Multirobot Coordination by Multiplayer Games

Arash Tavakoli and Nora Ayanian
Department of Computer Science
University of Southern California
Los Angeles, California 90089–0781
Email: {atavakol, ayanian}@usc.edu

I. Introduction

Distributed coordination of large teams of robots for solving collective tasks (tasks that require more than one individual to complete, with each individual performing a discreet part of the task) is a challenging problem [2]. Numerous animals exhibit distributed collective behavior (e.g., birds, fish, bees), and their study has led to novel approaches for multirobot coordination [3]. Human coordination, however, has received little attention in the multirobot coordination literature [4]. In computer science, behavioral experiments have been conducted to examine the ability of human subjects to solve complex global tasks in social networks in a distributed fashion using only local interactions [5].

Here, we describe an approach to collecting data of human coordination in collective tasks, toward the goal of learning novel methods for distributed multirobot coordination. The goal of our data collection is to distill human coordination capabilities into a form that can be more easily transferred into robotic systems. Humans are complex cognitive beings, and their actions are based on many factors, including rich perception, motor, and communication capabilities. Robots, however, have quite limited perception, motor, and communication capabilities, which makes transferring human-learned skills to robots challenging.

Thus, to conduct our investigations, we created a networked experimental platform that functions as an online multiplayer game. Using this platform, we explore the ability of human study participants to solve complex coordinated tasks as an agent with robot-like capabilities, including limited perception (based on lidar), no explicit communication capabilities (since peer-to-peer communication is challenging for large teams of robots), and limited motor capabilities. The tasks the participants solve are shape formation tasks (e.g. form a collective circle or square), which, while simple, have shown promise for inspiring novel methods of signaling without explicit communication for robots, as well as for localization. Here, we present and examine preliminary results of studies we have conducted using this platform, and discuss potential applications of knowledge gained from these experiments.

II. Methodology

We have conducted two one-and-a-half-hour long experimental sessions; here we discuss the second investigation, which had 25 participants, recruited from an undergraduate robotics course with third and fourth year university students. Participants were in a single computer lab classroom, with each participant running our networked experimental platform, described in Section III), on their computer. The platform consists of a graphical user interface (GUI), using which participants controlled their agent in and observed the collective arena (Fig. 1); an administrative interface for the experimenter, in which the experimenter determined the parameters of each task and terminated tasks when they were complete; and a server, which logged the actions of each participant. The server runs the backend processes, including recording each participant's data (position, color, Localized! and Done! signals, current timestamp) every 100 ms. Participants were instructed to interact only through the experimental platform, and wore earplugs throughout the session to discourage any other interaction.

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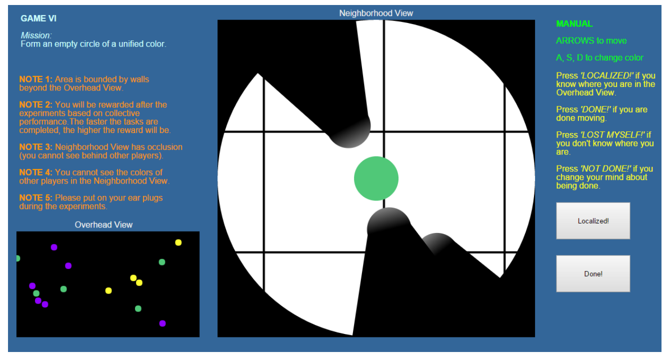
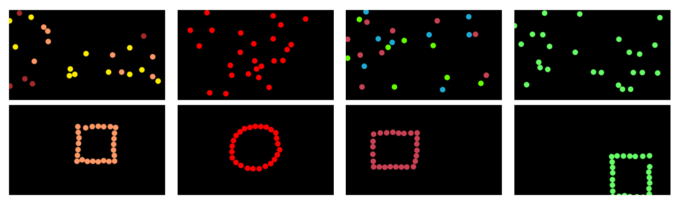


Fig. 1. Screenshot of participant application's GUI.



(a) Task 3 (b) Task 4 (c) Task 5 (d) Task 7

Fig. 2. Initial (top) and final (bottom) configurations for four tasks.

III. Participant GUI

Each participant controlled their agent's color and motion, and interacted with other agents within the arena on several tasks. Since we hypothesized that available perception affects the task outcome, tasks during the session had differing parameters, and thus variation in the GUI was necessary. The

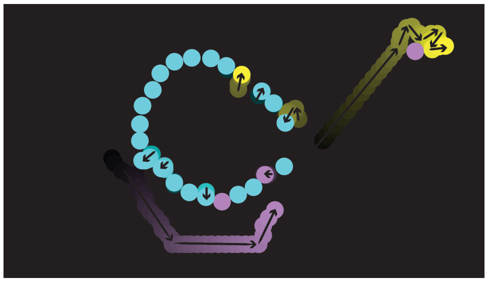


Fig. 3. The yellow agent leaves the formation to guide the purple agent. The faded tail indicates temporal progress.

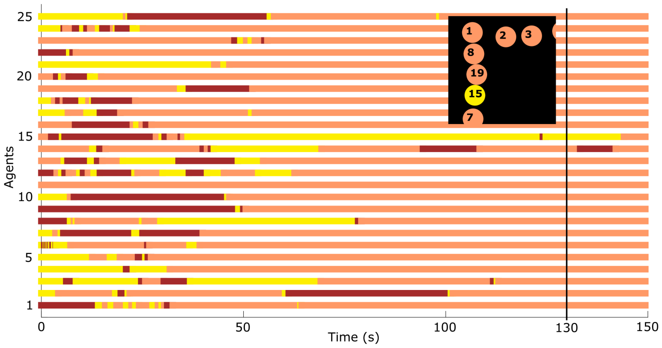


Fig. 4. Color of all agents for the full duration of task 3. After color consensus is reached, agent 15 remains a different color to maintain localization, an example of a high-level behavior which was observed in several tasks from several players. The inset shows agent 15 with neighbors at 130 s (marked). Other agents using color for localization can also be seen (e.g. 3, 14, 23, 25).

key consideration in GUI design was that the human-controlled agents' sensory and communication capabilities resembles those available to a low-cost robot platform, e.g., differential drive, a laser rangefinder or sonar, and an array of LEDs.

The GUI (Fig. 1) may contain a *Neighborhood View (NV)* and/or an *Overhead View (OV)*, depending on the task. The Neighborhood View provides local perception for each agent, modeled after a limited-range laser rangefinder, thus it has occlusions and shows no color. The Overhead View represents images of the arena from an overhead camera, broadcasted to all robots.

Each participant can change his or her agent's color with the A, S, D keys and move the agent with the up, down, left, and right keys. Participants are instructed to press the *Done!* button when they feel they do not need to take further action, and the *Localized!* button to indicate they have localized their agent in the Overhead View (these selections can be reverted by the participants). These indications cannot be observed by other participants; their sole purpose is for post-hoc analysis.

IV. Results

Table I lists the seven tasks and the capabilities given to the participants for each. Tasks 1, 2, 5, and 6 had both Overhead and Neighborhood Views. Tasks 3 and 4 had only the Overhead View, and task 7 had only the Neighborhood View. In tasks 1, 2, 3, 5, and 6, participants had to achieve color consensus.

Participants successfully completed all formation tasks (Fig. 2). In task 7, with only the Neighborhood View available, the task duration was significantly higher than when the

TABLE I
FORMATION TASK PARAMETERS AND COMPLETION TIMES

Order	1	2	3	4	5	6	7
Tasks	Rectangle	Circle	Square	Circle	Rectangle	Circle	Rectangle
Views	OV-NV	OV-NV	OV	OV	OV-NV	OV-NV	NV
# Colors	3	3	3	1	3	3	N/A
Time (s)	167	144	149	77	62	53	513

Overhead View was available, indicating the strong effect of global feedback (Table I). In contrast, tasks with only the Overhead View available did not have a significant effect on completion time.

To complete the task, most players first localized in the Overhead View. Several methods were used for localization, including changing color, moving in a specific direction, and moving in a defined pattern. These localization techniques are a method of active perception that can be easily translated into robotic systems.

Players did not have explicit communication capabilities, thus they developed novel signaling techniques. Signals included repeatedly colliding into other agents (Fig. 3) and rapidly changing color; these techniques can inspire new implicit communication techniques for multirobot systems.

Preliminary study results suggest the existence of a finite set of high-level behaviors from which each participant's strategies can be formed (Fig. 4). Most behaviors were similar among many players; however, certain roles and behaviors were more frequently adopted by some individuals. This natural heterogeneity in human teams, along with the stochasticity of human decision-making, plays an important role in the ability of human groups to solve complex collective tasks.

V. Conclusion and Future Work

In this abstract, we presented preliminary results of our study on crowdsourced human coordination, which resulted in novel signaling and localization techniques, which we plan to apply to multi-robot systems. Our ongoing work is focused on data interpretation and implementation of the high-level behaviors reported by the participants, with the goal of producing stochastic algorithms that can be implemented on real robots. Our future work will involve deploying this system on a crowdsourcing site, such as Amazon Mechanical Turk, Citizen Science, or CrowdFlower.

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