

Cultural Transmission in Robotic Swarms through RFID Cards

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Abstract—The recent development of economical high-capacity RFID cards has opened up a new opportunity for stigmergic robotic swarms. Through these cards, robotic agents can dynamically exchange more complex, logical information, such as the whole set of their behavioral rules or “culture”. To the best of our knowledge, this opportunity has not been explored in swarm robotics and other collective robotics communities. We have developed a prototypical robotic swarm system comprised of 8 low-cost OPEN-ROBOTS with the ability to avoid obstacles and exchange information with low-capacity RFID cards randomly distributed in an environment. To evaluate the effectiveness of our RFID-based cultural transmission technique, we created a realistic computer simulation to test the swarm’s competence in mapping a virtual multi-room house covered with 80 low-capacity RFID cards in under one hour. By increasing the probability that a robot adopts a random exploration behavior different from one “marked” on a card, the swarm is able to cover more of an environment with higher consistency between trials. This result indicates that encouraging diversity among agents supports robust emergent behavior and lays the groundwork for future experiments with higher-capacity RFID cards.

I. INTRODUCTION

SWARM robotics holds a great degree of promise for solving human problems that have been too complex to handle effectively with traditional means. Compared to traditional robotic solutions, swarms promise to be more reliable and cost-efficient due to their distributed nature and decreased per-unit cost [1]. How individual robots communicate with each other—directly or indirectly—has a large effect on the swarm’s ability to achieve a task at hand. Attempts at using Wi-Fi [2], [3] and other wireless communication techniques have run into difficulties due to environmental interference that leads to degradation in performance and robustness. Indirect communication—through objects left in the environment—can avoid interference entirely and even increase swarm robustness.

A popular medium for this type of communication is Radio-Frequency Identification cards or tags. Robots can read and write information to these objects and the information they create can be read or changed later by other robots. Most RFID-robotic research focuses on using the cards as a means of localizing objects in the environment [4], [5], [6], [7], [8], [9] or tracking the location or pose of the robot itself [3], [10], [11], [12], [13] or some combination thereof using SLAM (Simultaneous Localization and Mapping) techniques

[14], [15]. Much of this work focuses on decreasing localization error through statistical techniques like Kalman filtering [12], fuzzy inference techniques [8] or even through the use of multiple directional RFID antennas [9].

In an effort to mimic indirect communication in insect colonies, RFID cards have been used as a container for virtual pheromonal information [6], [5], [16]. In mapping applications, virtual pheromones are used to prevent trajectory overlap by individual robots [6] in an attempt to increase mapping performance. Most work in this area gets bogged down in accurate simulation of the concentration and diffusion of real chemicals [16] and thus ends up focusing on error minimization. RFID-pheromone environments are difficult to scale up into larger applications due to oversaturation of the limited memory of many RFID cards with too many pheromones [6].

Regardless of how RFID cards are used, by focusing too much on individual robots and individual task-completion, many of the benefits of truly decentralized swarming behavior are not realized. True “emergent problem solving” and “swarm problem solving” [1] occurs when the behavior of individual agents is not goal-oriented and is dictated by very simple local interaction rules. In this paper, we use a computer simulation of a physical robotic swarm system to demonstrate such problem solving as applied to the task of mapping an unknown environment. Our agents do not communicate with each other directly and do not have complicated task-completion or error-minimization algorithms. The simulated low-capacity RFID cards contain an index value that corresponds to a given set of local behavioral rules. Through modification of the probability of interaction with RFID cards by individual robots during a given robot/card encounter, we seek to create an effective tool for mapping. More importantly, we attempt to determine if RFID-based stigmergy can provide a feasible framework for cultural transmission or evolution.

In this paper, because we make frequent use of the terms “culture” and “cultural transmission”, it is important to note that our definition of culture may differ from others discussed in previous literature. We define “culture” simply as a kind of software or list of behavioral rules running on the hardware body of the robot. Since behavior modifications are occurring at the software level rather than at the hardware/morphological level, we consider the software rules to be the robot’s “culture”—even though these behavior changes do not involve any kind of individual learning or behavioral imitation, which are often considered to be central components of cultural processes [17], [18], [19]. This issue will be revisited in Discussion.

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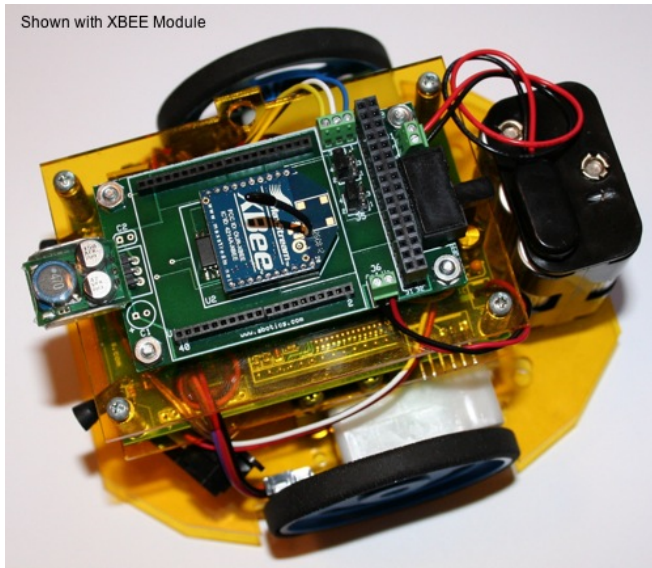


Fig. 1. Open-Robot with wireless XBee® ZigBee™ communication module and RFID tag reader (not visible).

II. SYSTEM DESCRIPTION

A. Physical Robots

The virtual robotic swarm system described in this paper's experiments is a direct analogue of a physical robotic swarm made of 8 OPEN-ROBOTS (Fig. 1) designed by Abraham Howell of *Abe Howell's Robotics* [20]. Unlike other commercially available robots such as the e-Puck [16] or LegoBots [5], the OPEN-ROBOTS are highly functional yet still extremely cost-efficient. The flexibility of these robots has already been demonstrated in several previous experiments, including a simulation of complex foraging behavior [21]. Our robots cost approximately \$450 each and can be constructed in under five hours with off-the-shelf materials.

The robot, powered by 6 rechargeable AA batteries, measures 4.5 inches in width, 5.75 inches in length, and 3.5 inches in height. It can move at approximately 9.2 cm/s and rotate at 92 degrees/second. Each of its two wheels are controlled by separate GM8 motors which are controlled by a PIC18F4520-based controller board with an integrated H-Bridge chip (allowing the motors to move forwards or reverse). The robot has five Sharp GP2D120 infrared sensors—three located on the front left, center and right of the robot, with the other two arranged in the rear. These infrared sensors are the primary tool with which the robots can detect and avoid obstacles. Two cadmium sulfide light sensors sitting above the front infrared sensors are used to detect ambient light conditions. To communicate with other agents or a central computer (if desired), the robots are equipped with XBee® ZigBee™ module. We decided to use this module as it consumes less power and is significantly cheaper than a Wi-Fi module. On the undercarriage of the robot is an approximately 2" x 3" rectangular antenna used to read and write data to the 1.5" diameter antennas in the RFID cards.

The expected read/write cycle is 0.17 seconds.

The robot is controlled by a serial-based boot-loadable firmware that is upgradeable and modifiable and exists in the PIC18F4520-based controller board mentioned above. This firmware allows the OPEN-ROBOT to be controlled through a serial-based command set. While serial commands can be sent wirelessly from a central computer to one or more robots, our physical tests do not use this. Instead, behaviors are tested on a simulator before being written to a robot's firmware. The robot's motion then depends solely on its local behavior and obstacle-avoidance rules.

B. Simulator

We have developed a flexible simulation platform to rapidly test the behavior of our OPEN-ROBOT swarm virtually before investing time and resources in physical experiments. The virtual world implemented in the simulation system is composed of OPEN-ROBOTS, low-capacity RFID cards and a complex to-scale environment in which these entities interact (Fig. 2). The platform allows for simulations to run in real-time or faster, if necessary.

Our virtual simulator was developed using 3DRad [22], an inexpensive, royalty-free video game development environment with a strong 3-D physics simulation engine. 3DRad has advanced rendering capabilities and can import 3D object data in various formats. The original 3D CAD data of the OPEN-ROBOTS, RFID cards and environments were imported to create a true-to-life virtual world (see Fig. 3). The behavioral rules of the robotic agents were written in AngelScript (similar in function and syntax to C) and integrated into the physics simulation. 3DRad simulates its virtual physics in discrete time steps at the rate of 75 frames-per-second. In view of this refresh rate, the OPEN-ROBOT's linear and angular velocities in the simulated world can be rescaled using a simulation speed factor so that the simulated motion is the same as or faster than that of the actual robot observed in the real world. Collisions between robots and other objects are detected by invisible "rays" that protrude two inches from the locations of virtual infrared sensors on the front of the robot. When the surface of another object crosses this ray, an imminent collision is detected and reacted to according to the behavioral rules given to each agent. Details of the collision detection process were calibrated to match the actual behavior of the physical infrared sensors.

III. EXPERIMENTS

The goal of our experiments was to determine, on average, what proportion of the open space in a given environment a swarm of robots could cover in a given time period. For all experiments, we used a swarm of 8 robots and 80 RFID cards with initial positions and orientations determined in a random fashion. Our simulated environment was a 54 square-meter, single-floor, five-room house acquired from Google 3D Warehouse [23], an online repository where users can upload 3D models using Google's free SketchUp modeling software. Using a format converter from 3DRad, this environment was converted into a suitable rigid body



Fig. 2. Eight robots exploring the ground floor of a virtual home filled with 80 randomly distributed RFID cards.

structure and skin mesh to be used in our simulations. Our assumption of eight agents in a 54 square-meter environment is fairly conservative compared to other experiments where anywhere from ten [5] to eighty [3] agents were used in environments as large as 600 square-meters.

Each of the eight robots, situated in random positions near the front door of the home, were randomly initialized with one of four possible exploration algorithms: *Wander*, *SpiralOut*, *WanderSpiral* and *RandomReaction*. All behaviors contain basic obstacle avoidance. If a robot detects an obstacle to its left or right, it will rotate away from that obstacle before continuing with its specific behavior. Each behavior determines what the robot will do when it is not avoiding obstacles. With the *Wander* algorithm, a robot simply moves forward in a straight trajectory. With *SpiralOut*, the robot makes a discrete rotation right, followed by a discrete motion forward. The size of these discrete steps (occurring during each time-step) depends on the simulation speed factor mentioned earlier. With *WanderSpiral*, the robot randomly chooses to either move forward or rotate right during each time step. Finally, with *RandomReaction*, the robot randomly chooses to either move forward, rotate right, or rotate left during each time step. Here, the resulting behavior is very similar to a random walk.

A simulation run is managed by two scripts. The first script randomizes the positions and orientations of the robots by the “front door” of the house. It also randomizes the positions and orientations of all RFID cards throughout the entire house. The randomization algorithms are created such that all objects are placed in open areas inside the house and do not overlap with other objects or the barriers. RFID cards may, however, be placed under the robots’ initial positions. Robots must be spaced at least 8 centimeters from one another while cards must be spaced at least, approximately 10 centimeters from other cards. These random initializations are used to prevent any behavior anomalies that come from the starting positions of the objects, rather than the emergent behavior from their interaction. The second script, activated once the

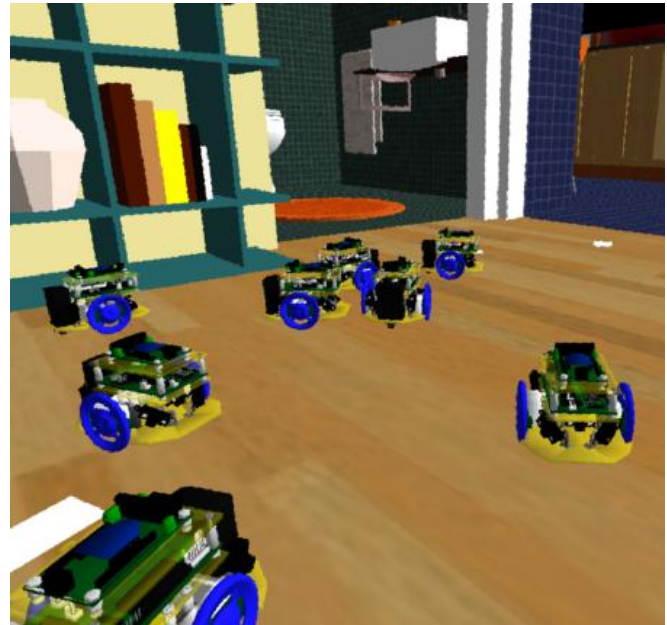


Fig. 3. Eight robots exploring a hallway with two nearby RFID tags.

first script has completed, runs continuously throughout the course of the simulation. It controls the behavior of all robots and sequentially checks for collisions between the robots, environment and RFID cards. Two internal arrays store the current behavioral state of the robots and each RFID card. The data stored in this array—a single integer corresponding to a given strategy—is designed to simulate data stored locally in the real robots and physical RFID tags. This information, along with the current position of every robot, is written to an external data file at each iteration of the script (time step).

The primary experimental parameter, κ , determines how all robots will interact with the RFID cards. See Fig. 4 for an overview of robot-RFID card interaction. If the RFID card has not been written to yet during a given time-step, the robot will write its strategy to the card. If a card has already been

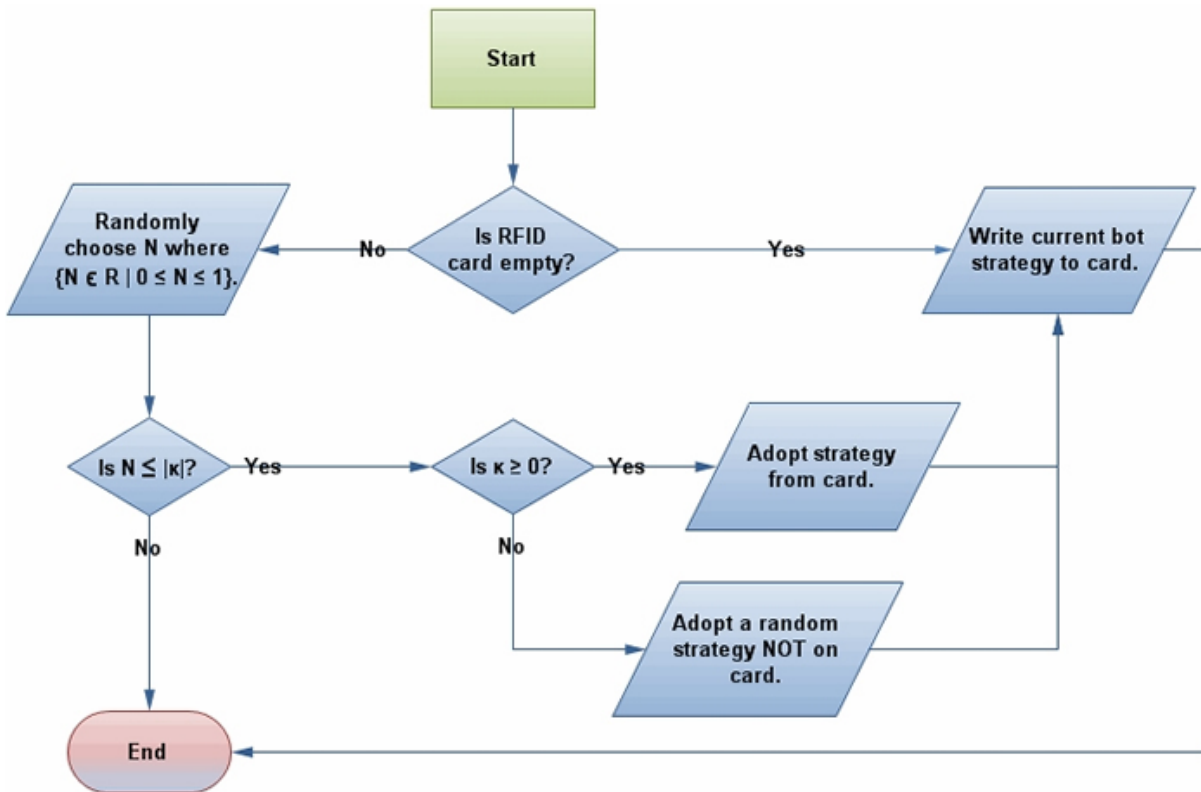


Fig. 4. Flowchart describing interaction between a robot and an RFID card in a single encounter event. Here, N is a random number between 0 and 1 belonging to the set of all Real numbers (indicated by R) and κ is the probability of a robot modifying its exploration strategy based on interaction with an RFID card.

written to and κ is positive, the robot will (with κ probability) adopt the behavior algorithm referred to on the card. If κ is negative, the robot will adopt (with $|\kappa|$ probability) a random behavior that is not present on the card.

To determine the effectiveness of the RFID-based communication described in the ‘System Description’ section, a series of five Monte Carlo simulations were performed for each κ value from -1 to 1 in intervals of 0.1 . Simulations were performed at $10\times$ real-time, so a simulated hour-long trial took only six real minutes.

Coverage trajectories for each trial, composed of hundreds of thousands of individual trajectory points, were examined through Monte Carlo integration using $100,000$ sample points (with radii corresponding to that of the robots) extracted from a rectangular space encompassing the entire home. The area of this space was larger than the actual area of the house (53.9 meters squared). Because of this, we normalized the results by finding the proportional difference between the true area and the rectangular space used for Monte Carlo integration and divided the coverage values by this number.

IV. RESULTS

Figure 5 illustrates an example of the characteristic trajectories of robots when κ was set to a positive value. Unlike other papers where maps were created by identifying boundaries between open spaces [14] and techniques were developed to prevent overlapping trajectories [3], our maps

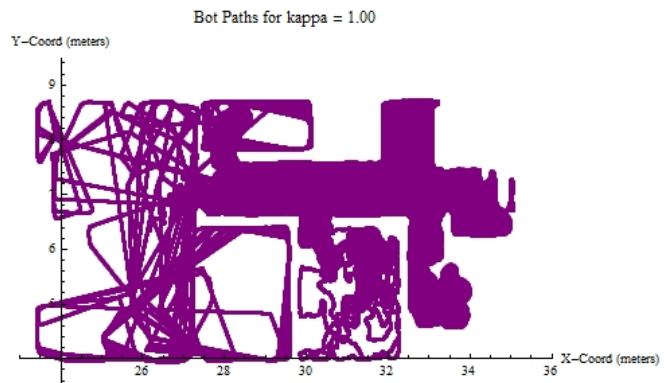


Fig. 5. An overlay of the trajectories of a swarm of 20 robots, each initialized with a random exploration strategy, over an hour in the virtual home covered in 60 RFID cards with $\kappa = 1$. The image, resulting from an earlier test of the simulator, demonstrates how robots with certain strategies (identified by the shapes of their characteristic trajectories) tend to self-organize into different areas of the house. While a 20-to-60 robot-to-card ratio was used in this example, the behavior is also characteristic of simulations with a 8-to-80 robot-to-card ratio used in the experiments.

depend on overlapping trajectories to fill in empty space. Areas without trajectories emerge as obstacles and boundaries in our maps.

Even though the robots were randomly initialized with a certain behavior, robots with a given behavior tended to self-organize into the same rooms during each simulation.

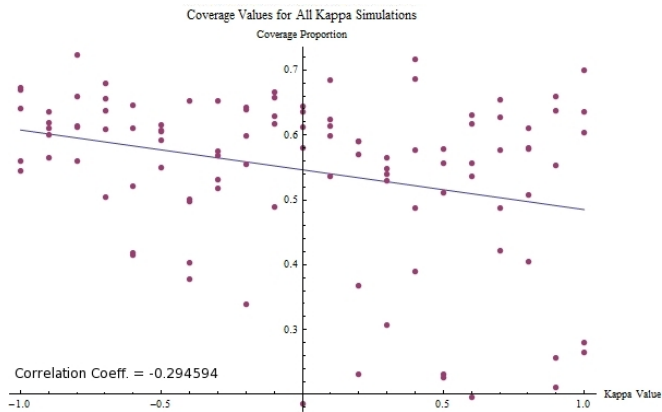


Fig. 6. A scatter plot of 105 coverage values, resulting from 5 trials with each of the κ values with a best fit line described by $y = 0.546415 - 0.061371x$, showing a statistically significant correlation ($p < 0.005$).

Robots with the *Wander* behavior usually ended up in large rooms (the living room/TV room) with open spaces and obstacles with open space between them. Robots with the *RandomReaction* usually ended up in smaller rooms (the bedroom and kitchen) with more closely spaced obstacles. The *Spiral* and *SpiralOut* behaviors tended to dominate the area near the front door of the house and the long adjacent hallway with no obstacles in it.

The data was organized into a series of scatter plots showing the individual coverage trajectories for each trial and their corresponding coverage values for each κ value. Figure 6 shows that, with both positive and negative κ values, high coverage rates were possible. However, with more negative κ values, the lower bound of possible coverage values for the simulations with lower negatives were concentrated around the higher coverage values. Figure 7 illustrates the robot trajectories from each of the five trials at $\kappa = -1, 0$ and 1 and demonstrates an increase in coverage consistency as κ is adjusted negatively. At $\kappa = 1$, room coverage ranges from 26.4% to 70.0% while at $\kappa = -1$, coverage ranges between 54.4% to 67.3%. While the highest coverage value, 70.0%, emerged when $\kappa = 1$, the most consistent performance occurred when $\kappa = -1$. Figure 8 indicates a positive correlation between the κ values and the variance of the five trials. The lowest κ value, -1 , has a variance close to zero, while higher κ values tend to have proportionally higher variance rates. Figure 9 highlights the dynamics of strategy adoption across various values of negative and positive κ . As opposed to indicating dominant strategies within the swarm, this figure demonstrates that the low performance variance associated with negative κ values corresponds with rapid shifting of strategies by the swarm, whereas the high performance variance associated with positive κ values corresponds with significantly less frequent shifting of strategies.

V. DISCUSSION

Our experiments demonstrated that indirect cultural transmission of behavioral rules results in robust emergent be-

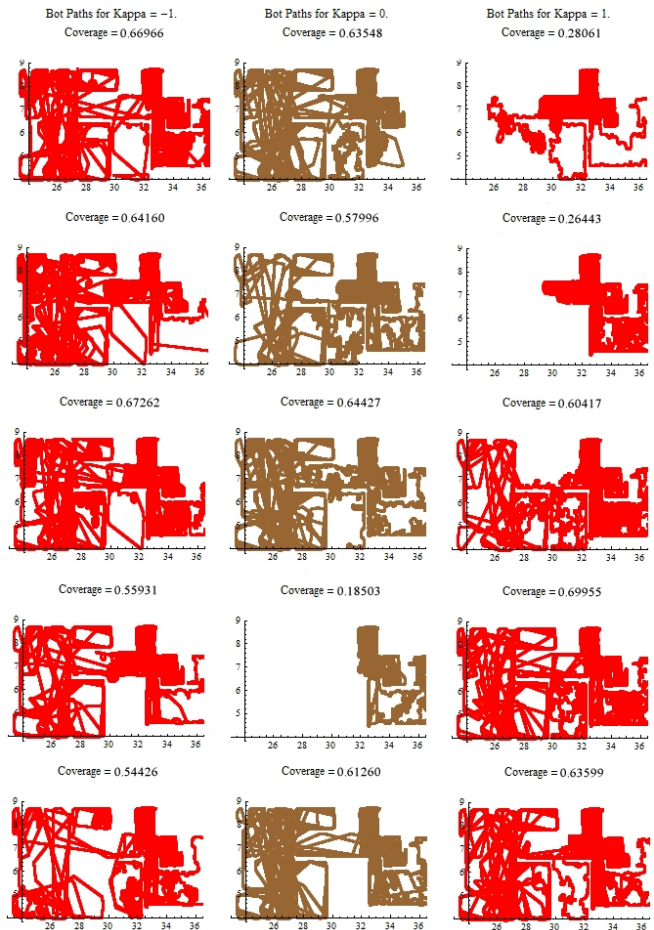


Fig. 7. Aggregated trajectories of robots in five trials with $\kappa = \{-1, 0, 1\}$. Axes correspond to X- and Y-coordinates of trajectories in meters.

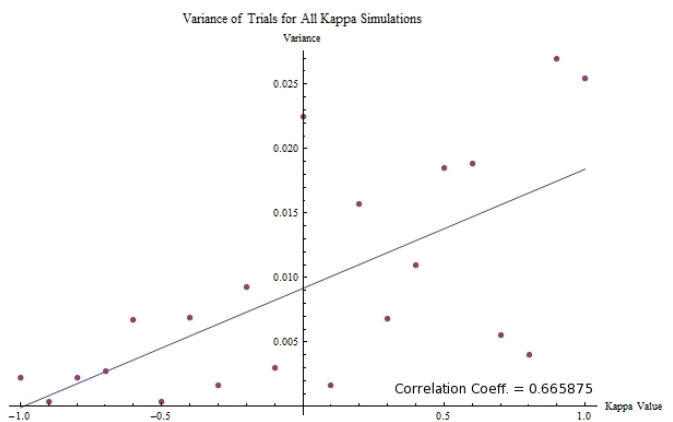


Fig. 8. Variance of the five trials for each κ as a function of κ with a best-fit line described by $y = 0.009168 + 0.009245x$, showing a statistically significant correlation ($p < 0.001$).

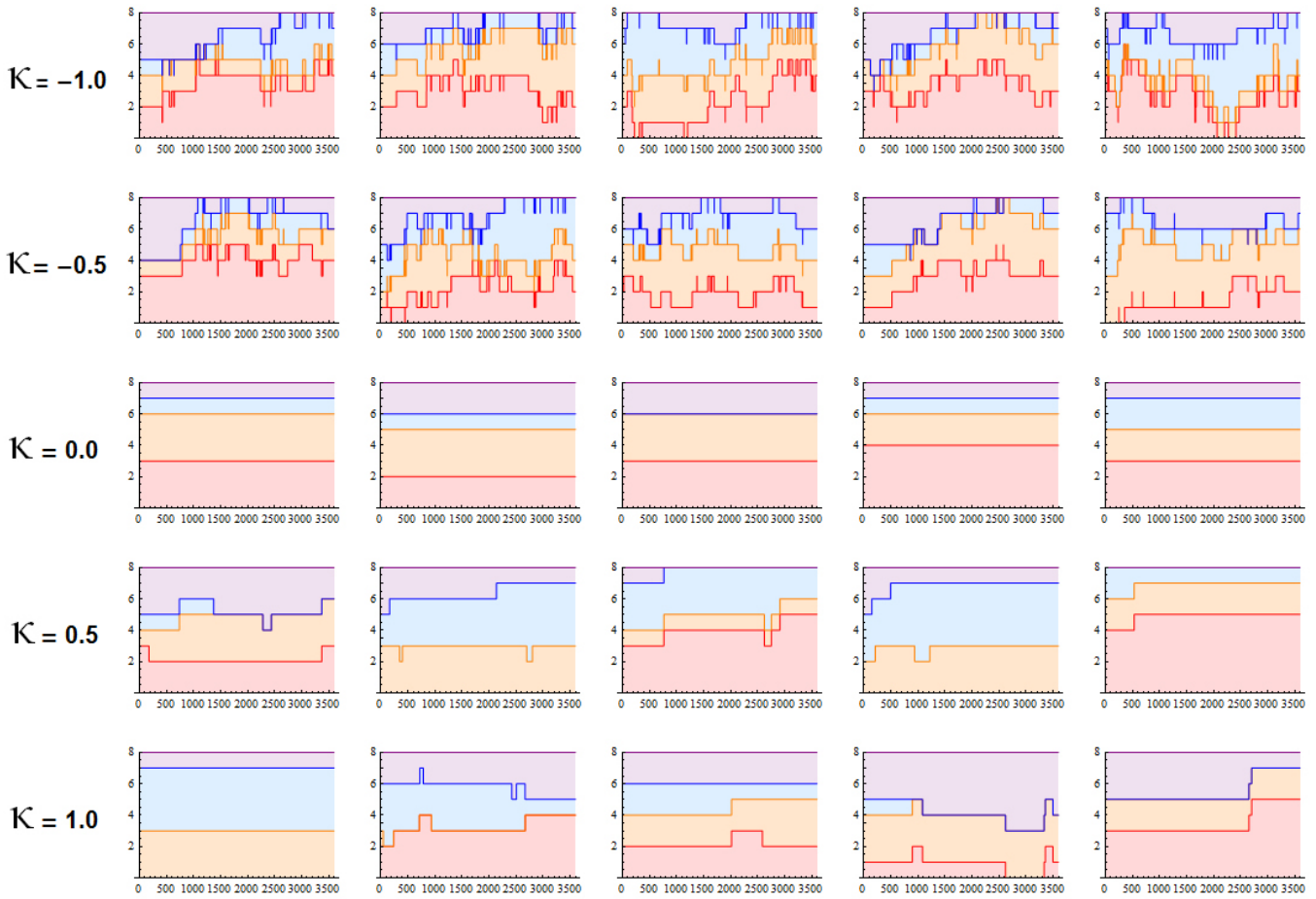


Fig. 9. Stacked line plots of the number of robots using each possible strategy in the five trials for each given κ value. Simulated time is represented on the X-axis in seconds and the number of robots using a given strategy is indicated by the Y-axis. The four shades in each graph (from bottom to top) correspond with the strategies *Wander*, *SpiralOut*, *WanderSpiral* and *RandomReaction* respectively. Since it is possible for a swarm to be randomly initialized with less than four strategies, not all shades may be present in all graphs.

behavior when diversity is encouraged and dominant behaviors are prevented from spreading throughout the entire swarm too early. Through manipulation of κ values, we were able to illustrate a significant correlation between probability of accepting diverse behaviors and the degree of variance in coverage values.

At first glance, it may appear that our results could be achieved without the use of RFID cards at all; robots could simply switch their behavior after random intervals of time. This explanation is not sound because it does not accurately describe the RFID-robot interaction in our system. In every simulation, all RFID cards are initially empty storage spaces—a robot interacting with a card does not always have the opportunity to adopt a new behavior. The adoption behavior is strongly dependent on the distribution of RFID cards and robots in the environment and the initial exploration behaviors of each robot. Furthermore, when κ is negative, the robots intentionally avoid redundancy by avoiding the adoption of a strategy already written to an RFID card. The more negative κ is, the more likely robots are to avoid redundant behaviors. The performance improvements resulting from more negative κ values is clearly apparent in

the results.

When $\kappa \geq 0$, greater κ values corresponded with higher variance in coverage. When the simulations are started, there usually are one or more RFID cards beneath the swarm. Behaviors such as *SpiralOut* and *SpiralWander* do not cover nearly as large a space as the other strategies, but they are very efficient at almost completely covering the local space around the robots. When all the robots are close together in the beginning, this means that these “spiral” strategies tend to hit RFID cards under the swarm before other robots. With high positive κ values, a majority of the swarm is more likely to adopt these globally inefficient behaviors and constrict them to the space near their starting positions. This “winner-takes-all” approach allows certain strategies to become locally adaptive, but it also makes the swarm very sensitive to initial conditions and less robust at mapping an environment.

When $\kappa < 0$, more negative κ values increase the probability of a robot adopting a behavior different from that on a card. By preventing the “winner-takes-all” scenario, the overall variance of the coverage decreased significantly without detrimental effects on performance. We effectively

increased the “diversity” of the swarm and avoided the pitfalls seen in other experiments where specialized task-completion algorithms can cause swarm behavior to become stuck in local performance minima [24]. In these instances, the “diversity” is manually added by a human operator. This diversity is illustrated by Figure 9, which indicates that negative κ values prevent any one strategy from persisting at a stable level for too long within the swarm. Positive κ values prevent such dynamic shifting in strategy usage, so performance can vary greatly depending on which strategy is dominant within the swarm.

Our findings are particularly important given concerns with the reliability of emergent behavior as problem solving tool. If significantly different patterns emerge with each experiment, the tool is not reliable. We demonstrated that a robust emergent behavior can emerge with the necessity of an outside human operator manually “encapsulating” behaviors into something useful [25]. The system moderates itself. Allowing agents to change through frequent indirect interactions causes the overall behavior of a swarm to be more consistent and thus more useful. In real-world applications—like search-and-rescue or minesweeping—consistent performance can be the difference between life and death.

Furthermore, the fact that consistent mapping performance arose solely from indirect interaction between robots suggests that the system can be scaled up as needed; adding a robot to the system does not necessitate any modifications to the environment, system rules or the programming of other robots. While direct communication between robots holds the possibility of increased mapping performance, it also increases local complexity and focus on individual robots as opposed to the swarm itself. Direct communication implies that each robot would need a specific ID so they could be differentiated from one another, a system to synchronize information between individuals, and the ability to store an “image” of the environment to provide a reference point. If individual learning was also implemented, it would necessitate additional increases in agent complexity as each robot would need additional software and hardware to store, process and synchronize this complex information. In our system, each agent only needs an RFID antenna and enough storage space for simple local interaction rules. Our system entirely avoids the issues of synchronization errors between robots, agent training (ensuring the agents don’t “overlearn” a given environment), and any communication interference that may arise from direct communication between robots via wireless links.

In future work, we will expand the scope of our experiments. Other researchers, such as Kleiner and Dornhege [14], have examined multi-robot systems in true three-dimensional SLAM environments where robots had to climb over boundaries. We would like to examine the effect of such “elevation” obstacles. We would also like to see if the overall emergent behavior of the swarms differs with varying ratios of robots-to-cards. We believe that increasing the density of the RFID cards and increasing the card-to-

robot ratio will further support the conclusions drawn in this paper. If successful, we will immediately begin working on physical experiments to confirm our virtual results.

In addition, the performance of our cultural transmission technique must be thoroughly examined in context to determine its relative usefulness in practical applications. We plan to perform an in-depth qualitative comparison between our technique and other social cultural and individual learning techniques in terms of mapping performance, general task achievement and cost-performance. These learning capabilities may involve intelligent reactions to repetitive sensor information or even the behavior of other robots. More advanced techniques may effect better performance at the cost of increased time and effort spent developing individual learning processes, although this cost-benefit compromise may change depending on the environment and local constraints placed on the system.

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