Socially Inspired Communication in Swarm Robotics

Nathan White, John Harwell, and Maria Gini

Department of Computer Science and Engineering, University of Minnesota
{whit2267,harwe006,gini}@umn.edu

Abstract. Localized communication in swarms has been shown to increase swarm effectiveness in some situations by allowing for additional opportunities for cooperation. However, communication and utilization of potentially outdated information is also a concern. We present an explicit non-directional goal-based communication model and message accept/reject scheme, and test our model in a set of object gathering experiments with a swarm of robots. The results of the experiments indicate that even low levels of communication regarding the swarm's goal outperform high levels of random information communication.

Keywords: Inter-robot communication · Swarm robotics · Foraging

1 INTRODUCTION

Swarm robotics is the study of large scale robotic systems that consist of many individual robots working cooperatively to achieve a goal [24,25,6,13,15,10]. These individual robots usually have limited capabilities, so it is very difficult and time consuming for a single robot to achieve the goal. Cooperation among the robots helps the swarm to achieve the goal more robustly. In a swarm each robot is autonomous, acting without a centralized controller. This allows for heterogeneous adaptation to environmental differences in spatially disparate parts of the swarm's operating area.

One popular application of swarm robotics is foraging. Foraging is the act of having robots grab blocks, representing food, in a given environment and return them to a central location (the "nest"). Foraging in swarm robotics attempts to replicate the efficiency observed in nature [17]. This replication of cooperation found in nature has multiple real-world applications. Companies such as NASA are considering swarms of robots that are able to cooperate and work together for potential excursions into the asteroid belt [23]. This would allow for cooperative exploration and communication back to Earth. Another application is the usage of swarm robotics to complete tasks within potentially dangerous regions [24]. One example of such tasks is the exploration of a burning building. Swarm robotics would allow for the searching of people to be rescued, with potentially lower search times and more flexibility, as the robots an search in parallel in different parts of the building.

Foraging tasks in swarm robotics has long been known to have better efficiency when communication is permitted [5]. This is due to the levels of cooperation that can be achieved when sharing information via communication. Any robust communication model should be able to increase swarm effectiveness. Furthermore, it should be able to determine what information is relevant to increasing the effectiveness and what is not, in order to minimize time lost due to out-of-date information.

In the realm of human communication, humans are able to communicate with any number of people within a given range, where the range is limited only by hearing capabilities and the speaker's volume. Humans are extremely good at cooperative work primarily due to their ability to communicate [26]. Like in swarm robotics, humans are independent agents, acting according to their internal knowledge and representation of the environment. However, unlike in swarm robotics, humans are capable of making irrational decisions [14], even forgoing given information if they believe their internal representation is more accurate than the information that was passed to them by communication.

While ignoring information is an important part of the process, it is useless without the ability to share information. Creating a communication model in swarm robotics based on humans means the model has to include both the chance of ignoring information and the chance of sharing information.

In this paper, we focus on a foraging scenario, where groups of robots have to gather blocks from a single source and transport them to a known nest location. Robots need to be capable of communication for improved cooperation opportunities. Within our scenario, we allow explicit non-directional communication of source locations to avoid wasted exploration time, but also allow for the potential to reject the integration of a message. By utilizing communication, we can expect to see more blocks being collected and less time spent in the exploration state.

We propose a new communication strategy for cooperative swarm robotics that utilizes a form of explicit non-directional communication. We explore this strategy's effectiveness within an ideal foraging scenario simulation, comparing it against a random cell selection (RCS) algorithm with high levels of communication, as well as a controlled random walk (CRW) swarm with no communication or memory of their environment. We view an ideal foraging scenario as one without obstacles with goal objects located in a consistent location. The results of our experiments indicate that any level of the communication of information relevant to the swarm's goal outperforms continuous information of random portions of the environment, but any communication outperforms no communication.

The remainder of this paper is split into six sections. In Section 2 we give a review of current applications and implementations of communication in swarm robotics. Then, in Section 3 we provide an in-depth analysis of the foraging scenario and solve it using our proposed communication implementation. Section 4 provides details for both the framework and the assumptions we use in our experimental setup. In Section 5 and Section 6 we describe in detail the experiments, followed by their results. The final section, Section 7, completes the paper, with the conclusions and potential ideas for future work.

2 Related Work

Communication strategies in swarm robotics are often inspired by ethology, the study of animal behavior. This is due to the fact the in the animal kingdom many creatures are social and operate collectively to achieve their goals. Several strategies have roots in the studies of bees and ants [13,11,8]. This is due to the fact that bees and ants commonly represent the two main methods for communication, explicit and implicit respectively.

Implicit communication is the use of the environment to share information with other individuals. In the case of ants, pheromone trails are utilized to mark the path traversed. Pheromone trails have been replicated in prior swarm robotics research [13,11,18,27,1]. Pheromone is left behind on the path an ant takes. The pheromone decays over time, so repeated usage of the trails strengthens them. The stronger the level of pheromone, the more ants are attracted to that specific pathway. In this way ants find the shortest paths.

Conversely, explicit communication is the act of communicating directly with other entities [28,4]. This can be done in many ways. In the case of bees, the medium is a form of dance, known as the waggle dance [9,22]. This dance may need to be repeated if the bees fail to find the location encoded within it. Using this method, robots have danced in order to communicate source locations to the rest of the swarm [21].

Regardless of the medium, the purpose is clear: to recruit other members of the swarm for cooperative task completion. There have been many variants in the implementations, all to increase the swarm effectiveness given their specific situation [17]. However, it is clear that communication is useful to increase the swarm effectiveness in accomplishing the task.

Arkin *et al.*, explored state based communication, where robots are only allowed to communicate their current task, purely as an aid, not as a necessary component in task completion [2,3]. Utilizing a shared memory location, agents iteratively update their current state and location. Communication is only utilized when a robot has no goals in its field of view. If no goals are within view, then the robot is able to access the shared memory location to find which robots have found a goal and where their location is, then is able to navigate in that direction.

However, while Arkin explored the usage of state-based communication, Balch studied the effects of goal and state based communication over no communication [5]. He noted that goal based communication, the communication of locations of a goal object or place, within a foraging scenario demonstrated a notable improvement over non communicating swarms, but only a small improvement over state based communication. To give our communication schema ideal conditions, we follow the principles of goal based communication, being able to transmit source locations to others within the swarm.

This has been explored further by Pugh [12]. Entities are able traverse the environment in search of a single food source. However, the food source requires three individual robots to lift it and move it to a nest location. Pugh *et al.* state that communication is promoted by this need for several entities to lift and transport the food. By communicating, the robots are able to gain more food through the course of the experiment, and spend less time exploring.

Arkin and Pugh aren't alone in their studies. Many researchers have utilized communication in order to increase their swarms effectiveness and ability to cooperate (e.g.,[13,11,18,27,1,21,20]). However, what is missing on all these studies is the ability of the robots to reject communication. As given in our description of swarm robotics, robots are individuals and as such can make decisions about their environment and the information available to them. This should include the information shared with them.

3 Problem Statement and Proposed Method

3.1 Problem Statement

Each robot keeps a 2D grid of its environment. We denote a unit area of this 2D grid as cell (i, j). Each cell consists of two layers: the first being the contents of (i, j), which is represented by $s \in \{Unknown, Empty, Has\_Block\}$, and the second layer is the pheromone level associated with (i, j).

When encountering a block within the environment, we say that a robot k visited cell (i, j) at time step t. As time progresses, after n time steps past t, in which robot k does not see the given cell, the pheromone will decay as in Equation (1), where τ_{ij} represents the pheromone level of cell (i, j), τ_{ij}^k is robot k's perception of pheromone levels at that cell location, $\rho \in [0, 1]$ is the pheromone decay parameter that controls the rate of decay, for our experiments we set n = 1 (the level is updated at every time step), and m = 1 (the amount of pheromone deposited per time step) [16].

$$\tau_{ij}(t+n) = \rho\tau_{ij}^k(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^k(t) \tag{1}$$

The pheromone decay function dictates how relevant a cell's information is. If a robot k receives a message m_i at time step t, denoted as $m_i(t)$, it should have an associated relevance given by Eqn. (1). Since the pheromone level of cell (i, j) indicates how relevant its information is. If the communicated pheromone level is lower than the current internal level that robot k has for that region, then the communicated information is potentially outdated and would be rejected (e.g., if robot k sends a message to robot l where $\tau_{ij}^k < \tau_{ij}^l$ for a cell (i, j) then robot l will reject the message).

Every robot is capable of sending at most 1 message per time step. Should robot k send a message m_i, every robot within a radius of r_k of robot k will have the message broadcast to them. A robot k has a probability $p_{send}(t)$ and $p_{receive}(t)$ of sending and receiving a message on a time step t, respectively.

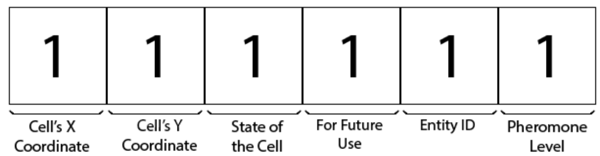

Fig. 1. Communication data packet structure. Each packet is represented as a byte vector, meaning each piece of information can be represented with a maximum of 1 byte. The 1 in each box represents the 1 byte limit, and each box is labeled with the information it is representing.

While probabilistic message transmission is not new, probabilistic message reception is new, and models (1) potentially bad environmental conditions that could cause unreliable communications, and (2) robot k's uncertainty about the trustworthiness of robot l's information.

Under this problem definition, swarms collectively solve a multi-objective optimization problem: minimizing the number of inaccuracies within each robot's internal representation of block locations ($I(N)$) while simultaneously trying to maximize the total number of blocks gathered ($B(N)$).

$$\max B(N) \min I(N) \tag{2}$$

Inaccuracies are calculated when cell (i, j) enters robot k's line of sight. If the cell's actual state doesn't match the state of the robot's internal representation, it is marked as inaccurate and recorded.

We therefore measure swarm performance in terms of this multi-objective formulation:

$$P(N) = \frac{B(N)}{I(N)} \tag{3}$$

3.2 Proposed Method

Before discussing the algorithm, we introduce the communication packet structure. Each packet is limited to 6 bytes of data, the structure for which is shown in Fig. 1. The first two bytes represent the (X, Y) coordinates of the cell (i, j). The third byte refers to the sending robot's internal knowledge of the current state of (i, j), which in our constrained foraging scenario is a subset of the complete set of states a cell can have. The set of cell states that we are interested in can be formulated as $s \in \{Unknown, Empty, Has\_Block\}$, where s is the current state of the cell (i, j). The fourth byte is reserved for future use. The fifth byte represents the ID of the entity located in cell (i, j). Finally, the sixth byte represents the pheromone level of the sending robot for the cell (i, j).

We utilize the explicit (sometimes called direct) communication strategy. At each time step of the simulation, robot k probabilistically sends one communication packet to every robot l in radius r_k defined by probability p_{send}. Similarly,

Algorithm 1 β_{send} and $\beta_{receive}$ are experimental parameters.

1: **function** COMMUNICATE
2: $\quad p_{send} \leftarrow rand()$
3: $\quad p_{receive} \leftarrow rand()$
4: $\quad$ **if** $p_{receive} < \beta_{receive}$ **then**
5: $\quad\quad Integrate\_Messages()$
6: $\quad$ **end if**
7: $\quad$ **if** $p_{send} < \beta_{send}$ **then**
8: $\quad\quad cell \leftarrow SELECT\_CELL()$
9: $\quad\quad send(cell)$
10: $\quad$ **end if**
11: **end function**
12: **function** SELECT_CELL
13: $\quad$ return $\max_{i,j} \frac{num_{ij}}{dist_{ij}} * \tau_{ij}(t)$
14: **end function**

each robot l in the radius probabilistically receives messages at each time step, defined by $p_{receive}$.

When a message is received, if robot k decides to accept message m_i, and internalize its contents, it treats all communicated data as if it was its own. That is to say that all communicated observations within the swarm are treated as if each individual robot had made the observation, when robot k accepts it. The process of internalizing the packet contents involves accessing robot k's 2D grid of the environment.

When robot k decides to send a message, it utilizes Algorithm 1 in order to select a cell (i, j) that maximizes line (13). The criteria for this equation are the number of blocks within the cell, num_{ij}, the euclidean distance from the cell to the nest, $distij$, and the pheromone level associated with the cell, τ_{ij}. Maximizing this function ensures trustworthy information is balanced with valuable information by trying to maximize both num_{ij} and τ_{ij} while minimizing $dist_{ij}$. For example, in the event there is a large store of blocks close to the nest with a low level of associated pheromone, it might be better to inform nearby robots of a different location, even if said location contains fewer blocks and lies just further away.

4 Experimental Framework

To conduct the experiments mentioned in this paper, we utilized the open-source FORDYCA [10] project, built on the ARGoS [19] simulator. The simulation's robots are modeled after an s-bot, developed during the Swarm-bots project [7].

The results of each experiment is averaged over 50 simulations. For all experiments conducted, we make the following assumptions:

– The robots are homogeneous, have an unlimited battery supply, and are able to communicate directly through range and bearing sensors.

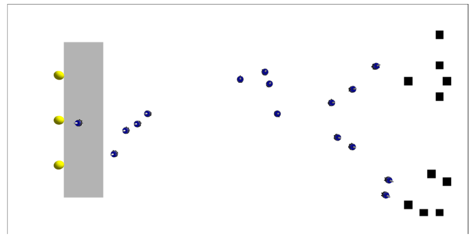

Fig. 2. ARGoS foraging scenario where blocks, represented as black cubes, are clustered in a single source on the right end of the arena. The grey rectangle represents the nest, and is colored due to the robot's ground sensors only detecting gray-scale. The yellow spheres above the nest are the light sources the robots use for self localization.

- All robots perform the entire foraging task.
- Robots are randomly distributed in the environment, but are able to self localize based upon a known light source that resides above the nest.
- The arena size is known to the robots, but not its contents.
- Transfer of objects between robots is not permitted.
- All foraging takes place in a flat, obstacle-less environment.
- The capacity of the nest is not limited.

5 Experiments

We test our proposed method on nine different sets of experiments in order to compare its performance against that of a similar communication schema with the cell selection method as random (RCS) using high probabilities for both sending and receiving. We also compare these results against a swarm with no communication that explores its environment through random movement (CRW), but retains no knowledge or assumptions about the location of food sources. Swarm performance is measured by Eqn. (3).

Table 1. Summary of parameters used for all experiments

Parameter	Value
r_k	2
ρ	0.001
Low	30%
Medium	60%
High	90%

Table 1 summarizes the values of the parameters that were kept constant throughout the experiments. The value r_k was selected to achieve a reliable communication distance that remained realistic in an area proportional to the

Table 2. Summary of the experimental scenarios used for testing the proposed method.

Experiment Set	β_{send}	$\beta_{receive}$
1	Low	Low
2	Low	Medium
3	Low	High
4	Medium	Low
5	Medium	Medium
6	Medium	High
7	High	Low
8	High	Medium
9	High	High

robot size. That is to say, the area for communication potential is not excessively large nor excessively small. The value chosen for ρ strikes a good balance between information relevance degradation and keeping viable blocks around long enough to prevent premature lapse into irrelevance. Low, Medium, and High refer to the probability for the sending/receiving probabilities, and are used in Table 2 to better convey the static associated value.

Table 2 displays a summary of the experiments conducted. We explore varying the communication probabilities at several fixed probabilities to determine where swarm effectiveness is maximized, while reducing the number of inaccuracies in internal environment representation. All nine sets of experiments are conducted with 128 robots, as well as a total of 75 source blocks located on the right end of the arena. All experiments were conducted using the arena displayed in Figure 2.

6 Results

For each experiment, we measure the total number of blocks gathered at the end of the experiment as well as the number of inaccuracies at every $\Delta t = 1000$ time steps. We define our swarm performance $P(N)$ as being the total number of blocks collected divided by the number of inaccuracies recorded.

The results indicate that even with a low chance of communication, information relevant to the goal of the swarm is much better than always communicating potentially random information, but that any level of communication outperforms swarms without it. RCS also had over double the number of inaccuracies regarding block locations than Experiment 9, the worst performing experiment. The performance of each experiment and RCS can be observed in Figure 3, where the difference between RCS and utility based selection becomes very apparent ($\sim 47\%$). Due to CRW not retaining knowledge of its environment, it has zero inaccuracies, however is included in our experiments to shows the performance difference of having any form of communication versus having none.

Table 3. Results of Experiments 1-9, the random cell selection algorithm (RCS), and the controlled random walk (CRW) swarm, with the total number of blocks collected and the total number of inaccuracies averaged 50 simulations per experiment, as well as the swarm performance as defined in Eqn. (3).

Experiment	Average Blocks Collected	Average Inaccuracies	Swarm Performance
1	995.88	1469.956	0.6775
2	991.26	1469.595	0.6745
3	972.54	1470.362	0.6614
4	975.94	1485.119	0.6571
5	989.76	1468.137	0.6742
6	1002	1447.042	0.6924
7	979.82	1453.959	0.6739
8	989.7	1475.9	0.6706
9	995.22	1502.555	0.6624
RCS	637.44	3554.704	0.1793
CRW	373.52	0	NaN

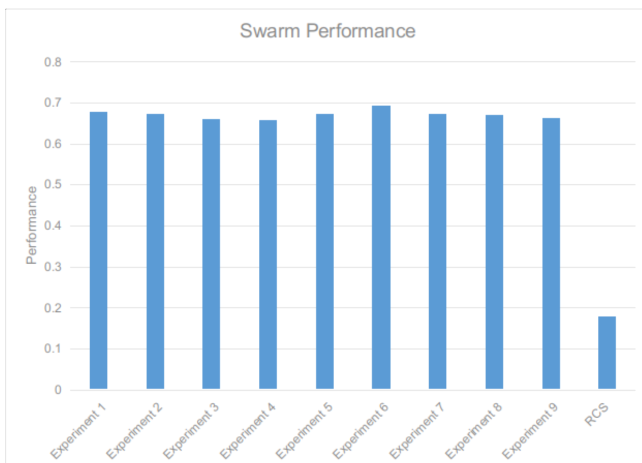

Fig. 3. Visualization of the performance of the Experiments 1-9 and RCS. CRW not depicted.

The similarities between both the low communication in Experiment 1 and the high communication in Experiment 9 indicate that communication occurs frequently enough that no additional useful information is communicated at higher levels. More specifically, the cell that was selected from the result of the utility function didn't vary frequently enough to warrant excess communication.

7 Conclusions and Future Work

We have presented a new communication schema for foraging in swarm robotics, adding the ability for robots to reject messages, an ability not present in previous work. We have shown that using this model, any level of relevant communication outperforms constant communication of random information.

One possible direction for future work would involve the presence of dynamic task allocation and caches. This would allow us to expand our communication implementation and include a combination of state and goal based communication to evaluate the impact it would have on task assignment and swarm efficiency. Another avenue for further work would be the testing of this implementation in more dynamic environments, where blocks are placed randomly or according to some function, as opposed to in a single location. With both of these possibilities, we plan to explore other communication algorithms and how the performance compares between them and the one presented in this paper.

In an effort to facilitate collaboration and future research, the code for this work is open source and available on github at $https://github.com/swarm-robotics/fordyca.git$.

Acknowledgements. We gratefully acknowledge Amazon Robotics, the MnDRIVE RSAM initiative at the University of Minnesota, and the Minnesota Supercomputing Institute (MSI) for their support of this work.

References

1. Arab, A., Carollo Blanco, Y., Costa-Leonardo, A.M.: Dynamics of foraging and recruitment behavior in the asian subterranean termite coptotermes gestroi (rhinotermitidae). Psyche (New York) (August 2014) (2012)
2. Arkin, R., Balch, T., Nitz, E.: Communication of behavorial state in multi-agent retrieval tasks. pp. 588–594 (1993)
3. Arkin, R., Hobbs, J.: Dimensions of communication and social organization in multi-agent robotic systems. In: From animals to animats 2: Proc. 2nd International Conference on Simulation of Adaptive Behavior. pp. 486–493 (1992)
4. Arvin, F., Samsudin, K., Ramli, A.R.: Development of ir-based short-range communication techniques for swarm robot applications. Advances in Electrical and Computer Engineering **10**(4), 61–68 (2010)
5. Balch, T.: Communication, diversity and learning: Cornerstones of swarm behavior. In: Sahin E., S.W. (ed.) Swarm Robotics. Lecture Notes in Computer Science, vol 3342, pp. 21–30. Springer (2005)
6. Brutschy, A., Scheidler, A., Ferrante, E., Dorigo, M., Birattari, M.: 'can ants inspire robots?' self-organized decision making in robotic swarms. In: IEEE International Conference on Intelligent Robots and Systems. pp. 4272–4273 (2012)
7. Dorigo, M.: SWARM-BOT: an experiment in swarm robotics. In: Proceedings 2005 IEEE Swarm Intelligence Symposium. pp. 192–200 (June 2005)
8. Ducatelle, F., Di Caro, G.A., Pinciroli, C., Gambardella, L.M.: Self-organized cooperation between robotic swarms. Swarm Intelligence **5**(2), 73–96 (2011)

9. von Frisch, K.: The dance language and orientation of bees. Harvard University Press, Cambridge (Massachusetts) **5** (06 1969)
10. Harwell, J., Gini, M.: Broadening applicability of swarm-robotic foraging through constraint relaxation. In: 2018 IEEE International Conference on Simulation, Modeling, and Programming for Autonomous Robots, (SIMPAR). pp. 116–122 (2018)
11. Hecker, J.P., Moses, M.E.: Beyond pheromones: evolving error-tolerant, flexible, and scalable ant-inspired robot swarms. Swarm Intelligence **9**(1), 43–70 (2015)
12. K. Pugh, J., Goodell, S., Stanley, K.: Directional communication in evolved multiagent teams. In: Proceedings of the Genetic and Evolutionary Computation Conference (GECCO) (07 2014)
13. Labella, T.H., Dorigo, M., Deneubourg, J.L.: Division of labor in a group of robots inspired by ants foraging behavior. ACM Transactions on Autonomous and Adaptive Systems **1**(1), 425 (2006)
14. Lee, M.D., Dry, M.J.: Decision making and confidence given uncertain advice. Cognitive Science **30**(6), 1081–1095 (2006)
15. Lerman, K., Martinoli, A., Galstyan, A.: A review of probabilistic macroscopic models for swarm robotic systems. Swarm Robotics Lecture Notes in Computer Science p. 143152 (2005)
16. Meng, Y., Gan, J.: A distributed swarm intelligence based algorithm for a cooperative multi-robot construction task. In: IEEE Swarm Intelligence Symposium (SIS). pp. 1–6 (Sep 2008)
17. Mohan, Y., Ponnambalam, S.G.: An extensive review of research in swarm robotics. In: 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC) (2009)
18. Payton, D., Estkowski, R., Howard, M.: Compound behaviors in pheromone robotics. Robotics and Autonomous Systems **44**, 229–240 (09 2003)
19. Pinciroli, C., Trianni, V., Ogrady, R., Pini, G., Brutschy, A., Brambilla, M., Mathews, N., Ferrante, E., Caro, G.D., Ducatelle, F., et al.: ARGoS: A modular, multi-engine simulator for heterogeneous swarm robotics. In: 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems (2011)
20. Pini, G., Gagliolo, M., Brutschy, A., Dorigo, M., Birattari, M.: Task partitioning in a robot swarm: A study on the effect of communication. Swarm Intelligence **7**(2-3), 173–199 (2013)
21. Pitonakova, L., Crowder, R., Bullock, S.: Information flow principles for plasticity in foraging robot swarms. Swarm Intelligence **10**(1), 33–63 (2016)
22. Riley, J.R., Greggers, U., Smith, A.D., Reynolds, D.R., Menzel, R.: The flight paths of honeybees recruited by the waggle dance. Nature **435**(7039), 205–207 (2005)
23. Rouff, C., Vanderbilt, A., Hinchey, M., Truszkowski, W., Rash, J.: Properties of a formal method for prediction of emergent behaviors in swarm-based systems. In: Proceedings of the Software Engineering and Formal Methods, Second International Conference. pp. 24–33. SEFM '04 (2004)
24. Sahin, E.: Swarm robotics: From sources of inspiration to domains of application. In: Sahin E., S.W. (ed.) Swarm Robotics, p. 1020. Lecture Notes in Computer Science 3342, Springer (2005)
25. Sharkey, A.J.C.: Swarm robotics and minimalism. Connection Science **19**(3), 245–260 (2007)
26. Smith, E.A.: Communication and collective action: Language and the evolution of human cooperation. Evolution and Human Behavior **31**(4), 231–245 (2010)
27. Sumpter, D.J., Beekman, M.: From nonlinearity to optimality: Pheromone trail foraging by ants. Animal Behaviour **66**(2), 273–280 (2003)

28. Trianni, V., Labella, T.H., Dorigo, M.: Evolution of direct communication for a swarm-bot performing hole avoidance. In: Dorigo, Birattari, Blum, Gambardella, Mondada, Stutzle (eds.) Ant Colony Optimization and Swarm Intelligence, pp. 130–141. Lecture Notes in Computer Science, vol 3172, Springer (2004)