

Coordination and learning in multirobot systems

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Finding methods for generating coherent, robust, useful, and adaptive behavior in groups of autonomous robots is an increasingly active area of research. The incremental approach to robotics—first studying control and learning in a single robot—is not sufficient or even relevant (for some problems)

to the multirobot coordination and learning problem. Instead, the problem requires a general approach—fundamentally different from most of today’s robot control and learning—to make the necessary strides in this challenging domain.

Defining the problem

Nature presents us with numerous examples of highly efficient, adaptive, and fault-tolerant distributed multiagent systems in which individuals (insects, animals, humans, cultures, nations) successfully cope

with incomplete and noisy information (state, knowledge), nondeterministic environments, delayed feedback in response to actions, collaborators, opponents, and competition for resources. The robotics domain presents many of the same challenges:

- robot sensors provide noisy and incomplete information,
- effectors slip and accumulate errors,
- communication is typically low-bandwidth and lossy,
- resources (time, battery power) are

limited,

- feedback may be delayed or in some cases absent,
- other robots get in the way, and
- the world can appear hostile, inconsistent, and nonstationary.

Single-robot control can encounter many of these challenges, but multirobot coordination faces and amplifies them all. As a result, some critics claim that the field of robotics is far from being ready to tackle the problem and should first focus on the single-agent, single-robot case.

A different view

At the USC Robotics Research Lab, our work with robots (see Figures 1–3) argues for a different view. Based on our research of situated, embodied systems,^{1–3} we suggest that control and learning in multirobot systems must be addressed as a separate, novel, and unified problem—not an additional “module” in a single-robot approach. We propose a bottom-up methodology to produce the desired system behavior. This behavior results from

- the interaction dynamics between the robots and their environment (including other robots and potentially the user) and
- the biases and constraints introduced by the system designer.

This approach contrasts sharply with the traditional “strong control” methodology that imposes top-down structure on the desired solution.

Adding flexibility. We seek to remove the abstraction barrier between the agent and the group and, in some cases even more profoundly, between the different processing elements in and between individual robots. Responding to the ever-changing dynamics—as well as individual failures

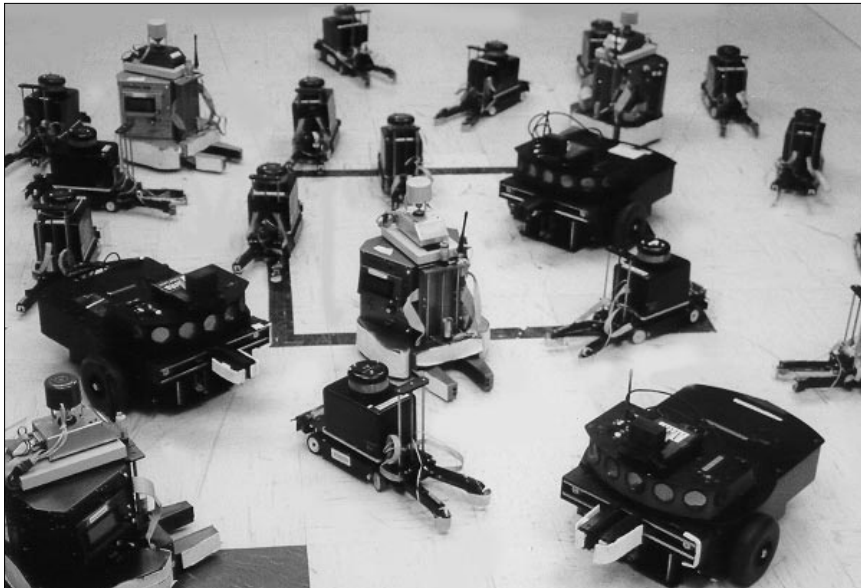


Figure 1. A heterogeneous group of mobile robots, all equipped with mobile bases, grippers, and radios for communication. The group includes three Real World Interface Pioneers, also equipped with seven sonar sensors and a color camera; four IS Robotics R2e mobile robots, equipped with infrared and tactile sensors; and a dozen R1 robots.

New directions for New Directions

With this issue, we will be making the “New Directions” department into a regular feature of *IEEE Intelligent Systems*. Our goal is to present articles on some of the exciting new technologies and theoretical directions that are being pursued by the AI research community’s emerging stars. In each article, young researchers will share their thoughts on how their fields are developing, what exciting innovations their laboratories are producing, and what they feel are some of the important directions that AI scientists should be exploring. In short, this forum is intended to provide a showplace for the AI researchers who will be the future leaders of our field. —*James A. Hendler*

and inconsistencies—in multirobot systems, this approach allows us more flexibility and robustness. Furthermore, the approach lets us directly address the properties of distributed systems, which include locality, nonstationarity, and noise. Then, rather than trying to design solutions that attempt to avoid these properties, we incorporate them into a system’s dynamics. We focus on the system’s efficient, rather than optimal, behavior. In the complex multirobot domains we are addressing, optimality is difficult to specify and evaluate, and is often ill-defined due to nonstationarity. To quickly exploit dynamics and respond and adapt to changes, we look for solutions that combine built-in knowledge and bias with real-time environment interaction.

Learning behavior. Our approach uses *behaviors*, goal-driven control laws, as a substrate for representation, control, and learning. The behaviors couple sensory inputs and effector outputs, and programmers use them to construct flexible internal representations (such as for constructing world models, storing history, and reinforcing behavior use).⁴ The whole system is a distributed collection of agents and robots, each controlled by a collection of behaviors. We do not impose centralized control at any level. If appropriate, we can add hierarchies a priori or establish them dynamically. If desired, we can also impose external inputs, influences, and constraints on individuals or the entire group to guide runtime behavior.

We have successfully applied this approach to several problems in the multirobot domain. We started by designing a basis behavior set (consisting of safe-wandering, following, homing, aggregation, and dispersion) for a collection of up to 13 interacting mobile robots. We then used the basis set as a substrate for demonstrating higher-level behaviors, such as foraging (used as a prototype for collection, clean up, mine clearance, and distributed mapping) and flocking (coordinated movement). The basis set then became a substrate for learning—we demonstrated

- a group learning to forage,
- the same group learning social rules (yielding and proceeding),
- coordinated object moving, and
- discovery of novel, refined, and specialized strategies based on the history of behavior use.^{5,6}

Currently, we are developing learning by imitation, thereby facilitating even richer interaction dynamics, and applying the approach to the higher-dimensional manipulator coordination domain.

Focus on dynamics. It is critical to focus on studying the dynamics of interaction in real (that is, existing) situated (and embodied) systems and the ways they can be manipulated and controlled. These cannot be studied in the abstract nor can they be observed in isolated components. We have already shown that, through principled design, we can directly harness these dynamics to produce controllable, predictable (at the group level), and scalable collective-robot behavior. This approach will bring us closer to more successful modeling of biological multiagent systems and to creating useful artificial ones.

Finding new solutions

What is novel and general about our approach? First, we do not divide the system’s representation into low- and high-level layers that employ very different rep-



Figure 2. Four IS Robotics R2e mobile robots engaged in collecting pucks and following a human. The robots are equipped with mobile bases, grippers, infrared and tactile sensors, and radios for communication.

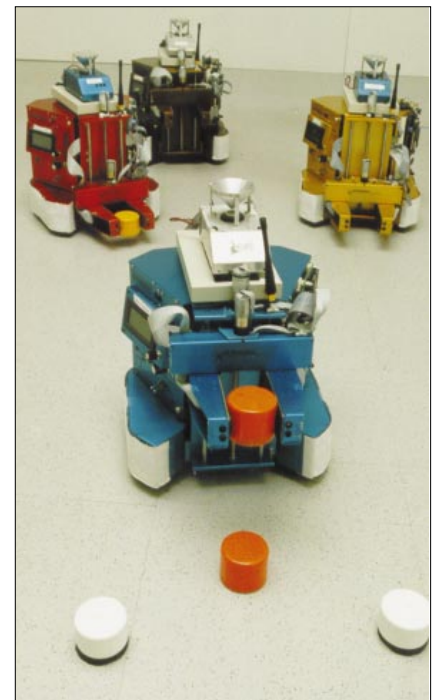


Figure 3. Four IS Robotics R2e mobile robots engaged in puck collecting.



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representations and time-scales and require an intermediate “translation” layer—typical of hybrid systems.⁷⁻⁹ This lack of abstraction barrier is crucial in multirobot systems, where a lack of representational inconsistency allows us to eliminate the abstraction barrier between single-robot and multirobot control. Second, our unified treatment of sensing and action (in the behavioral framework, similar to schemas¹⁰) allows for flexible generation of active, distributed representations. These can then scale to the needs of multirobot tasks and be flexibly distributed over multiple agents with different amounts of available information. Third, the approach enables flexible learning by providing a rich substrate (in which

the behavior structure elevates the representation level and includes some built-in knowledge and bias) and by eliminating a rigid dependence on either low-granularity control or symbol manipulation. Perhaps most importantly, the fully distributed, bottom-up philosophy imposes constraints on the types of solutions that will be found, and points us toward efficient solutions that are not always intuitive, given our generally top-down views of control.¹¹

While our approach departs from “strong control,” it does not relinquish control. The system produces the desired output, but often by using a different, novel, and more efficient solution. Finally, because of its low computational and communication overhead, our approach allows us to approach a large number of problems that top-down control could not address. Distributed bottom-up control is very general and applies to numerous domains featuring a multitude of potentially heterogeneous agents (where heterogeneity may arise from a priori bias or from online learning). We believe that this approach will become increasingly dominant in situated agents—from disembodied information agents on the Web, to sensory arrays and intelligent buildings and structures, to embodied robotic systems. ■

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