

# Crowdsourced Coordination Through Online Games

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

**Abstract**—We have conducted two investigations on the ability of human participants to solve challenging collective coordination tasks in a distributed fashion with limited perception and communication capabilities similar to those of a simple ground robot. In these investigations, participants were gathered in a laboratory of networked workstations and were given a series of different collective tasks with varying communication and perception capabilities. Here, we focus on our latest investigation and describe our methodology, platform design considerations, and highlight some interesting observed behaviors. These investigations are the preliminary phase in designing a formal strategy for learning human-inspired behaviors for solving complex distributed multirobot problems, such as pattern formation.

## I. INTRODUCTION

Distributed coordination of large teams of robots for solving collective tasks is a challenging problem [1]. While group behaviors of numerous species (e.g., ants, bees, birds, fish, bats) have motivated novel approaches to coordination of multirobot teams [2], few works exist in multirobot control inspired by human group behavior [3]. In cognitive science, experimental approaches have been used for modeling self-organization in crowds and pedestrian motion [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].

We have used an experimental approach similar to that of Kearns [5] to explore the ability of human participants to solve complex coordinated tasks using limited perception and communication capabilities similar to those of a simple ground robot. To conduct our investigations, we created a networked experimental platform through which we enforced limitations on participants’ communication and perception capabilities.

## II. METHODOLOGY

To date, we have conducted two one-and-a-half-hour long experimental sessions. The *pilot 1 investigation* had 15 simultaneous participants, and the *pilot 2 investigation* had 25. Participants were recruited from a convenience population, and included both male and female university students in their 20s, all enrolled in a robotics course. In each session, participants were gathered in a classroom and each participant was assigned a computer workstation to run our networked experimental platform (Section III). Using the graphical user interface (GUI), participants were able to control their *agent*’s

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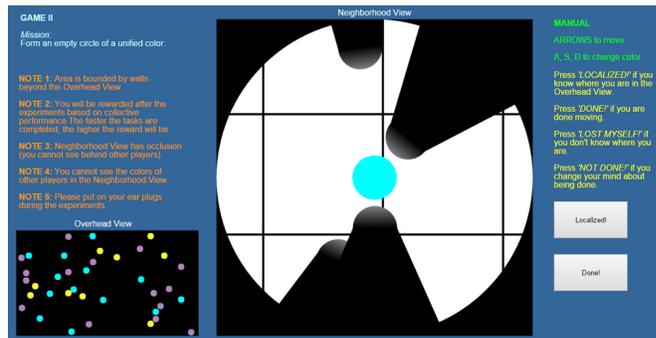


Fig. 1. Sample screenshot of participant application’s GUI.

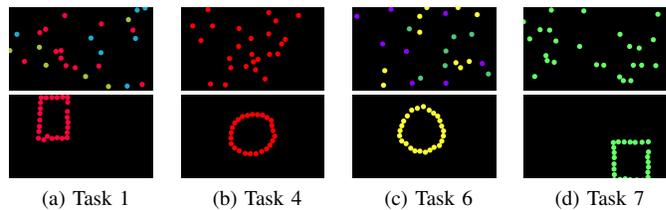


Fig. 2. Initial random configurations (Top) and final formations (Bottom) for a representative set of tasks in pilot 2.

motion and color in a collective workspace (called the *arena*), and interact with the other participants’ agents. Each session was composed of several *tasks* in which participants were asked to solve a collective pattern formation problem in the arena. These tasks were terminated by the *experimenter* once there was no further activity by the agents.

In both investigations, participants were instructed to interact only through the experimental platform. To minimize the influence of verbal communication, participants in the second investigation wore earplugs throughout the session.

In the second investigation, a collective reward (pizza) was given to incentivize faster completion of the tasks. The reward started at a maximum value of \$500, and decreased as time progressed according to a sigmoid function.

## III. EXPERIMENTAL PLATFORM

A networked experimental platform was created for our investigations. A key consideration in the platform design was for the sensory and communication capabilities of the human-controlled agents to resemble those available to our in-house robotic platform: a low-cost differential-drive robot which features a laser rangefinder for proximity sensing, a 9-axis IMU, and an array of LEDs for color signaling. The experimental platform is comprised of two major elements: (1) the *participant application*; and (2) the *server*.

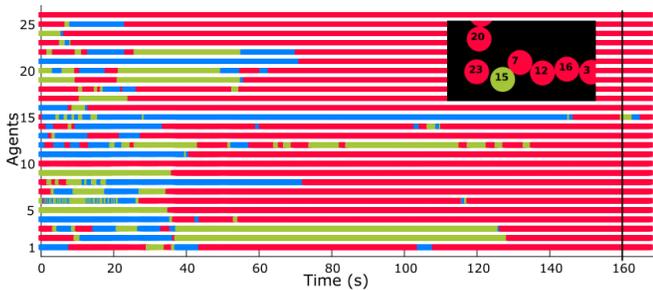


Fig. 3. Color of all agents for the full duration of task 1. The inset indicates an instance of color signaling by agent 15 to notify neighbors (agents 7, 23) to adjust their position at 160 s (marked), well after color consensus is achieved.

The participant application’s GUI (Fig.1) shows, depending on the task, one or both of the *Neighborhood View (NV)* and the *Overhead View (OV)*. The Neighborhood View (or local view), which provides local perception for each agent, emulates our ground robot’s omnidirectional distance sensor with limited range. Thus, occlusion and lack of color detection are accounted for in the Neighborhood View. The Overhead View (or global view) emulates a downward-facing overhead camera that broadcasts images of the arena to all robots.

Participants can maneuver their agent with the up, down, left, and right keys, and change its color with the A, S, D keys. The *Localized!* button is used to indicate that a participant has localized their agent in the Overhead View, and *Done!* is used to indicate that a participant feels they may not need to take any further actions. These buttons can be reverted by the participant to indicate that the previously indicated conditions no longer hold. They are provided for the sole purpose of post hoc analysis and cannot be seen by other participants.

The server runs the backend processes, including recording each participant’s data (position, color, Localized! and Done! signals, current timestamp) every 100 ms.

#### IV. INVESTIGATIONS

Each session was initiated with a training period, in which the GUI was explained and a practice game was held.

The initial pilot incorporated a wide range of formation tasks. The reason for this was twofold: (1) to examine human subjects’ ability to solve a range of complex coordinated tasks using the restrictive GUI; (2) to improve our experimental methodology in future investigations.

The second pilot focused on the formation of circles and rectangles with varied GUI capabilities in each task (Table I). In color-enabled tasks, participants had to achieve consensus on the formation color. To reduce possible biases from performing similar tasks consecutively, tasks were ordered based on formation objective, color options, and available views.

On completion of each task, participants were given a task-specific probe in which they were asked to describe their strategies, the team roles they adopted, and any interesting behaviors they observed. Following the session, a comprehensive probe asked participants to describe their localization strategies, signaling mechanisms, and general preference on adopting some roles over the others.

TABLE I  
FORMATION TASKS IN PILOT 2 AND ELAPSED TIMES TO COMPLETE THEM

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

#### V. RESULTS

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 Overhead View was available, indicating a strong effect of global feedback (Table I).

**Robustness.** In task 1, an additional uncontrolled agent was mistakenly introduced. As with all other agents, it was initialized with a random position and color (red). Participants accommodated for the faulty agent by forming the rectangle around it and adopting the same color.

**Signaling Mechanisms.** In the absence of verbal communication, participants used motion and color to convey messages to their neighbors. Observed signals included repeatedly colliding into another agent and rapidly changing color (Fig. 3).

**High-Level Behaviors.** Probe responses suggest the existence of a finite set of high-level behaviors from which each participant’s strategies can be formed.

**Emergence of Roles.** A wide range of team roles were observed during the tasks. These team roles are more complex than only leader-follower roles and emerge dynamically depending on the circumstances.

**Heterogeneity.** Different levels of traits such as stability and patience were observed among participants. These intrinsic characteristic differences may explain why certain roles and behaviors were more frequently adopted by some individuals.

#### VI. FUTURE WORK

Ongoing work is focused on data interpretation and implementation of the high-level behaviors reported by the participants. The resulting algorithms will be tested in simulation of similar coordinated collective tasks. Future work will involve designing a formal experimental protocol for learning distributed multirobot coordination policies from our data.

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