

Formica ex Machina: Ant Swarm Foraging from Physical to Virtual and Back Again

Joshua P. Hecker¹, Kenneth Letendre^{1,2}, Karl Stolleis¹,
Daniel Washington¹, and Melanie E. Moses^{1,2}

¹ Department of Computer Science, University of New Mexico, Albuquerque, USA

² Department of Biology, University of New Mexico, Albuquerque, USA
{jhecker,melaniem}@cs.unm.edu, {kletendr,stolleis}@unm.edu

Abstract. Ants use individual memory and pheromone communication to forage efficiently. We implement these strategies as distributed search algorithms in robotic swarms. Swarms of simple robots are robust, scalable and capable of exploring for resources in unmapped environments. We test the ability of individual robots and teams of three robots to collect tags distributed in random and clustered distributions in simulated and real environments. Teams of three real robots that forage based on individual memory without communication collect RFID tags approximately twice as fast as a single robot using the same strategy. Our simulation system mimics the foraging behaviors of the robots and replicates our results. Simulated swarms of 30 and 100 robots collect tags 8 and 22 times faster than teams of three robots. This work demonstrates the feasibility of programming large robot teams for collective tasks such as retrieval of dispersed resources, mapping, and environmental monitoring. It also lays a foundation for evolving collective search algorithms *in silico* and then implementing those algorithms *in machina* in robust and scalable robotic swarms.

1 Introduction

One goal of swarm robotics is to engineer groups of simple, low-cost robots that can cooperate as a cohesive unit to accomplish collection and exploration tasks such as mapping, monitoring, search and rescue, and foraging for resources in unmapped environments [4,5,8]. Ideally, robotic swarms are capable of exploring unknown environments without the benefit of prior knowledge to guide them. Individuals must adapt to sensor error and motor drift, and the swarm must function given variation, errors, and failures in individual robots.

Biology often provides inspiration for approaches to achieve these design goals [4,6,8,18]. Biologically-inspired decentralized approaches have enhanced scalability and robustness by removing single points of failure from communication bottlenecks and rigid control structures. Such approaches have not yet reached the level of emergent coordination observed in natural systems [24].

Our robots are designed to mimic colonies of seed harvester ants who forage using a combination of individual memory and pheromone trails. Robots are

equipped with a sensor suite which mimics the real ants: time-based odometry approximates physical location analogous to the ants' stride integration [26], and ultrasound ranging measures distance to objects and corrects for drift similar to an ant's landmark-based navigation [13]. Pheromone-like communication of previously successful search locations is used to improve search performance. Robots search for radio-frequency identification (RFID) tags, and upon finding them, return to a central 'nest.' Robot locations are transmitted over one-way wireless communication to a server for data logging; occasional two-way communication allows virtual pheromones to direct robots to previously found tag locations.

We program our robots with search algorithms derived from our previous work that used an agent-based model (ABM) guided by genetic algorithms (GA) to replicate foraging behaviors of seed harvester ants [11,15]. We duplicate parameters from the ant model in the robots. We modified the ABM to replicate the constraints of the robot hardware, and to model the behavior and environment of the robots in their search for RFID tags. This parallel physical and simulated implementation allows us to compare results from analogous experiments *in machina* as implemented in physical robots and *in silico* in the ABM (as in [7,16]). In additional ABM experiments we scale up the size of the swarm, the number of tags, and the size of the area in which the simulated robots search.

2 Background

Swarm Robotics: Like ant colonies and other complex biological systems, robotic swarms have potential to utilize efficient, robust, distributed approaches to physical tasks. Effective algorithms for swarm robotics must extend beyond simulation to intelligently deal with the complexities of navigating in real environments [7,16,17]. Our approach balances the benefit of centralized information exchange with the scalability of decentralized autonomous search [2,19,23]. We use evolutionary algorithms to determine the parameters of individual behavior that result in effective collective action, as in [9,11,22,25].

Biological Ants: Our algorithms are largely inspired by foraging in *Pogonomyrmex* desert seed-harvester ants [10]. These foragers typically leave their colony's single nest, travel in a relatively straight line to some location on their territory, and then switch to a correlated random walk to search for seeds.

When a forager finds a seed, it brings it directly back to the nest. Foragers often return to the location where they previously found a seed in a process called site fidelity [3,10,20], which reduces future search times. It is unclear exactly how often these ants lay and follow pheromone trails [12,13,21], but our recent work indicates occasional laying of pheromone trails to dense piles of food may be an effective component of these ants' foraging strategies [11,15].

Models: We used GAs to find the optimal balance of site fidelity and pheromone communication in simulated ant colonies [15]. We simulated ant foraging using a set of ABMs of foragers on a grid, with parameters that specify how ants travel from the nest, search, and use site fidelity and pheromone communication. These parameters are optimized by a GA to maximize seed intake rate.

Previous simulations show that ants increase foraging rates with rare pheromone use ($< 10\%$ of foraging trips), particularly in the clustered distribution where the intake rate doubles with the addition of pheromone [15].

The ant foraging ABM was modified to model our swarm robots and our experimental setup. The simulation provides both a theoretical benchmark and a basic architecture for using GAs to optimize simulated robots within the constraints imposed by the physical hardware. All *in machina* experiments have been duplicated *in silico*.

3 Methods

3.1 Hardware

Our robots use an Arduino microcontroller with a compass, ultrasound, wireless card, and RFID reader. These allow the robots to localize at a central ‘nest,’ measure distance (object 100 cm away: mean error = 2.7 cm, $\sigma = 2.24$), and calculate odometry (round trip of 10 m: mean error = 21 cm, $\sigma = 6.6$). Robots avoid collisions by rotating clockwise until the object has been cleared.

3.2 Search Algorithm

The search behavior used by the robots to locate RFID tags is shown in Fig. 1.

1. Set Search Location: Robots begin at the nest in the center and randomly select an initial search site location, encoded as a distance d and heading h .
2. Travel to Search Site (yellow path) Traveling robots go straight to the search location while avoiding collisions with other robots, correcting for motor drift, and communicating events to the server for later analysis.
3. Search for Tag (blue path): The robot moves in a correlated random walk with direction θ at time t drawn from a normal distribution centered around direction θ_{t-1} and standard deviation $SD = \omega + \gamma/t_s^\delta$. ω determines the degree of turning during an uninformed search. In a search informed by memory or communication, γ/t_s^δ determines an initial additional degree of turning which decreases over time spent searching. This mimics ants’ tight turns in an initially small area that expand to explore a larger area over time [11].
4. Travel to Nest (pink path): The robot returns to the known nest location. In pheromone experiments, the tag location (d, h) is reported to the server if $C > 1$, where C is the count of other tags detected in the 8-cell neighborhood of the collected tag in the simulation or discovered in one 360° rotation of the real robot.
5. Set Next Search Location: On subsequent trips, d and h are determined by either returning to the previously found tag location if $C > 0$, otherwise d and h are communicated from the pheromone list on the server.

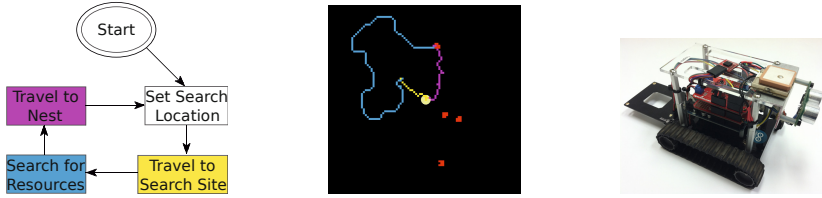


Fig. 1. A robot begins its search at a globally shared central nest site (center circle) and **sets a search location**. The robot then **travels to the search site** (yellow line). Upon reaching the search location, the robot **searches for tags** (blue line) until tags (red squares) are found. After searching, the robot **travels to the nest** (purple line).

3.3 Experimental Design

Each experimental trial on a concrete surface runs for a maximum of one hour. A cylinder marks the center ‘nest’ to which the robots return once they have located a tag. This center point is used for localization and error correction by the robots’ ultrasonic sensors. All robots involved in a trial are initially placed near the cylinder. We program each robot to stay within a 3 m radius ‘virtual fence’. In every experiment, 32 RFID tags are arranged in one of three different patterns: random, clustered, or power law (Fig. 2). Experiments are replicated under identical conditions for individual robots and for groups of three bots.

Robot locations are continually transmitted over one-way WiFi communication to a central server and logged for analysis. When a tag is found, its unique identification number is transmitted back to the server, providing us with a detailed record of tag discovery. Tags can only be read once, simulating seed retrieval. The central server also acts as a coordinator for virtual pheromone trails using two-way communication. Locations deemed important enough to require a pheromone value (i.e. those with two or more tags discovered by the robot) are added to a list data structure with a pheromone value of 1. Each location’s associated pheromone value p_i is decayed exponentially over time by the server: $p_{t+1} = p_t * .995^\eta$, where η is the number of seconds between time t and $t + 1$. When a location’s pheromone value has dropped below a threshold of 0.001, it is removed from the list. As each robot returns to the nest, the server selects a location from the list (if available) and transmits it to the robot.

Our simulations replicate the physical dimensions of the robots, their speed while traveling and searching, and the area over which they can detect an RFID tag, with spatial dimensions that reflect the distribution of tags in the 3 m area. Like the real robots, simulated robots avoid collisions by turning to the right to move past other robots, and search for a simulated hour.

We also simulated the behavior of the robots in a much larger area in which tags are distributed in the same density but in such large numbers that even large swarms of robots collect only a fraction of the available tags. We simulated 1, 3, 30, and 100 robots to observe the scaling properties of the system.

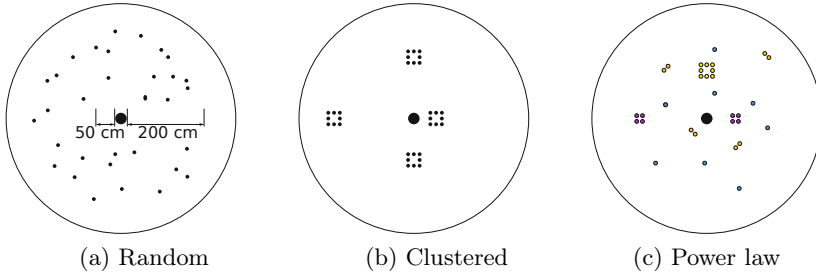


Fig. 2. 32 RFID tags scattered in a ring between 50 cm and 200 cm in (a) the uniform random distribution. The clustered distribution (b) has four piles of eight tags placed at 90° intervals at 50, 100, 150, and 200 cm in relation to the central nest. The power law distribution (c) uses piles of varying size and number: one large pile of eight tags at 125 cm, two medium piles of four tags at 75 and 175 cm, four small piles of two tags at 50, 100, 150, and 200 cm, and eight randomly placed tags.

4 Results

We analyze the rates at which robots retrieve tags from each distribution, individually or in teams of three, in real robots and in simulation. Unless otherwise noted, results for each experimental treatment are averaged over five robot experiments and twenty simulations. Error bars indicate one standard deviation.

Time to collect 32 tags is shown in Fig. 3. In robots and in simulation, three robots collect tags faster than one robot, however, the speedup varies over the course of the experiments (i.e., the red and blue lines are not parallel). When we average time to collect n tags, where n varies between 1 and the maximum number of tags collected, we find that 3 robots collect tags approximately twice as fast as 1 robot.

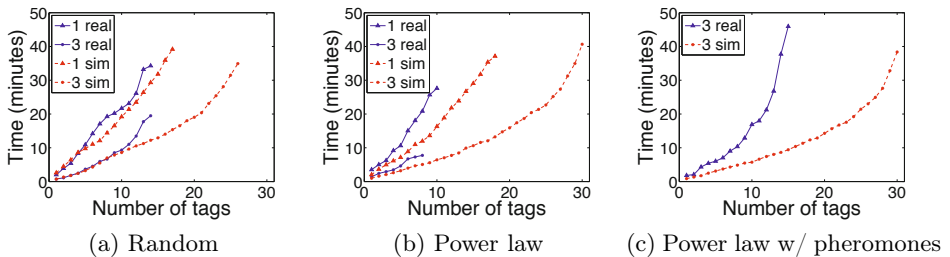


Fig. 3. Time for 1 and 3 robots, real and simulated, to collect tags arranged in (a) random and (b) power law distributions using only site fidelity, and (c) for 3 robots on a power law distribution using pheromones and site fidelity.

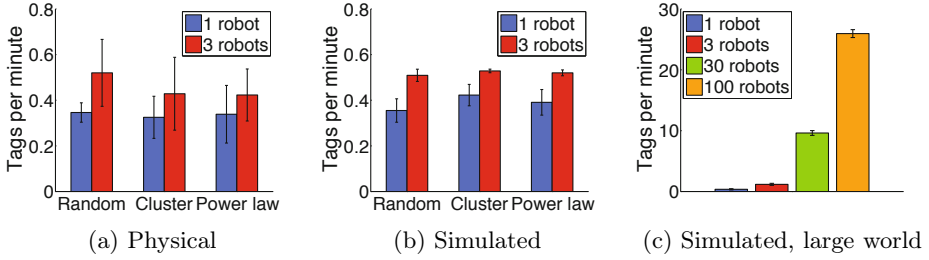


Fig. 4. Rate of tag discovery per minute of experiment time for 1 and 3 (a) physical and (b) simulated robots in the 3 m area using only site fidelity, as well as (c) 1, 3, 30, and 100 simulated robots collecting tags in a large world with site fidelity and pheromones.

Figure 4 shows the the rate of tag collection per minute of experiment time for physical and simulated robots. Each bar denotes the collection rate over a particular tag distribution. We were not able to distinguish a significant effect of tag distribution on tag collection rate by the robots (General Linear Model [GLM]: $p > 0.1$; $n = 18$); but we did find a significant effect of distribution on tag collection rate using the larger sample size in simulation (GLM: $p < 0.001$; $n = 120$). In the simulations, the fastest tag collection was in the clustered distribution, followed by power law and then random distributions.

5 Discussion

We used ABMs and GAs to translate foraging behaviors of seed harvesting ants into algorithms for teams of RFID tag-seeking robots. We tested two algorithms: one in which robots rely on individual memory of locations of previously found tags (mimicking site fidelity), and one in which robots share tag locations as waypoints (mimicking pheromones) via a server that acts as the robots' nest.

Three robots find tags approximately twice as fast as 1 robot when using site fidelity. Site fidelity is an effective foraging strategy in ants and robots. It is extremely simple and easily encoded into very simple devices, including devices much simpler than the robots we used here. The approach is also highly parallelizable because it requires no communication among robots or the server.

Our approach, similar to [7], lays a foundation to explore the interplay between simulation and experiments with real robots. Simulated and real experiments with 1 and 3 robots using site fidelity show similar foraging rates (Fig. 3(a),(b) and Fig. 4(a),(b)), although simulated robots are slightly faster. This results from real robots having more difficulty with avoiding each other, physical hardware limitations, imperfect localization, and the possibility that real robots confuse each other with the nest.

Simulated foraging is highly scalable whether using site fidelity alone, or site fidelity augmented with pheromones when multiple tags are found in the same

location. When we scale up to 100 robots in unbounded environments with many tags, teams of 100 robots collect resources 66 times faster than a single robot (Fig. 4(c)). This 34% decline in per-robot efficiency results from increased travel distance—an unavoidable consequence of central place foraging [14].

We implemented pheromone communication in real robots by having robots report found tag locations to a central server. Mimicking a strategy that was effective in our ant simulations, robots communicated a location as a waypoint to the server if the robot saw at least 2 additional tags in the vicinity. The server implements a simple pheromone algorithm and reports those locations to other robots. When we add this pheromone-like behavior to our robots, we observe robots clearing large clusters of tags faster; however, pheromones decreased the average tag collection rate in real robots relative to tag collection using only site fidelity. We attribute the lack of success primarily to error propagation: pheromones decrease performance when robots get lost and communicate incorrect locations to other robots, similar to [1].

Our results suggest that the approach of combining individual memory with communication at a central nest can transform simple robots into effective swarms that are scalable and robust to the loss or malfunction of a few individuals. Results of our 3 robot experiments include several instances in which one robot became lost or malfunctioned, but the other two robots continued their task. Such systems could be used for search and rescue, searching for resources or obstacles, and even biomedical applications using nano-robots.

Our next steps are to use a GA to optimize parameters that maximize efficiency and/or robustness in the robot ABM, and then import those parameters into the robots. For example, currently the robots report a pheromone to the server if there are 2 or more additional tags in the local neighborhood of the last tag found. We will use the GA to optimize the decision to lay pheromone and follow pheromone trails vs. returning to the last site food was found, optimizing the balance between shared and private information. Preliminary analysis suggests that the GA can evolve a pheromone-laying rule that significantly improves foraging over our current implementation. We will also extend analysis to different distributions, and will increase scalability by mimicking features of large ant colonies such as the use of mobile nests and of multiple nests.

Acknowledgments. This work was funded by NSF EF #1038682 and DARPA CRASH #P-1070-113237.

References

1. Bailis, P., Nagpal, R., Werfel, J.: Positional communication and private information in honeybee foraging models. *Swarm Intelligence*, 263–274 (2010)
2. Banerjee, S., Moses, M.: Scale invariance of immune system response rates and times: perspectives on immune system architecture and implications for artificial immune systems. *Swarm Intelligence* 4(4), 301–318 (2010)
3. Beverly, B., McLendon, H., et al.: How site fidelity leads to individual differences in the foraging activity of harvester ants. *Behavioral Ecology* 20(3), 633–638 (2009)

4. Bonabeau, E., Dorigo, M., Theraulaz, G.: *Swarm intelligence: from natural to artificial systems*. Oxford University Press, USA (1999)
5. Cao, Y., Fukunaga, A., Kahng, A.: *Cooperative mobile robotics: Antecedents and directions*. *Autonomous Robots* 4(1), 7–27 (1997)
6. Deneubourg, J., Goss, S., Franks, N., Sendova-Franks, A., et al.: The dynamics of collective sorting robot-like ants and ant-like robots. In: *From Animals to Animats: Proc. of the 1st Int'l Conf. on Simulation of Adaptive Behavior*, pp. 356–363 (1991)
7. Dorigo, M., Floreano, D., et al.: *Swarmanoid: a novel concept for the study of heterogeneous robotic swarms*. Tech. rep., Technical Report TR/IRIDIA/2011-014, IRIDIA, Université Libre de Bruxelles, Brussels, Belgium (2011)
8. Dorigo, M., Sahin, E.: *Swarm robotics—special issue editorial*. *Autonomous Robots* 17(2-3), 111–113 (2004)
9. Dorigo, M., Trianni, V., Şahin, E., Groß, R., Labella, T., et al.: *Evolving self-organizing behaviors for a swarm-bot*. *Autonomous Robots* 17(2), 223–245 (2004)
10. Flanagan, T., Letendre, K., Moses, M.E.: *Quantifying the Effect of Colony Size and Food Distribution on Harvester Ant Foraging*. *PLoS ONE* (in review)
11. Flanagan, T., Letendre, K., et al.: *How Ants Turn Information into Food*. In: *Proceedings of the 2011 IEEE Conference on Artificial Life*, pp. 178–185 (2011)
12. Gordon, D.: *The spatial scale of seed collection by harvester ants*. *Oecologia* 95(4), 479–487 (1993)
13. Hölldobler, B.: *Recruitment behavior, home range orientation and territoriality in harvester ants, Pogonomyrmex*. *Behav. Ecol. and Sociobio.* 1(1), 3–44 (1976)
14. Krieger, M., Billeter, J., Keller, L.: *Ant-like task allocation and recruitment in cooperative robots*. *Nature* 406, 992–995 (2000)
15. Letendre, K., Moses, M.E.: *Ant foraging strategies: Site fidelity and recruitment alone and in combination* (in review)
16. Mayet, R., Roberz, J., Schmickl, T., Crailsheim, K.: *Antbots: A feasible visual emulation of pheromone trails for swarm robots*. *Swarm Intell.*, 84–94 (2011)
17. Moeslinger, C., Schmickl, T., Crailsheim, K.: *Emergent flocking with low-end swarm robots*. *Swarm Intelligence*, 424–431 (2011)
18. Mondada, F., Pettinaro, G., Kwee, I., Guignard, A., Gambardella, L., Floreano, D., Nolfi, S., Deneubourg, J., Dorigo, M.: *SWARM-BOT: A swarm of autonomous mobile robots with self-assembling capabilities*. In: *Proc. of the Intl. Workshop on Self-organisation and Evolution of Social Behaviour*, pp. 307–312 (2002)
19. Moses, M., Banerjee, S.: *Biologically Inspired Design Principles for Scalable, Robust, Adaptive, Decentralized Search and Automated Response (RADAR)*. In: *Proceedings of the 2011 IEEE Conference on Artificial Life*, pp. 30–37 (2011)
20. Moses, M.: *Metabolic scaling from individuals to societies*. Ph.D. thesis, University of New Mexico (2005)
21. Mull, J., MacMahon, J.: *Spatial variation in rates of seed removal by harvester ants (Pogonomyrmex occidentalis) in a shrub-steppe ecosystem*. *Am. Nat.* (1997)
22. Nolfi, S., Florin, D.: *Evolutionary robotics: The biology, intelligence, and technology of self-organizing machines*. MIT Press (2000)
23. Parker, L.: *Designing control laws for cooperative agent teams*. In: *IEEE International Conference on Robotics and Automation*, pp. 582–587. IEEE (1993)
24. Sharkey, A.: *Robots, insects and swarm intelligence*. *Artificial Intelligence Review* 26(4), 255–268 (2006)
25. Trianni, V., Nolfi, S.: *Engineering the Evolution of Self-Organizing Behaviors in Swarm Robotics: A Case Study*. *Artificial Life* 17(3), 183–202 (2011)
26. Wittlinger, M., Wehner, R., Wolf, H.: *The ant odometer: stepping on stilts and stumps*. *Science* 312(5782), 1965 (2006)