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Issues and approaches in the design of collective autonomous agents *

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Abstract

The problem of synthesizing and analyzing collective autonomous agents has only recently begun to be practically studied by the robotics community. This paper overviews the most prominent directions of research, defines key terms, and summarizes the main issues. Finally, it briefly describes our approach to controlling group behavior and its relation to the field as a whole.

1. Introduction

The problem of synthesizing and analyzing collective autonomous behavior has only recently begun to be practically studied by the robotics community. This paper gives on overview of the directions taken by the different areas of artificial intelligence and robotics and the progress that has been made. Section 2 overviews the relevant work in the field. Section 3 defines key terms and summarizes some of the main issues. Section 4 describes the fundamental means of approaching the multi-agent control and analysis problem. Section 5 briefly describes our approach to controlling group behavior and relates it to the field as a whole.

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2. Overview of multi-agent work

2.1. Physical multi-robot systems

The last decade has witnessed a shift in research emphasis toward physical implementations of robotics in general and mobile robotics in particular. Most of the work in robotics so far has focused on control of a single agent, but a few efforts have begun to address multi-robot systems. Fukuda et al. [24] and subsequent works describe an approach to coordinating multiple homogeneous and heterogeneous mobile robotic units, and demonstrate it on a docking task. Caloud et al. [8] and Noreils [47] remain faithful to the state-based framework, and apply a traditional planner-based control architecture to a box-moving task implemented with two robots in a master–slave configuration. Kube et al. [37] and Kube and Zhang [36] describe a series of simulations of robots performing a collection of simple behaviors that are being incrementally transferred to physical robots. Barman et al. [4] report on a preliminary testbed for studying control of multiple robots in a soccer-playing task. Parker [49,48] describes a behavior-based task-sharing architecture for controlling groups of heterogeneous robots, and demonstrates it on a group of four physical robots performing toxic waste cleanup and box pushing. Donald et al. [18] reports on the theoretical grounding for implementing a cooperative manipulation task and demonstrate it on a pair of sofa-moving robots. Perhaps closest in philosophy as well as the choice of task to ours is work by Altenburg [1], describing a variant of the foraging task using a group of LEGO robots controlled in reactive, distributed style, and Beckers et al. [5], demonstrating a group of four robots with large numbers of simple agents. Representative work in swarm intelligence [25,13,20,30,51,38,6,14], deals with problems and approaches related to those treated by DAI (see below) but employs agents of comparatively low cognitive complexity.

2.2. *Artificial life*

The field of artificial life (Alife) focuses on bottom-up modeling of various complex systems, including simulations of colonies of ant-like agents [12,11,19,56]. Deneubourg et al. [16] and related work have experimented with real and simulated ant colonies and examined the role of simple control rules and limited communication in producing trail formation and task sharing. Deneubourg et al. [17] define some key terms in swarm intelligence and discuss issues of relating local and global behavior of a distributed system. Assad and Packard [2] and Hogeweg and Hesper [28] and related work also report on a variety of simulations of simple organisms producing complex behaviors emerging from simple interactions. Schmieder [52] reports on an experiment in which the amount of "knowledge" agents have about each other is increased and decreased based on local encounters. Werner and Dyer [58] and MacLennan [40] describe systems that evolve simple communication strategies. On the more theoretical end, Keshet [34] describes a model of trail formation that fits biological data.

Our own work is related to artificial life in that both are concerned with exploiting the dynamics of local interactions between agents and the world in order to create complex global behaviors. However, work in Alife does not typically deal with agents situated in physically realistic worlds. Additionally, it usually treats much larger populations sizes that the work presented here. Finally, it most commonly employs genetic techniques for evolving the agents' comparatively simple control systems.

2.3. *Distributed artificial intelligence*

Distributed Artificial Intelligence (DAI) also deals with multi-agent interactions (see [26] for an overview). DAI focuses on negotiation and coordination of multi-agent environments in which agents can vary from knowledge-based systems to sorting algorithms, and approaches can vary from heuristic search to decision theory. In general, DAI treats cognitively complex agents compared to those considered by the research areas described so far. However, the types of environments it deals with are relatively simple and low complexity in that they feature no noise or uncertainty and can be accurately characterized.

DAI can be divided into two subfields: Distributed Problem Solving (DPS) and Multi-Agent Systems (MAS) [50]. DPS deals with centrally designed systems solving global problems and using built-in cooperation strategies. In contrast, MAS work deals with heterogeneous, not necessarily centrally designed agents faced with the goal of utility-maximizing coexistence.

Examples of DPS work include Decker and Lesser [15], addressing the task of fast coordination and reorganization of agents on a distributed sensor network, and Hogg and Williams [29] showing how parallel search performs better with distributed cooperative agents than with independent agents. Examples of MAS work include Ephrati [22], describing a master–slave scenario between two agents with essentially the same goals, and Miceli and Cesta [46], using estimates of usefulness of social interactions for agents to select whom to interact with. Along similar lines, Kraus [35] studies negotiations and contracts between selfish agents; Durfee et al. [21] discusses game-theoretic and AI approaches to deals among rational agents.

Certain aspects of DAI work are purely theoretical and address the difficulty of multi-agent planning and control in abstract environments (e.g. Shoham and Tennenholtz [53]). Some DAI work draws heavily from mathematical results in the field of parallel distributed systems (e.g. Huberman [32], Clearwater et al. [10], and many others). DAI and Alife merge in the experimental mathematics field that studies computational ecosystems, using simulations of populations of agents with well defined interactions. The research is focused on global effects and the changes in the system as a whole over time. This process of global changes is usually referred to as "co-evolution" [33]. Co-evolution experiments are usually used to find improved search-based optimization techniques [27]. Often the systems studied have some similarities to the global effects found in biological ecosystems, but the complex details of biological systems are not modeled.

3. Key terms and definitions

Previous section offered a glimpse at the highly varied directions and approaches to studying multi-robot and multi-agent systems. One of the main hurdles in the way of cross-fertilization between research directions is inconsistent vocabulary. This section defines and overviews some of the key terms in order to make the described research accessible.

3.1. Behaviors and goals

In the last few years the notion of *behavior* as a fundamental building block has been popularized in the AI, control, and learning communities. From the perspective of the output of the system, we view behavior as a regularity in the interaction dynamics between the agent and the environment. This working definition is consistent with [55,54,7], and others. As a control structure, we define behavior to be a control law for reaching and/or maintaining a particular goal. For example, in the robot domain, *following* is a control law that takes inputs from an agent's sensors and uses them to generate actions which will keep the agent moving within a fixed region behind another moving object. This definition specifies that a behavior is a type of an operator that guarantees a particular goal, whatever its type. The goals are typically determined by the programmer. *Attainment goals* are terminal states; having reached a goal, the agent is finished. Such goals include reaching a home region and picking up an object. *Maintenance goals* persist in time, and are not always representable with terminal states, but rather with dynamic equilibria to be maintained. Examples include avoiding obstacles and minimizing interference. Situated agents can have multiple concurrent goals, including at least one attainment goal, and one or more maintenance goals.

In the scope of our work, *interaction* is mutual influence on behavior, and *ensemble, collective* or *group behavior* is an observer-defined temporal pattern of interactions between multiple agents. Of the innumerably many possible such behaviors for a given domain, only a small subset is relevant and desirable for achieving the agents' goals.

3.2. Communication and cooperation

Communication and cooperation have become popular topics in both abstract and applied multi-agent work [60,20,1]. Communication is the most common means of interaction among intelligent agents. Since any observable behavior and its consequences can be interpreted as a form of communication, we propose a stricter classification.

Direct communication is a purely communicative act, one with the sole purpose of transmitting information, such as a speech act, or a transmission of a radio message. The message need not be symbolic, as it commonly is not in nature. *Directed communication* is direct communication aimed at a particular receiver. Such communication can be one-to-one or one-to-many, in all cases to identified receivers. In contrast to direct communication, *indirect communication* is based on the observed behavior of other agents. This type of communication is referred to as *stigmergic* in biological literature, where it refers to communication based on modifications of the environment rather than direct message passing.

Cooperation is a form of interaction, usually based on some form of communication. Certain types of cooperative behavior depend on directed communication. Specifically, any cooperative behaviors that require negotiation between agents depend on directed communication in order to assign particular tasks to the participants. Analogously to communication, *explicit cooperation* is defined as a set of interactions which involve exchanging information or performing actions in order to benefit another agent. In contrast, *implicit cooperation* consists of actions that are a part of the agent's own goal-achieving behavior repertoire, but have effects in the world that help other agents achieve their goals.

3.3. Interference and conflict

All approaches to multi-agent control must deal with *interference*, any influence that opposes or blocks an agents' goal-driven behavior. In societies consisting of agents with identical goals, interference manifests itself as competition for shared resources. In diverse societies, where agents' goals differ, more complex conflicts can arise, including goal clobbering, deadlocks, and oscillations. Two functionally distinct types of interference appear in multi-agent systems: interference caused by multiplicity, called *resource competition*, and interference caused by goal-related conflict, called *goal competition*.

Resource competition includes any interference resulting from multiple agents competing for common resources, such as space, information, or objects. As the size of the group grows, this type of interference increases, causing the decline in global performance, and presenting an impetus for the use of social rules.

Resource competition manifests itself in homogeneous and heterogeneous groups of coexisting agents. In contrast, goal competition arises between agents with different goals. Such agents may have compatible high-level goals (such as, for example, a family may have), but individuals may pursue different and potentially interfering subgoals, i.e. they can be "functionally heterogeneous." Such heterogeneity does not arise in SIMD-style groups of functionally identical agents in which all are executing exactly the same program at each point in time.

Goal competition is studied primarily by the Distributed AI community [26]. It usually involves predicting other agents' goals and intentions, thus requiring agents to maintain models of each other (e.g. [31,46]). However, such prediction abilities require computational resources that do not scale well with increased group sizes. One means of simplifying prediction is through the use of social rules which attempt to eliminate or at least minimize both resource and goal competition. In particular, their purpose is to direct behavior away from individual greediness and toward global efficiency. In certain groups and tasks, agents must give up individual optimality in favor of collective efficiency. In those cases, greedy individualistic strategies perform poorly in collective situations because resource competition grows with the size of the group.

Since social rules are designed for optimizing global resources, it is in the interest of each of the individuals to obey them. However, since the connection between individual and collective benefit is rarely direct, societies can harbor deserters who disobey social rules in favor of individual benefit. Game theory offers elaborate studies of the effects of deserters on individual optimality [3], but the domains it treats are typically much more cleanly constrained than environments in which robots are situated. In particular, game theory deals with rational agents capable of evaluating the utility of their actions and strategies. In contrast, our work is concerned with situated domains where the agents cannot be assumed to be rational due to incomplete or nonexistent world models and models of other agents, inconsistent reinforcement, noise, and uncertainty.

Optimality criteria for agents situated in physical worlds and maintaining long-term achievement and maintenance goals are difficult to characterize and even more difficult to achieve. While in game theory interference is a part of a competing agent's predictable strategy, in the embodied multi-agent domain interference is largely a result of direct resource competition, which can be moderated with relatively simple social rules.

4. Approaches to multi-agent control

The problem of *multi-agent control* can be viewed at the individual agent level and at the collective level. The two levels are interdependent and the design of one is, or should be, strongly influenced by the other. However, multi-agent control grew out of individual agent control, and this history is often reflected in the control strategies at the collective level. Individual agent control strategies can be classified into reactive, behavior-based, planner-based, and hybrid approaches (see Matarić [42,41] for detailed comparisons and discussion).

Extending the planning paradigm from single-agent to multi-agent domains requires expanding the global state space to include the state of each of the agents.

Such a global state space is exponential in the number of agents. Specifically, the size of the global state space G is $|G| = s^a$, where s is the size of the state space of each agent, here assumed to be equal for all agents, or at worst the maximum for all agents, and a is the number of agents. Exponential growth of the state space makes the problem of global on-line planning intractable for all but the smallest group sizes, unless control is synchronized and has SIMD form, i.e. all agents perform the same behavior at the same time. Furthermore, since global planning requires communication between the agents and the controller, the bandwidth can grow with the number of agents. Additionally, the uncertainty in perceiving state grows with the increased complexity of the environment. Consequently, global planner-based control approaches do not appear well suited for problems involving multiple agents acting in real-time based on uncertain sensory information.

Since hybrid systems typically employ a planner at the high level, in terms of multi-agent extensions they can be classified into the planner-based category. The collective behavior of a hybrid system would generally be a result of a plan produced by a global controller and distributed over independent possibly partially autonomous modules.

At the other end of the control spectrum, extending the reactive and behavior-based approaches to multi-agent domain results in completely distributed systems with no centralized controller. The systems are identical at the local and global levels: at the global level the systems are a collection of reactive agents each executing task-related rules relying only on local sensing and communication. Since all control in such distributed systems is local, it scales well with the number of agents, does not require global communication, and is more robust to sensor and effector errors. However, global consequences of local interactions between agents are difficult to predict. Thus, centralized approaches have the advantage of potential theoretical analysis while parallel distributed systems typically do not lend themselves to traditional analytical procedure.

4.1. Analysis of behavior

Multi-agent systems are typically complex, either because they are composed of a large number of elements, or because the inter-element interactions are not simple. Systems of several situated agents with uncertain sensors and effectors display both types of complexity. This section addresses how these properties affect their behavior and its analysis.

The exact behavior of an agent situated in a nondeterministic world, subject to real error and noise, and using even the simplest of algorithms, is impossible to predict exactly. Similarly, the exact behavior of each part of a multi-agent system of such nature is also unpredictable since a group of interacting agents is a dynamical system whose behavior is determined by the local interactions between individuals. In natural systems, such interactions result in the evolution of complex and stable behaviors that are difficult to analyze using traditional, top-down approaches. We postulate that in order to reach that level of complexity synthetically, such behaviors must be generated through a similar, interaction-driven, incrementally refined process.

Precise analysis and prediction of the behavior of a single situated agent, specifically, a mobile robot in the physical world, is an unsolved problem in robotics and AI. Previous work has shown that synthesis and analysis of correct plans in the presence of uncertainty can be intractable even in highly constrained domains [39,9,23] and even on the simplest of systems [54]. Physical environments pose a great challenge as they usually do not contain the structure, determinism, and thus predictability usually required for formal analysis [7]. The increased difficulty in analyzing multi-agent systems comes from two properties intrinsic to complex systems:

(1) the actions of an agent depend on the states/actions of other agents;
(2) the behavior of the system as a whole is determined by the interactions between the agents rather than by individual behavior.

In general, no mathematical tools are available for predicting the behavior of a system with several, but not numerous, relatively complex interacting components, namely a collection of situated agents. In contrast to physical particle systems, which consist of large numbers of simple elements, multi-agent systems in nature and AI are defined by comparatively small groups of much more complex agents. Statistical methods used for analyzing particle systems do not directly apply as they require minimal interactions between the components [57,59].

The difficulty in analyzing complex multi-agent systems lies in the level of system description. Descriptions used for control are usually low level, detailed, and continuous. In contrast, planning and analysis are usually done at a high level, often using an abstract, discrete model. A more desirable and manageable level may lie in between the two.

Instead of attempting to analyze arbitrary complex behaviors, our work focuses on providing a set of behavior primitives that can be used for synthesizing and analyzing a particular type of complex multi-agent systems. The primitives provide a programming language for designing analyzable control programs and resulting group behaviors. We describe the approach next.

5. The basic behavior approach

Our work is based on the belief that intelligent collective behavior in a decentralized system results from *local interactions* based on simple rules. *Basic behaviors* are proposed as a methodology for structuring those rules through a principled process of synthesis and evaluation. We postulate that, for each domain, a set of behaviors can be found that are *basic* because: (1) they are required for generating other behaviors, and (2) they constitute a minimal set the agent needs to reach its goal repertoire. The process of choosing the set of basic behaviors for a domain is dually constrained: from the bottom up by the agent and environment dynamics, and from the top down by the repertoire of the agent's goals.

Fig. 1. The mobile robots used to demonstrate and verify our group behavior and learning work. These robots demonstrated group avoidance, following, aggregation, dispersion, flocking, wandering, foraging, docking, and learning to forage.

Mobile robots require an effective set of basic behaviors in the spatial domain that enable them to employ a variety of flexible strategies for interaction and object manipulation. The efficacy of such strategies relies on maximizing synergy between agents: achieving the necessary goals while minimizing inter-agent interference. We propose the following empirically derived set of basic behaviors for mobile robots interacting and moving around objects in the plane: *avoidance, following, aggregation, dispersion, homing*, and *wandering*. According to our definition, the above behavior set is minimal and basic in that its members are not further reducible to each other, and they are sufficient for achieving our set of pre-specified goals. A number of other utility behaviors can be a part of an agent's repertoire, such as *grasping* and *dropping*, the only other behaviors we used in our work.

The basic behavior set is evaluated by formally specifying each of the behaviors and comparing those to the specification of the set of goals (or tasks) given to the group. We have provided specifications and algorithms for each of the basic behaviors, implemented them on a collection of robots, and evaluated them based on the following criteria: *repeatability, stability, robustness*, and *scalability*. For details see Matarić [42]. The criteria were applied to the data obtained by running a large number of trials (at least 50) of each basic behavior on a collection of over 20 physical mobile robots equipped with on-board power, sensors, and control (Fig. 1). Each of the robots is a 12-inch long steerable car base equipped with a suite of infra-red sensors for collision avoidance and puck detection, micro switches and bump sensors for contact detection, and radios and sonars for triangulating their position relative to two stationary beacons, and broadcasting word-sized messages within a limited radius. The basic behaviors, each consisting of one or a small set of simple rules, generated robust group behaviors that met the prespecified evaluation criteria. The top row of Fig. 2 shows a typical data set[2].

[2] The Real Time Viewer software used to gather, display, and plot the robot data was written by Matthew Marjanović.

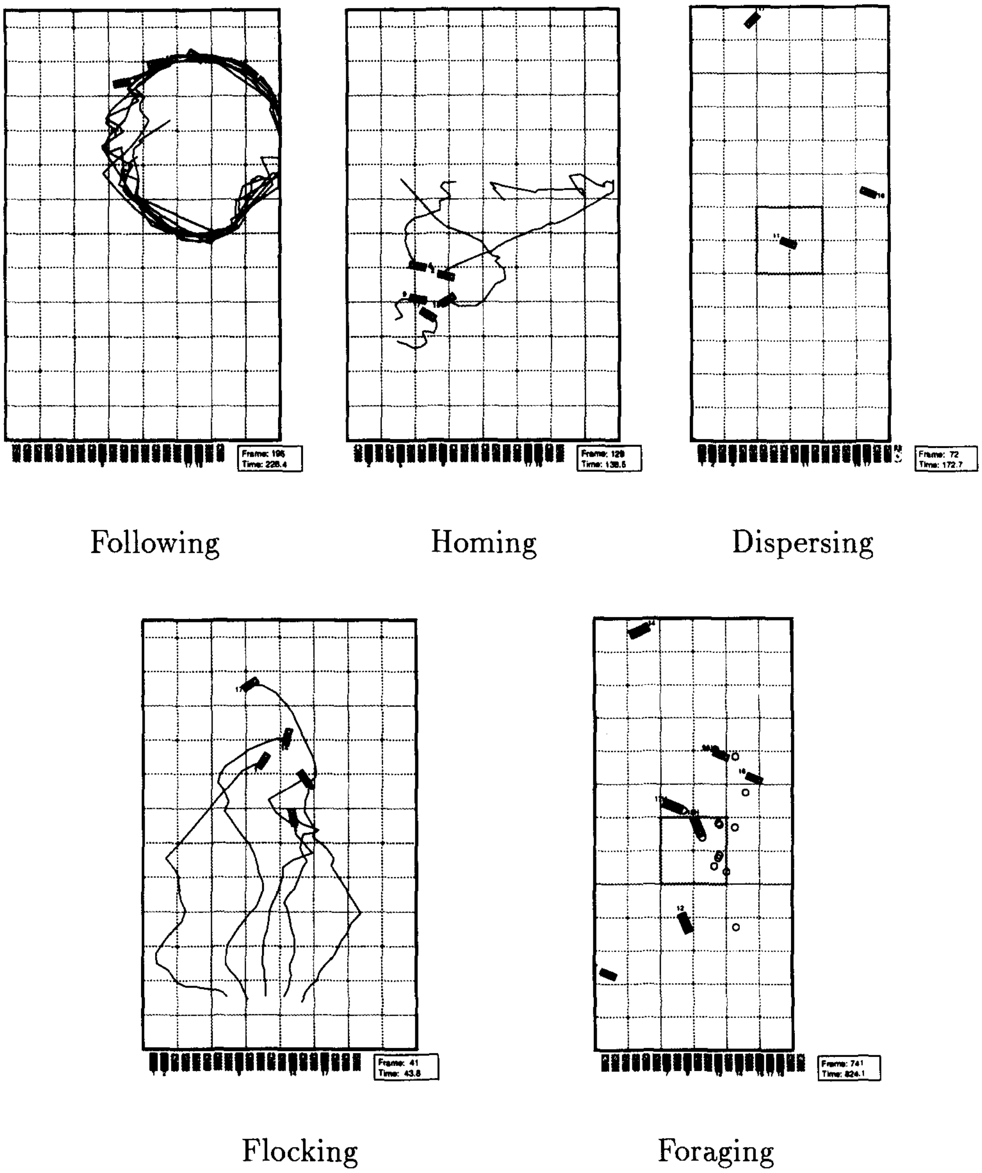

Fig. 2. Real robot data for basic and composite behaviors. The robots are scaled down and plotted as black rectangles with arrows indicating their heading. The row at the bottom indicates the robots that were used in the particular experiment. Small boxes on the right indicate the elapsed time in seconds for each of the runs. The top row shows examples of real robot data for three basic behaviors: following, homing, and dispersing; the second row shows examples of robot data for two different composite group behaviors: flocking and foraging. The foraging behavior of 7 robots is shown after 13.7 minutes of running; collected pucks are in the box.

Basic behaviors are intended as building blocks for achieving higher-level goals and can be embedded in an architecture that allows two types of combination: direct (by summation) and temporal (by switching). Direct combinations execute multiple behaviors concurrently and combine their outputs. In contrast, temporal combinations execute only one behavior at a time, by switching between them. The architecture allows for multiple applications of the combination operators to basic behavior subsets.

To demonstrate the operators, we implemented two higher-level behaviors, flocking and foraging. Example data from those is illustrated in the bottom row of Fig. 2. We generated simple and robust *flocking* behavior by summing the outputs of *avoidance*, *aggregation* and *wandering*. When *homing* was added, the flock could direct itself toward a particular goal location. In all cases, the flocks had no fixed leaders, and were not vulnerable to failures of individual robots.

A more complex example of a high-level behavior we demonstrated is *foraging*. It was implemented by applying a temporal combination operator to switch between *avoidance*, *dispersion*, *following*, *homing*, and *wandering* under appropriate sensory conditions. Those basic behaviors, along with the abilities to pick up and drop pucks, were sufficient to produce a robust and flexible collective foraging behavior that consisted of collecting all of the pucks in the area and depositing them in the home region while avoiding collisions and minimizing interference.

In addition to empirically testing the behaviors and their combinations, we compared our methodology to a centralized, "total knowledge" approach applied to dispersion and aggregation tasks. The experimental results showed that the simple, fully distributed strategies converged only a constant factor slower than the centralized approach. The details of the experiments can be found in [42].

6. Learning in complex group environments

In addition to serving as building blocks for control, basic behaviors are also an effective substrate for learning. We demonstrated a methodology for automatically generating higher-level behaviors by having the agents learn through their interactions with the world and with other agents, i.e. though unsupervised *reinforcement learning* (RL).

RL has been successfully applied to a variety of domains where the agent-environment interaction can be described as a Markov Decision Process (MDP). However, that assumption does not directly apply to the stochastic, noisy, and uncertain multi-agent environments. We implemented a reformulation of the traditional RL model consisting of states, actions, and reinforcement in order to make it applicable to our domain. Instead of using actions, our system learns at the level of basic behaviors that hide low-level control details, and are more general and robust.

The use of behaviors allows for clustering states into *conditions*, the necessary and sufficient subsets of state required for triggering the behavior set. Conditions are many fewer than states, so their use diminishes the agent's learning space and speeds up any RL algorithm [44].

We also introduced two ways of shaping the reinforcement function to aid the agent in the nondeterministic, noisy, and dynamic environment. We used *heterogeneous reward functions*, which partition the task into subgoals, thus providing more immediate reinforcement. We also introduced *progress estimators*, functions associated with particular conditions, that provided some metric of the learner's performance during execution of a particular behavior. Progress estimators decrease the learner's sensitivity to noise and minimize the likelihood of thrashing and receiving fortuitous rewards.

We validated the proposed RL formulation on the task of learning to forage. The behavior space included the foraging subset of basic behaviors described above, augmented with *grasping*, *dropping*, and *resting* (an opportunity for the robots to recharge). The state space was effectively reduced to the power set of the following conditions: *have-puck?*, *at-home?*, *night-time?*, and *near-intruder?*.

We implemented different versions of reinforcement learning algorithms in our domain and compared their performance over a large number of trials. The popular standard RL Q-learning was implemented and used as the control, and compared to an algorithm using heterogeneous reward functions, and to one using those in addition to progress estimators. Our approach outperformed the alternatives, consistently converging to the correct policy within 15 minutes. The analysis of the data yielded a measure of learning difficulty within the lifetime of a single foraging trial. For a detailed description of the learning algorithms and the data see [44].

7. Summary

This paper has reviewed the key terms, issues, and approaches in multi-robot and situated multi-agent control. We described the challenges of principled synthesis and analysis of collective behavior, and proposed a methodology for structuring the process of designing group behaviors for multi-robot systems.

The basic behavior approach is general and biologically rooted [42]. Therefore, we believe it is applicable to various domains of multi-agent interaction featuring complex dynamics, unpredictability, and uncertainty in sensing and action. The methodology is invariant to group size and interaction type. We have demonstrated it on over 20 agents situated in the spatial domain, applied it to smaller groups of more heterogeneous agents [43,45], and are currently testing it on heterogeneous groups. We also plan to apply it to more abstract domains.

This work is intended as a foundation in a continuing effort toward studying and synthesizing increasingly more complex behavior. The work on basic behaviors distills a general approach to control, planning, and learning. The work also empirically demonstrates some challenging problems and offers some effective solutions for designing group behavior.

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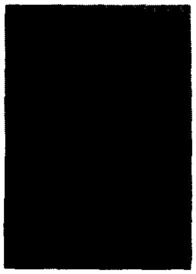

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