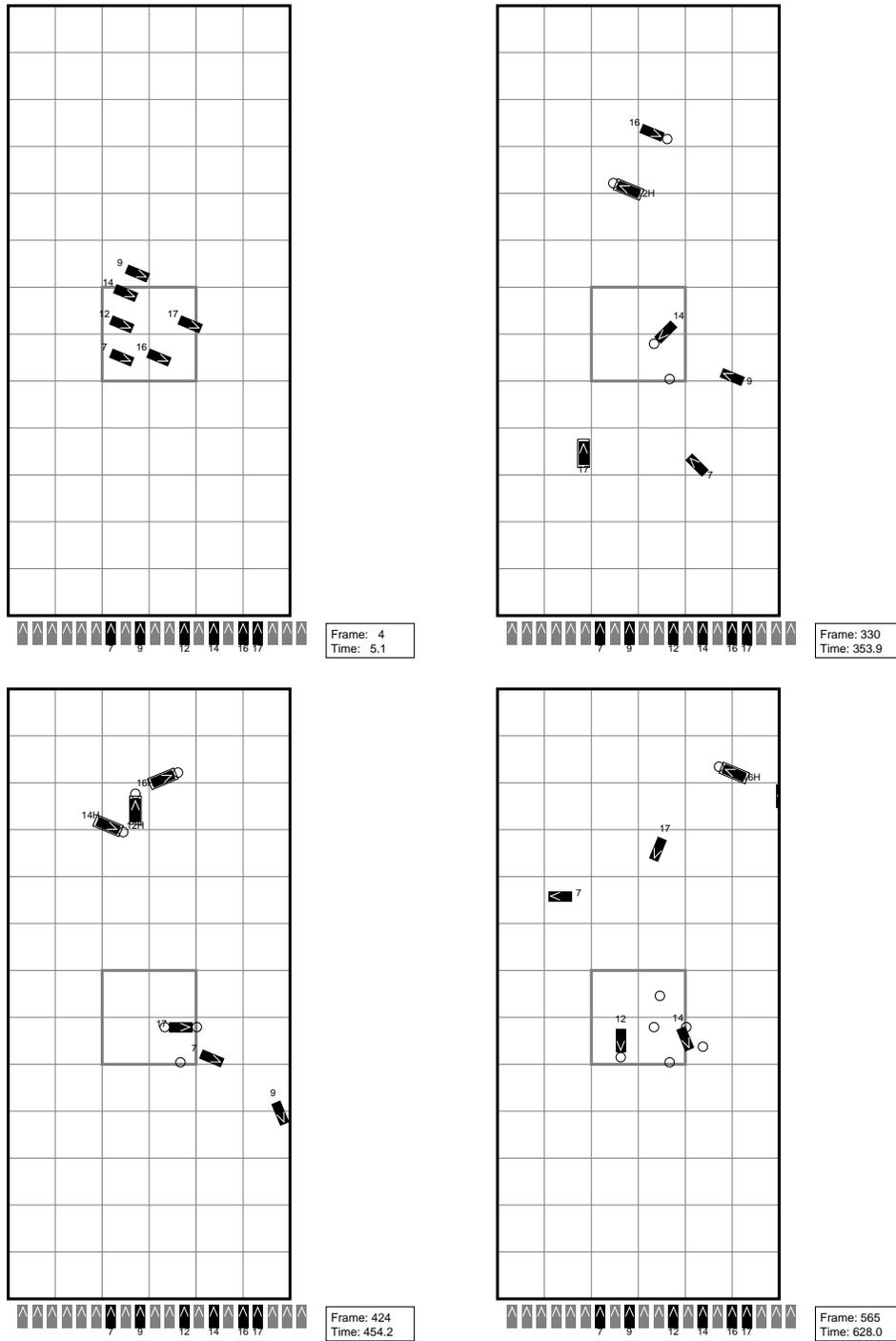


Figure 13: *Foraging* behavior of six robots. The robots are initiated in the home region. The pucks are initially clustered at the bottom center of the workspace. After *dispersing*, they *safe-wander* and search for pucks, pick them up, and take them home. If they encounter another robot with a puck 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.

mentary 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*.

8 Related Work

Group behavior has been studied by a variety of disciplines ranging from biology and ethology to sociology and AI. In its attempt to contribute to group behavior synthesis, our approach spans a number of disciplines, most notably AI, robotics, Artificial Life (Alife), 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 multi-agent 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 & Buss (1989) deal with coordinating multiple interlocking robotic units, Caloud, Choi, Latombe, LePape & Yim (1990) and Noreils (1993) apply a planner-based controller to a pair of box-pushing robots in a master-slave configuration, Kube & 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 robot, and Matarić, Nilsson & Simsarian (1995) use the described basis behaviors in a box-pushing task with a pair of legged robots. Unlike our work, most of the multi-robot 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 Altenburg (1994) on a variant of foraging using a group of LEGO robots controlled in reactive, distributed style, and Beckers, Holland & Deneubourg (1994) demonstrating clustering 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 like ours have been implemented, including Steels (1989) describing simple agents using self-organization to perform a gathering task, Brooks, Maes, Matarić & Moore (1990) showing a fully decentralized collection of non-communicating collecting agents, and Arkin et al. (1993) demonstrating a schema-based approach on a retrieval task. More complex simulations are being introduced, using realistic physics models of the agents, such as in the work of Hodgins & Brogan (1994) describing herds of hopping robots.

Alife work most relevant to ours features simulations of colonies of ant-like agents, as described by Corbara, Drogoul, Fresneau & Lalande (1993), Colorni, Dorigo & Maniezzo

(1992), Drogoul, Ferber, Corbara & Fresneau (1992), and many others. Similar to our approach, many such Alife 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 & Lachaud (1987), Deneubourg & Goss (1989), Deneubourg, Goss, Franks, Sendova-Franks, Detrain & Chretien (1990), and their other work, have examined the role of simple control rules and limited communication in producing trail formation and task sharing. Deneubourg, Theraulaz & 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 successfully transferred to physical robots.

9 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).

In order 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 subsequently evaluated the described basis behaviors in a series of experiments demonstrating a group of four mobile robots learning to forage, i.e. adaptively discovering an efficient foraging strategy comparable to the one described above. The robots were able to automatically acquire foraging within 15 minutes. Details of the experiments and results can be found in Matarić (1994a) and Matarić (1994c). 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 are currently 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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