

An ant-inspired model for multi-agent interaction networks without stigmergy

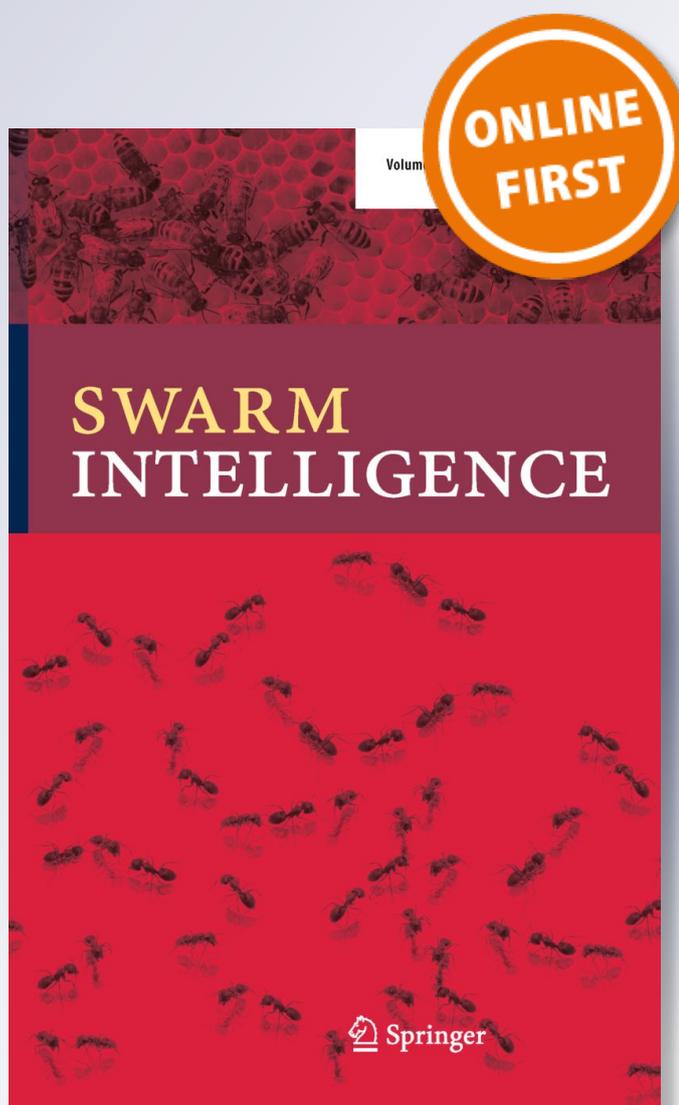
Andreas Kasprzok, Beshah Ayalew & Chad Lau

Swarm Intelligence

ISSN 1935-3812

Swarm Intell

DOI 10.1007/s11721-017-0147-4



Your article is protected by copyright and all rights are held exclusively by Springer Science+Business Media, LLC, part of Springer Nature. This e-offprint is for personal use only and shall not be self-archived in electronic repositories. If you wish to self-archive your article, please use the accepted manuscript version for posting on your own website. You may further deposit the accepted manuscript version in any repository, provided it is only made publicly available 12 months after official publication or later and provided acknowledgement is given to the original source of publication and a link is inserted to the published article on Springer's website. The link must be accompanied by the following text: "The final publication is available at link.springer.com".

An ant-inspired model for multi-agent interaction networks without stigmergy

Andreas Kasprzak¹  · Beshah Ayalew² · Chad Lau³

Received: 27 April 2017 / Accepted: 8 November 2017
© Springer Science+Business Media, LLC, part of Springer Nature 2017

Abstract The aim of this work is to construct a microscopic model of multi-agent interaction networks inspired by foraging ants that do not use pheromone trails or stigmergic traces for communications. The heading and speed of each agent is influenced by direct interactions or encounters with other agents. Each agent moves in a plane using a correlated random walk whose probability distribution for heading change is made adaptable to these interactions and is superimposed with probability distributions that emulate how ants remember nest and food source locations. The speed of each agent is likewise influenced by a superposition of impetus and resistance effects that arise from its recent interactions. Additionally, the agents use a quorum sensing mechanism to trigger a non-deterministic decentralized congestion avoidance scheme. A discrete-time non-deterministic recruitment model is adopted and incorporated to regulate the population of foraging agents based on the amount of food perceived to exist in the environment. Simulation experiments were conducted to evaluate and demonstrate how agents employ the interaction network when foraging in open and closed environments as well as in scenarios with narrow pathways that trigger congestion.

Keywords Ant foraging · Interaction networks · Multi-agent systems · Decentralized decision making · Self-organization

✉ Andreas Kasprzak
akasprz@clemson.edu

Beshah Ayalew
beshah@clemson.edu

Chad Lau
clau@harris.com

¹ Clemson University International Center for Automotive Research, 5 Research Drive, Greenville, SC 29607, USA

² Clemson University International Center for Automotive Research, 5 Research Drive, Suite 342 CGEC, Greenville, SC 29607, USA

³ Harris Corporation, 2400 Palm Bay Rd NE, Palm Bay, FL 32905, USA

1 Introduction

Social insects such as ants, bees, and wasps are known to exhibit complex group-level problem solving capabilities, despite the simplicity of the capabilities and behaviors of the individual insect. This observation has inspired a surge of research efforts to derive computational models that abstract the behavior of social insects. Such models for ant colonies have received significant attention following their successful application to many different types of combinatorial optimization problems. The first of these models and algorithms were proposed by Dorigo (1992). Today, various refinements of ant colony optimization (ACO) algorithms have been applied to optimization problems ranging from the traveling salesman problem (Stützle and Dorigo 1999) to data network routing and scheduling (Di Caro and Dorigo 1998) to protein folding (Shmygelska et al. 2002). Further applications influenced by models of the behaviors of ants and other social insects include multi-agent systems for swarm robotics (Şahin 2005; Dorigo et al. 2014), reconfigurable manufacturing systems (Leitão et al. 2012) and other systems relying on self-organizing principles, such as sensor networks, computing grids and software for business processes and network security (Foukia and Hassas 2004). Most discussions on ant-based foraging are based on mimicking ants that communicate through pheromone secretions and create probabilistically optimal trails between places of interest, like the nest (or a home base) and a food source. This kind of indirect communication by altering the environment is known as stigmergy. However, depositing environmental markers may be costly or impractical for artificial systems such as transportation networks and swarms of drones in which we aim to incorporate features of our model. For example, using roadside infrastructure for indirect communication between vehicles is expensive and too restrictive for transportation networks. Therefore, instead of stigmergy, we lean on the fact that many species of insects, especially of the Hymenoptera order, also possess spatial abilities enabling them to navigate their environments, including returning to the nest without the use of a trail (Collett et al. 2013). These primarily exploit the guidance abilities afforded by the interactions between agents.

The direct encounters or interactions between agents may be interpreted and used in different ways. In some ant species, such as the ant *Lasius niger*, the encounters manifest as repulsive interactions where ants turn away from each other to prevent congestion (Koutsou and He 2009). We explore an alternative concept: in lieu of turning away from each agent encountered, the individual agent counts interactions from the recent past and modifies its walk accordingly. When registering many interactions, indicating congestion, agents will move both faster and more directly in order to clear the congested area. Behaviors observed in *Cataglyphis velox*, which have been shown to move more erratically close to the nest (Wystrach et al. 2015), contradict our model in this case. We alter several other naturally occurring behaviors as well to emphasize congestion avoidance. For that reason, our model also employs quorum sensing, a mechanism used by the ant *Temnothorax albipennis* (Pratt et al. 2002) and certain honeybee species (Seeley and Visscher 2004), to choose between future nest sites for purposes of emigration (Pratt 2005). The quorum sensing (QS) mechanism is also used for similar purposes by honey bees (Foss 2016) and by the bacteria *Vibrio harveyi* (Withers et al. 2001). A good discussion of the non-deterministic, yet resilient and robust characteristics of QS can be found in Hamar and Dove (2012). In this paper, we apply the QS mechanism to trigger a non-deterministic congestion avoidance scheme. By estimating the density of other individuals in their environment, the agents can collectively change their behavior (Franks et al. 2015). We use this to trigger a congestion avoidance behavior in our agents wherein they try to estimate the center of the congested area and avoid it, finding

alternate routes to their destination. This behavior is similar to that observed in pheromone-laying ants, which form additional trails under crowded conditions (Dussutour et al. 2004). A related study of lane formation and congestion avoidance with pheromone trails, specific to the behavior of the army ant *Eciton burchelli*, was conducted by Couzin and Franks (2003). With pheromone trails absent in our model, the mechanism we propose enables a similar behavior especially in environments consisting of narrow pathways.

There have been many other efforts at modeling multi-agent traffic. The simplest models adopt the total asymmetric simple exclusion process (TASEP) (Cremer and Ludwig 1986) offered for modeling ants, cars and pedestrians. Therein, the agents are treated as particles. In the TASEP process, the particles enter a one-dimensional lattice, composed of individual cells, from one direction. A particle can only advance if the next cell is empty. If the cell is occupied, it must wait. The process can be extended to an n-dimensional grid of cells forming a cellular automaton, in which the cells are updated according to some rule and with regard to the states of both the cell being updated as well as its surrounding cells. By using a two-dimensional cellular grid, for example, various types of traffic such as trails of ants and pedestrians (Schadschneider et al. 2003), as well as of vehicular traffic of whole cities (Rosenbluth and Gershenson 2011), may be simulated. Since cells are updated only based on their own state and that of cells in their immediate surroundings, these models are computationally efficient and lend themselves to large-scale computation. The model we propose in this paper differs from these cell-based approaches in that instead of cell states, our model updates the motion state of each individual agent at each time step, regardless of its spatial location. This is similar to one-dimensional trail models as those explored by Chaudhuri and Nagar (2015), though our model relies on direct touch instead of distance information. Additionally, each agent in our model makes probabilistic decisions about its heading and speed based on its interactions with others in its immediate surroundings.

The behaviors to be outlined in this paper are loosely based on those described in Gordon's book "Ant Encounters" (Gordon 2010) for red harvester ants. We have recently come across yet another work (Greenfield 2013) that attempts to simulate the seed foraging behavior of the ants described in Gordon's book. The model described therein draws heavily on cell-grid-based modeling notions that complicate congestion modeling. For example, in that model, ants occupying a grid cell are assumed to walk over each other in heavy traffic. In our work, we construct a simulation model with deeper granularity and flexibility: the agents move on a continuous 2D plane in one of 360 discrete directions, and the speed and direction of motion of each agent can change at every time step based on its local interactions. The agent's motion across its search space is modeled as a correlated random walk where an agent's orientation and speed at the current time step is the basis for its speed and orientation at the next time step. This captures the observation that an ant is more likely to continue on its current path in the short term than to turn drastically, but its orientations will become uniformly distributed in the long term (Benhamou 2006). The basic probability distribution we adopt for modeling the change in heading of the random walk of an individual agent is a von Mises distribution, but the concentration parameter of the distribution is adapted according to the recent interactions each agent experiences. We also introduce notions of a *base compass* and *food compass* to model an agent's/ant's memory of the location of the base and of the last location at which food was found. We will be referring to the objects that the agents are to retrieve as "food", but they can of course be any number of things. The "task" to be completed by the agents is to retrieve all the food items and return them to the base. We combine this with a decentralized congestion and wall avoidance mechanism based on quorum sensing and a notion of an avoidance sector that each agent estimates. In addition, we implement the recruitment algorithm model proposed in Prabhakar et al. (2012)

to regulate the rate at which agents leave the base. A model following similar rules was evaluated by Garnier et al. (2013), with a focus on the geometry of the foraging environment and the decision-making process between trail bifurcations. Additionally, Garnier's model was evaluated using Alice micro-robots instead of a computer simulation.

The simulation model of the interaction network proposed here is a discrete-time non-deterministic model that captures the decentralized decisions by individual agents, which subsequently create emergent collective behaviors such as the establishment of chains of agents to food sources, avoiding congested areas and walls, and regulation of the foraging population based on the availability of food. However, we do not claim that the model is faithful to the behavior of any particular species of ants or insects, but rather combines features that have been observed across various species of insects with extrapolations and designs of our own. Our eventual goal is to abstract observations from this microscopic model of a multi-agent interaction network to offer insights for the practical design and management of decentralized networks with minimal needs for extra infrastructure, stigmergy, memory, and bandwidth.

The rest of the paper is organized as follows: Sect. 2 describes the modeling framework in detail, including navigation and communication between ants, recruitment strategy, and congestion and wall avoidance. Section 3 applies the model to several environments and scenarios and analyzes the results. Section 4 offers some conclusions, including the future envisaged applications of the model.

2 Modeling

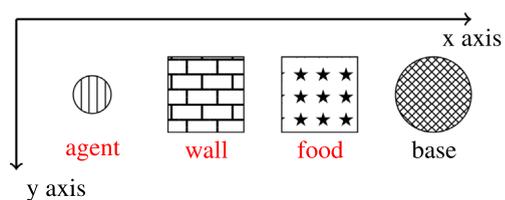
This section details the different components of the model. We start with a brief description of the modeling environment and list some basic assumptions in Sect. 2.1, followed by the model for the navigation and communication in Sect. 2.2, the recruitment model in Sect. 2.3, and the decentralized avoidance mechanisms in Sect. 2.4. Finally, pseudocode of the agent's decision loop is given in Sect. 2.5.

2.1 Environment

The environment in our model is a two-dimensional plane of infinite length and width, though square wall segments may be used to create obstructions, hallways, and other navigational features. Geometrically, agents and the base are modeled as circles, while walls and food items are modeled using squares. The relative size of the main objects in the model is illustrated in Fig. 1. Agents are homogeneous in size, while the lengths of the sides of wall segments, food items, and the diameter of the base are twice that of an agent's.

Additionally, the following assumptions are made: the base is an unlimited source of agents. Agents that return to the base with food, and therefore memory of that food source's

Fig. 1 Objects in the simulation



location, are placed in a FIFO (first in, first out) queue. If the queue is empty, a new agent is recruited to forage. Otherwise, the agent at the front of the queue is released in accordance with the recruitment algorithm to be detailed later. Recruited agents possess a random initial heading selected from a uniform distribution. All objects in the model (agents, food, etc.) are represented as rigid, inelastic bodies, unable to move through each other. Collisions between an agent and other agents or objects constitute the basic interactions to be used by the rest of the model. Each collision event is recorded by each agent. An agent that collides with the base while returning to it is removed from the 2D plane and put in a queue to be released again in accordance with the recruitment algorithm.

2.2 Navigation and communication

The motion of the agents is modeled using a correlated random walk. The change in direction from step i to step $i + 1$, denoted by θ , is sampled from the von Mises distribution with probability density function given by (Codling 2003):

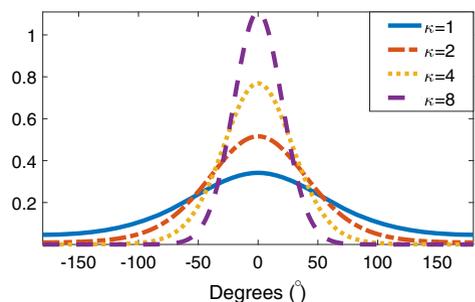
$$f(\theta) = M(\theta; \mu; \kappa) = \frac{1}{2\pi I_0(\kappa)} e^{\kappa \cos(\theta - \mu)} \tag{1}$$

where θ takes values in $[0^\circ, 360^\circ)$, μ is the mean heading change, κ is the concentration parameter, which varies the intensity of the peak of the distribution about the mean, and I_0 is the modified Bessel function of the first kind of order 0. Early uses of the von Mises distribution include the modeling of the movement of mammals such as foxes (Siniff and Jessen 1969), but it has since been applied to model a wide range of biological motions, including those of ants (Fink et al. 2014).

A key feature of this distribution that we exploit for modeling the persistence of an agent's movement in a specific direction is the concentration parameter κ , whose effect on the distribution is shown in Fig. 2. A low value of κ leads to an erratic walk, causing an agent to, on average, remain in its immediate surroundings. A high value leads to a highly correlated walk in which the agent likely continues in its current direction.

We use the above observation to implement an important feature: *the effect of agent encounters*. The concentration parameter κ is made dependent on recent encounters with other agents. The only information transmitted during the interaction is whether or not the encountered agent is carrying food, and, if it is, its current heading. To model the limited memory of such agents, the impact of each encounter is modeled to decrease exponentially with time. From these recent interactions, an agent computes its κ with:

Fig. 2 Examples of different κ values used in the von Mises distribution



$$\kappa(t) = \kappa_{\min} + \sum_{i=1}^n Ae^{-T(t-t_i)} \tag{2}$$

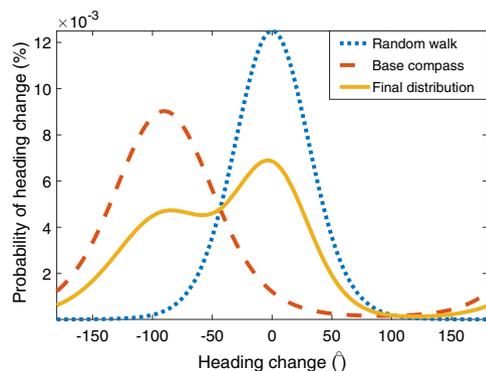
where n is the number of interactions and t_i is the time of each interaction's occurrence. A and T are parameters, while κ_{\min} denotes the minimum concentration parameter of an agent and is used to retain an amount of directionality in the absence of interactions. Note that the above continuous time equation is implemented in discrete time after discretizing it at the sampling rate of the simulation.

In our model, agents who are in densely traveled areas and experience more interactions travel in a straight line, leading to a subsequent decrease in the density of agents. On the other hand, agents who are further away from the base and therefore, less likely to experience many interactions, will move more erratically. By doing so, they are more likely to remain in their current area and not travel too far without further interactions. The result is a more even distribution of agents compared to a static random walk with a constant concentration parameter. This specific property of the model is discussed further in Sect. 3.1. If the agent encountered is carrying food, then the foraging agent will change its heading to the opposite of the food-bearing agent in an effort to locate the source of the food. Given that multiple agents are returning to the base with food, the foraging agent will be able to follow this impromptu trail followed by returning agents to the neighborhood of the food source. These encounters simultaneously increase the concentration parameter of the foraging agent, making it less likely to change direction.

Agents return to the base either because they found food or to save energy. To do so, they continuously integrate their path in order to maintain an internal vector of the base's location, similar to ants (Wohlgemuth et al. 2001). This effective base compass is integrated into our model as a second von Mises distribution whose mean always points in the direction of the base relative to the agent's current heading. The two von Mises distributions are added and normalized, and the agent chooses its next heading from the resulting distribution. Figure 3 illustrates the implementation of this concept for an agent whose current heading is at a 90° angle to the base. The combination of multiple sources of information pertaining to the agents' random walk with homing trajectories has been observed in *Cataglyphis fortis* (Collett and Collett 2002) and is similar to cue integration, wherein multiple sources of information are averaged based on their relative importance (Wystrach et al. 2015).

In several simulation experiments that used a fixed base compass, combined with an interaction-adapted random walk, individual agents exhibited odd behaviors such as overshooting the base or becoming stuck along long obstacles. In these cases, the correlated

Fig. 3 Example combination of the von Mises probability distributions for the base compass and the correlated random walk



random walk dominated the agent's navigation at high interaction rates. Therefore, in our model, the base compass distribution's concentration parameter is adapted with interactions as above, while that of the correlated random walk is held at a minimum value k_{\min} when agents are returning to the base. This configuration emphasizes returning to the base over exploration and area coverage. Since the density of agents, and therefore encounters, generally increases as distance to the base decreases, the returning agents' confidence in their heading should also increase accordingly.

Once an agent has found food and successfully returned to the base, it is very likely to be sent out again in the near future (Gordon 2010), when the likelihood of retaining memory of the food's location is high. We model this behavior in the form of another von Mises distribution oriented toward the location of the food. It operates just like the base compass and will be referred to as the food compass. However, unlike the base compass, the concentration parameter κ is not influenced by interactions. Instead, interactions still affect the concentration parameter of the correlated random walk as described above. The food compass's distribution and that of the correlated random walk are added and normalized. The agent chooses its next heading from the resulting distribution. In this manner, the food compass embeds a small, consistent bias toward the food source. If an agent with a food compass arrives at the general area in which it has previously found food, the feature ceases to have any impact on the agent's navigation. This helps the agent avoid staying in the area after the food source has been consumed.

Just like its heading, an agent's speed is impacted by its recent interaction memory. When encountering other agents, an agent desires to move faster either to cover more space, or in order to reach a food source faster. We refer to this as the agent's *impetus*. Yet at the same time, its speed is impeded by the interaction itself: the agents need to shuffle past each other to continue, and touch each other for the interaction to occur. We refer to this opposing effect as *resistance*. We model the combined effect as a sharp decrease in speed followed by a prolonged, but smaller increase in speed:

$$v(t) = v + \sum_{i=1}^{\infty} I e^{-\lambda_I(t-t_i)} - \sum_{i=1}^{\infty} R e^{-\lambda_R(t-t_i)} \tag{3}$$

where v is the default speed at which an agent travels without any interactions, and t_i is the time for the i th interaction. The impetus and resistance parameters I , λ_I , R and λ_R are selected such that $I < R$ and $\lambda_I < \lambda_R$. The resistance parameters R and λ_R are made larger than the impetus parameters I and λ_I in order to achieve an initial decrease in speed. These effects of the interactions are continually added to the default speed v as the interactions happen. Note that the effect of older interactions on the speed diminishes exponentially as time goes on and that the above continuous time equation is implemented in discrete time in the multi-agent simulation.

2.3 Recruitment

Since the multi-agent simulation model is primarily motivated by the foraging behavior of ants, the recruitment of foraging agents from the base is abstracted via a discrete-time recruitment model proposed by Prabhakar et al. (2012):

$$\alpha_k = \max(\alpha_{k-1} - q D_{k-1} + c A_k - d, \underline{\alpha}), \alpha_0 = 0 \tag{4}$$

$$D_k \sim \text{Poisson}(\alpha_k) \tag{5}$$

where α_k is the rate at which agents are recruited from the base at the k th time step, A_k is the number of returning food-bearing agents at the k th time step, and the actual number of agents departing the base, D_k , is set to a Poisson random variable with α_k as its mean. The coefficient q , c , and d control the contributions of other terms already defined, while $\underline{\alpha}$ denotes the minimum recruitment rate from the base.

Agents leave the base at a minimum rate $\underline{\alpha}$ and return to the base after a certain period if they do not find any food in order to conserve energy. We refer to this period as a *timeout*. Agents that return to the base without food do not count toward A_k . Therefore, in the absence of a food source, the population of foraging agents will eventually stabilize as ants return at the same rate at which they are sent out. When an agent encounters food, it immediately attempts to return to the base. The number of returning food-bearing agents A_k increases the amount of outgoing agents D_k . As already noted, food-bearing agents are assumed to retain memory of the food source's location; and they are likely to be sent back out first in order to retrieve more (Gordon 2010).

2.4 Decentralized avoidance mechanisms

The correlated random walk, the *base* and food compass and speed modifications described above are sufficient for the multi-agent model to simulate foraging behaviors in an unrestricted environment up to a certain agent density. However, scenarios that constrict agent movement such as walls and tunnels require additional behavior modifications. Large concentrations of agents can lead to traffic jams and pile-ups. We propose a mechanism whereby agents sense or estimate the density of agents based on interaction rates and subsequently the center of the congested area, and use this information to make decisions that help them avoid high-traffic areas. Similarly, agents can be made to avoid contact with a wall or obstruction for a certain time after an initial encounter. These behaviors are entirely decentralized actions consistent with the rest of the model. We detail this congestion and obstruction avoidance mechanisms and behaviors in the following subsections.

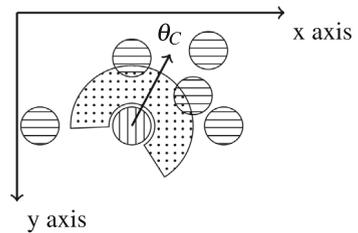
2.4.1 Congestion avoidance

As mentioned in the introduction, the quorum sensing mechanism is known to be used by certain species of ants, bees and bacteria for the purposes of collective site selection and emigration. Since the agents in our simulation model already count interactions for navigation purposes (to update their correlated random walk's heading and speed), we use quorum sensing as a trigger for their avoidance strategy. Agents also keep track of the directions from which they have experienced recent contacts/interactions for a certain period of time. Then, each agent estimates an average direction which ideally points toward the center of the congestion as experienced by it. This direction is computed using:

$$\theta_C = a \tan \left(\frac{\sum_{i=1}^m \sin(\theta_i)}{\sum_{i=1}^m \cos(\theta_i)} \right) \tag{6}$$

where θ_C is the heading pointing to the perceived center of congestion, θ_i the direction of contact of a given recent interaction and m is the total number of recent interactions retained during a small time frame. Through experimentation, we arrived at 4 s as an acceptable value for our simulations. Higher numbers of interactions enable the agent to more precisely estimate both the level and the perceived center of the congestion. Once the agent estimates the direction of the congestion, it creates an avoidance area/sector of a certain number of degrees equally distributed on either side of the congestion direction vector. To be consistent

Fig. 4 Example congestion avoidance sector



with the non-determinism of the modeling approach, the avoidance sector itself is estimated as a function of the interaction rates as described below. This sector is then excluded from possible headings that the agent might choose at its next decision step, in order to get away from the area of congestion. The probabilities of the remaining directions are re-normalized, and used for further heading decisions by the agent.

In Fig. 4, a foraging agent (vertical lines) has recently encountered several other agents (horizontal lines). Given the directions of the interactions, the foraging agent estimates the average direction of the congestion (dots) and decides to avoid the area. The estimation of the avoidance sector is randomized using a von Mises distribution, whose mean is estimated from recent interactions according to Eq. 6, and the arc of the congestion avoidance sector is also made dependent on the perceived amount of congestion experienced by the agent by selecting the sector angle as $\angle_S = 2\kappa$, where κ is the concentration parameter (variance) of its heading distribution which is already updated with interactions as discussed before. Consequently, an agent experiencing mild congestion will estimate a small congestion avoidance sector with a random mean, while an agent experiencing high congestion will estimate a large congestion avoidance sector whose mean is more likely to be true to the actual center of congestion. As we illustrate later, this feature has been found to significantly increase the performance of the avoidance mechanism in constricted areas.

2.4.2 Behavior near obstructions

Collisions with obstructions, obstacles or walls, are handled in a similar manner to congestion. When an agent comes into contact with a wall, it will avoid possible further contact with the wall for a certain period of time. It avoids the wall by creating a 180° avoidance sector whose central angle is perpendicular to the encountered wall. Consequently the agent will, for the near future, only move parallel to or away from the wall. Upon wall contact, the direction parallel to the wall and closest to the agent's heading upon contact is the most likely to be chosen as the next heading. Due to the peaked shape of the von Mises distribution, when parallel to the wall, an agent is most likely to continue moving alongside it or away at a slight angle. For our model, we chose 2 s as the time span for which this behavior persists. At base speed, an agent will traverse the length of 2.5 wall segments during that time before resuming its normal behavior.

2.5 Pseudocode

The individual agent's decision loop is outlined in Algorithm 1. The decision loop combines all elements of the modeling approach described in the preceding sections. The agent makes decisions several times a second, but continues moving in between decisions. Therefore, interactions and encounters with obstacles can occur in between decision points.

Algorithm 1 Agent Decision Loop

```

1: procedure DECISION_LOOP
2:   repeat
3:     calculate  $\kappa$  ▷ Equation 2
4:     calculate Speed ▷ Equation 3
5:     if time spent foraging > timeout then
6:       returning = true
7:     end if
8:     calculate heading change ▷ See function CALCULATEHEADINGCHANGE
9:     move
10:    until agent has returned
11:  end procedure
12:
13: function CALCULATEHEADINGCHANGE
14:  if returning or carrying food then
15:    add base compass distribution
16:  else if has food memory then
17:    add food compass distribution
18:  end if
19:  if recently contacted walls then
20:    avoid walls
21:  end if
22:  if  $\kappa$  > congestion threshold then
23:    estimate mean congestion angle ▷ Equation 6
24:    avoid congestion
25:  end if
26:  choose heading change from final distribution
27: end function

```

3 Experiments and results

The simulation model was built in Unity3D 5. It uses Unity's 2D physics system for purposes of collision detection. The physics time step is set to 0.02 s, and agents make decisions every 0.1 s. Experiments were run for 600 s and repeated 100 times for each scenario and averaged results are reported, unless otherwise noted. At every time step, we log data about each agent: its speed, position, ID and concentration parameter. Additionally, time stamps of agents leaving the base and picking up food as well as interaction events are logged for further analysis.

The values of model parameters used in the experiments are listed in Table 1. The recruitment algorithm is tuned to provide a steady growth of foraging agents as long as food is available. Navigational parameters are set to have agents move erratically in the absence of encounters, but move with purpose upon encountering other agents. The memory of an interaction is set to decay to negligible amounts after 10 s, and each agent's *timeout* is set to 180 s. Many of these parameter values were chosen through numerous trials in our simulation environment defined earlier. If different simulation time and spatial scales (agent size, and object/tile sizes, etc) are selected, one could arrive at other parameter combinations that work with the main modeling components.

For the simulation, samples that satisfy the Von Mises distribution (for the correlated random walk, base and food compasses, as well as the randomized congestion avoidance sector) are obtained using the following procedure: the possible heading change of an agent was discretized to 360° values. The probability values corresponding to each degree heading change are assembled in the probability vector $P = (p_1, p_2, \dots, p_d)$ based on the von Mises distribution. From this, the cumulative probability vector $C = (c_1, c_2, \dots, c_d)$ is defined as

Table 1 Parameters used in the implementation

	Parameter	Symbol	Value
Recruitment	Minimum recruitment rate	α	1
	Foraging parameter	q	0.05
	Forager return parameter	c	0.005
	Decay parameter	d	0
Navigation	Minimum κ	κ_{\min}	3.5
	Minimum compass κ	κ_{radar}	4.5
	Interaction amplitude	A	2
	Interaction decay	T	20
	Timeout (s)		180
Speed	Impetus amplitude	I	1.5
	Congestion amplitude	C	3.5
	Impetus decay	λ_I	2
	Congestion decay	λ_C	1
	Default speed	v	20
Memory	Interaction memory		10 s
	Wall memory		2 s
	Congestion memory		4 s
	Quorum threshold	T_q	40
	Decision interval		0.1 s

$c_j = \sum_{i=1}^j p_i$ where $j \in 1, 2, \dots, d$, where d is the index of the degree heading change under consideration. Then, a uniform random value $0 < x < 1$ is found and j determined s.t. $c_{j-1} < x \leq c_j$.

In the following sections, we describe the following scenarios which showcase certain behaviors of the multi-agent interaction network as captured by our proposed simulation model: coverage of the search space, foraging behavior and congestion avoidance evaluated in open and restricted environments.

3.1 Coverage of search space

We first compare the multi-agent interaction network with a network created using agents with fixed/static concentration parameters. The latter is a network in which agents are indifferent to interactions. The minimum concentration parameter for the interaction network is selected experimentally as $\kappa_{\min} = 3.5$, forming a relatively peaked distribution that can still be adapted substantially by interactions to higher values of κ . Agents are released from the base at a rate of 1 agent per second in unrestricted environment. As there is no food source in this scenario, the rate of recruitment does not increase. The tile size used to quantize the data constitutes a square with side length equal to an agent's radius. The environment is devoid of obstructions for these experiments.

Figure 5, which portrays the coverage of the area around the base, shows that the agents cover a mostly regular circular region, decreasing in density inversely to the distance from the base. This coverage map looks visually the same both for the random walk with static κ and the interaction network with adaptive κ (coverage map not shown for the former). However, there are major differences in how coverage is achieved with and without the

Fig. 5 Agent density with the interaction network

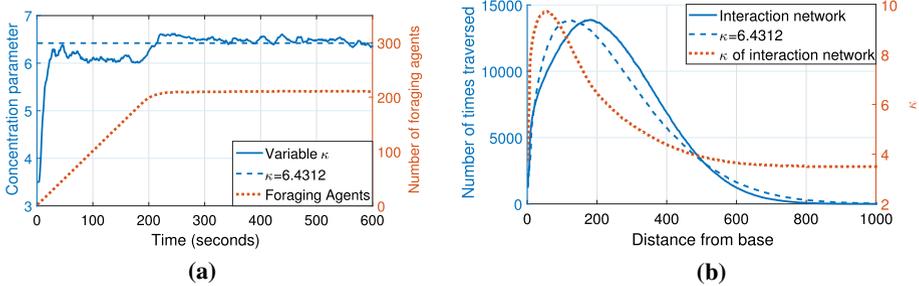
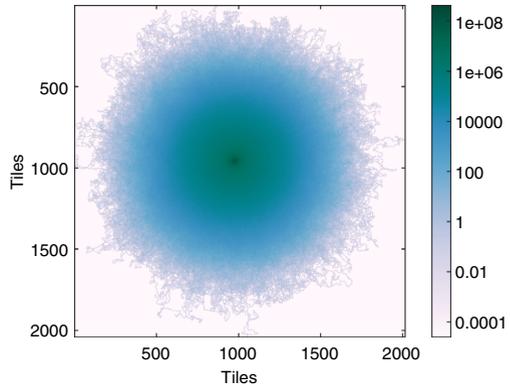


Fig. 6 Characteristics of coverage using the interaction network. **a** κ and foraging population over time. **b** Agent density and κ over distance

interaction network. To analyze this, experiments were run at a static $\kappa = 6.4312, 5.0, 6.0$ and 7.0 to compare with the interaction network with the adaptive κ . The value $\kappa = 6.4312$ is the average concentration parameter of the agent population that employs the interaction network.

Figure 6a shows that the average concentration parameter of the foraging agents stabilizes quickly. As the population levels off due to agents returning to the base, the average concentration parameter slightly increases due to the increase in interactions between the returning and foraging agents. The distribution of agents around the base is similar between the interaction network and one where agents do not interact but instead possess a concentration parameter κ equal to the mean κ of the interaction network ($\kappa = 6.4312$), as seen in Fig. 6a. However, as depicted in Fig. 6b, most of the interactions, and therefore, the highest agent concentration parameters are found closer to the base. That is, the interactions near the base effectively push the agents away from it as can be seen in the shifted location of the most traversed tiles for the case with the interaction network. This behavior clearly differs from that with the static case that uses the average $\kappa = 6.4312$.

When comparing the statistics of the tiles covered with the interaction network to those of several static κ cases, as shown in Table 2, the interaction network is not as efficient. Although its mean κ is high at 6.4312 , the cumulative coverage with the interaction network over the 600 s is close to that of the static case with $\kappa = 5.0$. However, this outcome can be attributed to the sharp drop-off in the concentration parameter of the agent population in the interaction network as the distance from the base increases (see Fig. 6b). The drop-off leads

Table 2 Statistics of tiles discovered over 600 s

Algorithm	κ value	Tiles discovered	SD
Static κ	5.0	1,120,086.01	33,644.11
	6	138,621.00	43,038.18
	6.4312	1,386,542.73	42,644.36
	7.0	1,484,031.90	44,276.23
Interaction network	Variable	1,171,721.83	30,156.08

to more random motion of agents and to a slightly denser spread of agents as illustrated in Fig. 6b. This behavior may be beneficial when responding to environmental factors, e.g., in the desert for the harvester ants mentioned earlier. Furthermore, as will be evident next, the interaction network is crucial to successful foraging and congestion avoidance.

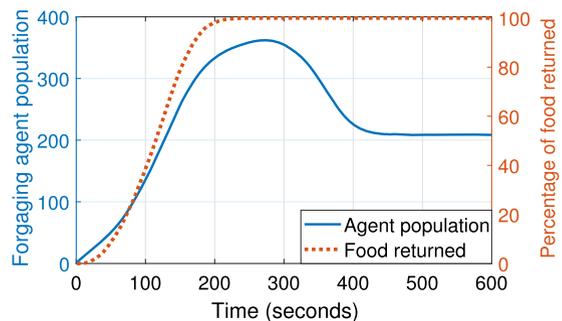
3.2 Foraging behavior

To study the foraging behavior captured by the model, we situated the base in an open environment without obstructions and located a food source at three distances from the base: at 20, 40, or 60 times the agent radius. The food piles are comprised of 20 stacks arranged in a 3×3 rectangle. Here, the recruitment algorithm outlined in Sect. 2.3 becomes important as the rate of food-bearing agents returning to the base causes more agents to be sent out in response to the availability of food, as seen in Fig. 7. Once the food source has been used up, the population of foraging agents returns to a steady state as more agents are still recruited at the minimum rate and they return to the base after their timeout of 180 s.

Figure 8a shows the impact of distance of the food source from the base. We observe that a linear increase in distance of the food source leads to a roughly linear increase in task completion time. The shape of the curves is reminiscent of a sigmoid or Gombertz function: As individual agents establish a memory of the food source and point more agents toward the food source on their return trip; this leads to higher recruitment and the rate of food pickup increases. As the food source diminishes, the rate again decreases as the stacks closest to the base are used up, and the chance of an agent encountering a food stack diminishes.

The coverage map in Fig. 8b shows a high concentration of agents between the base and the food source at a distance of 60 times the agent radius to the right of the base. There is a clear interaction chain created by the direct contact between food-bearing and foraging agents, both with and without food compass. However, a part of the agent population still covers other areas around the base in search of additional food sources.

Fig. 7 Foraging population compared to perceived availability of food over time



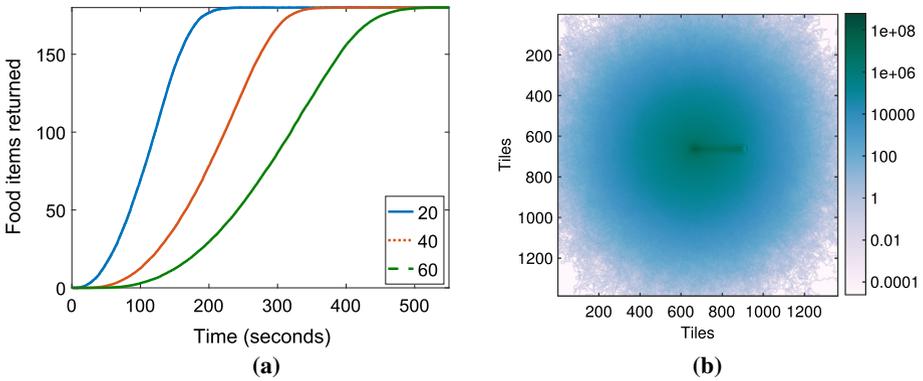


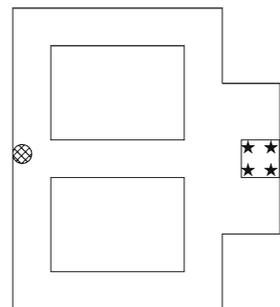
Fig. 8 Foraging behavior with interaction network in open environment. **a** Food retrieval over time for various distances of food source. **b** Foraging heatmap showing the interaction chain as a dark line from base (middle) to food source (right)

3.3 Congestion avoidance

As described in Sect. 2.4, after the congestion direction is estimated by an agent, it establishes an avoidance sector, a set of directions that it will not consider as long as its concentration parameter is above the quorum sensing threshold required to trigger the congestion avoidance behavior. In the non-deterministic (randomized) implementation, the avoidance sector is modeled using a von Mises distribution with the mean estimated from recent interactions and its sector $\angle S = 2\kappa$. In order to evaluate the congestion avoidance feature of the interaction network, we consider the bottleneck scenario shown in Fig. 9, which is designed to encourage congestion with narrow pathways. In this scenario, the base is on the left and the food is on the right.

We compare the non-deterministic (randomized) avoidance scheme with an implementation that uses a static avoidance sector. The latter does not vary the center of the sector around the mean, but it computes a variable sector size based on the κ parameter. Figure 10a illustrates that the non-deterministic approach significantly reduces interactions past 150 seconds in the simulation. This enables the agents to return food even after the population increased to a point where the simulation without a randomized sector is starting to reach deadlocks around 200 s. This is indicated by the sharp decrease in food returns. When evaluating κ with respect to distance from the base, as shown in Fig. 10b, we note a high amount of congestion

Fig. 9 Bottleneck scenario



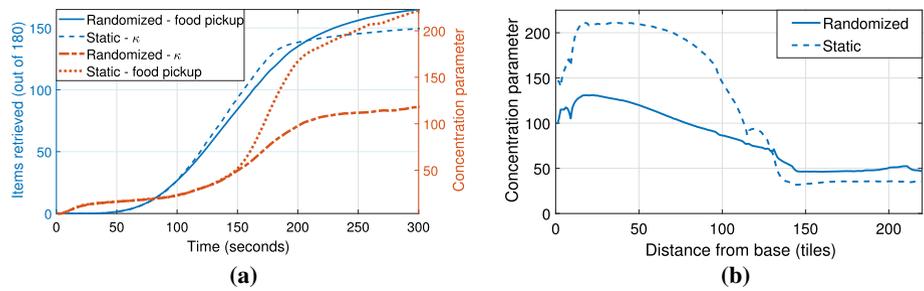


Fig. 10 Decentralized congestion avoidance in the bottleneck scenario. **a** κ and food pick up over time. **b** κ with respect to distance from the base

close to the base and at the beginning of the pathways for the case with the static avoidance sector, while the randomized version shows a more even distribution of interactions.

We have omitted discussion of simulation results without congestion avoidance, as they lead to deadlocks in all 3 possible pathways between the base and the food. As a result, the agents are unable to complete retrieval of all food available.

4 Conclusion

This work detailed a non-deterministic multi-agent simulation model comprised of agents that do not use stigmergy for mutual communication. Instead, agents primarily interact via direct physical contact. The model has three main components: (1) navigation and communication, which rely on an interaction-adapted correlated random walk superimposed with notions of a base compass and food compass as well as speed updates due to impetus and resistance effects arising from the same interactions, along with decaying memory of these interactions; (2) a decentralized congestion and wall avoidance scheme which is triggered with quorum sensing; and (3) a previously proposed recruitment model that regulates the foraging population. The performance of the overall multi-agent model is illustrated with simulations of search space coverage and foraging in open environments and congestion avoidance in constricted scenarios.

The main conclusion is that it is possible to create common collective behaviors using only the rates of direct encounters/interactions between agents, as opposed to reliance on pheromone trails or other stigmergic cues for communication. The interaction network is able to achieve behaviors such as targeted food retrieval with interaction chains as well as traffic balancing across multiple pathways in a completely decentralized manner. However, unlike traditional stigmergic models, the present model requires superpositions of the correlated random walk of each agent with other secondary distributions of, for example, the food compass and base compass to achieve these behaviors. Furthermore, the communication requirements are minimal—for a majority of encounters/interactions the fact of their occurrence is enough, without the need to exchange any information. Only in certain circumstances, like interactions between food-bearing and foraging agents, is any additional information exchanged on encounter between the agents. A non-deterministic collision avoidance scheme is also proposed in which each agent uses the same interaction rates to probabilistically estimate a congestion sector and avoid the area. Finally, we remark that while the key parameters of the multi-agent simulation model we used in our illustrations are given in Table 1, one can easily

scale these parameters to examine the collective coverage, foraging and avoidance behaviors in different time and length scales.

Some interesting analyses can be pursued as future work on the proposed model. For example, the trade-off between food retrieval and exploration of the environment can be further characterized in relation to individual agents—such as what percentage of agents form the interaction chains from the base to the food sources, compared to the percentage that explore the rest of the environment. By extension, we might explore the percentage of agents actually retrieving food, given that agents who have previously returned with food are recruited again for subsequent trips. The response of the interaction network to a changing environment, such as appearing and disappearing food sources or obstacles, would need to be characterized as well. Finally, it is necessary to do a systematic robustness analysis with respect to the parameters required for the different aspects of the model to function—base speed, span rate, memory decay rates, agent geometry, etc.—and to establish specific relationships between these parameters that will result in a successful, optimal interaction network.

We aim to abstract observations from this microscopic model of a multi-agent interaction network and apply them to the design and management of decentralized mobile radio networks such as those that could be deployed on individual vehicles and field robots. Attractive scenarios for this include those where infrastructure such as roadside units or cell towers are not readily available or are very costly. These are similar to environments unsuitable to pheromone trails or other stigmergic traces. We envision such networks to provide services as alternative to those employing vehicle-to-infrastructure communication. Specific aspects include decentralized congestion management of the radio networks and/or of the traffic of the mobile agents utilizing such a network. A preliminary example of extending the basic ideas of the presented model for decentralized vehicular traffic congestion management appears in our recent work (Kasprzok et al. 2017).

References

- Benhamou, S. (2006). Detecting an orientation component in animal paths when the preferred direction is individual-dependent. *Ecology*, *87*(2), 518–528.
- Chaudhuri, D., & Nagar, A. (2015). Absence of jamming in ant trails: Feedback control of self-propulsion and noise. *Physical Review E*, *91*, 012706.
- Codling, E. A. (2003). *Biased random walks in biology*. PhD thesis, The University of Leeds, UK.
- Collett, M., Chittka, L., & Collett, T. S. (2013). Spatial memory in insect navigation. *Current Biology*, *23*(17), R789–R800.
- Collett, T. S., & Collett, M. (2002). Memory use in insect visual navigation. *Nature Reviews Neuroscience*, *3*(7), 542–552.
- Couzin, I. D., & Franks, N. R. (2003). Self-organized lane formation and optimized traffic flow in army ants. *Proceedings of the Royal Society of London B: Biological Sciences*, *270*(1511), 139–146.
- Cremer, M., & Ludwig, J. (1986). A fast simulation model for traffic flow on the basis of boolean operations. *Mathematics and Computers in Simulation*, *28*(4), 297–303.
- Di Caro, G., & Dorigo, M. (1998). AntNet: Distributed stigmergetic control for communications networks. *Journal of Artificial Intelligence Research*, *9*, 317–365.
- Dorigo, M. (1992). *Optimization, learning and natural algorithms*. Ph.D. Thesis, Politecnico di Milano, Italy.
- Dorigo, M., Birattari, M., & Brambilla, M. (2014). Swarm robotics. *Scholarpedia*, *9*(1), 1463. <https://doi.org/10.4249/scholarpedia.1463>.
- Dussutour, A., Fourcassie, V., Helbing, D., & Deneubourg, J. L. (2004). Optimal traffic organization in ants under crowded conditions. *Nature*, *428*(6978), 70–73.
- Fink, G., Haack, J., McKinnon, A., & Fulp, E. (2014). Defense on the move: Ant-based cyber defense. *IEEE Security & Privacy*, *12*(2), 36–43.

- Foss, R. (2016). A self-organising network model of decision making by the honey bee swarm. *Kybernetes*, 45(3), 358–70.
- Foukia, N., & Hassas, S. (2004). Managing computer networks security through self-organization: A complex system perspective. *Engineering Self-Organising Systems*, 2977, 124–138.
- Franks, N., Stuttard, J., Doran, C., Esposito, J., Master, M., Sendova-Franks, A., et al. (2015). How ants use quorum sensing to estimate the average quality of a fluctuating resource. *Scientific Reports*. <https://doi.org/10.1038/srep11890>.
- Garnier, S., Combe, M., Jost, C., & Theraulaz, G. (2013). Do ants need to estimate the geometrical properties of trail bifurcations to find an efficient route? A swarm robotics test bed. *PLoS*, 9(3), <https://doi.org/10.1371/journal.pcbi.1002903>.
- Gordon, D. (2010). *Ant encounters: Interaction networks and colony behavior*. Princeton: Princeton University Press.
- Greenfield, G. (2013). On simulating seed foraging by red harvester ants. In *2013 IEEE symposium on artificial life* (pp. 105–112). IEEE.
- Hamar, J., & Dove, R. (2012). Quorum sensing in multi-agent systems. *INSIGHT*, 15(2), 35–37.
- Kasprzok, A., Ayalew, B., & Lau, C. (2017). Decentralized traffic rerouting using minimalist communications. In *IEEE international symposium on personal, indoor and mobile radio communications*, 08–13 October 2017, Montreal, QC, Canada.
- Koutsou, A., & He, S. (2009). Study of ants' traffic organisation under crowded conditions using individual-based modelling and evolutionary computation. In *2009 IEEE congress on evolutionary computation (CEC 2009)* (pp. 3330–3337). IEEE.
- Leitão, P., Barbosa, J., & Trentesaux, D. (2012). Bio-inspired multi-agent systems for reconfigurable manufacturing systems. *Engineering Applications of Artificial Intelligence*, 25(5), 934–944.
- Prabhakar, B., Dektar, K. N., & Gordon, D. M. (2012). Anternet: The regulation of harvester ant foraging and internet congestion control. In *2012 50th annual Allerton conference on communication, control, and computing (Allerton)* (pp. 1355–1359).
- Pratt, S. C. (2005). Quorum sensing by encounter rates in the ant *Temnothorax albigipennis*. *Behavioral Ecology*, 16(2), 488–496.
- Pratt, S., Mallon, E., Sumpter, D., & Franks, N. (2002). Quorum sensing, recruitment, and collective decision-making during colony emigration by the ant *Leptothorax albigipennis*. *Behavioral Ecology and Sociobiology*, 52(2), 117–127.
- Rosenblueth, D., & Gershenson, C. (2011). A model of city traffic based on elementary cellular automata. *Complex Systems*, 19(4), 305.
- Şahin, E. (2005). Swarm robotics: From sources of inspiration to domains of application. In: E. Şahin, W. M. Spears (Eds.), *Swarm Robotics. SR 2004*. Lecture notes in computer science (Vol. 3342, pp. 10–20). Berlin, Heidelberg: Springer.
- Schadschneider, A., Kirchner, A., & Nishinari, K. (2003). From ant trails to pedestrian dynamics. *Applied Bionics and Biomechanics*, 1(1), 11–19.
- Seeley, T. D., & Visscher, P. K. (2004). Quorum sensing during nest-site selection by honeybee swarms. *Behavioral Ecology and Sociobiology*, 56(6), 594–601.
- Shmygelska, A., Aguirre-Hernández, R., & Hoos, H. H. (2002). An ant colony optimization algorithm for the 2D HP protein folding problem. In: M. Dorigo, G. Di Caro, M. Sampels (Eds.), *Ant Algorithms. ANTS 2002*. Lecture notes in computer science (Vol. 2463, pp. 40–52). Berlin, Heidelberg: Springer.
- Siniff, D. B., & Jessen, C. (1969). A simulation model of animal movement patterns. *Advances in Ecological Research*, 6, 185–219.
- Stützle, T., & Dorigo, M. (1999). *ACO algorithms for the traveling salesman problem* (pp. 163–183). Hoboken: Wiley.
- Withers, H., Swift, S., & Williams, P. (2001). Quorum sensing as an integral component of gene regulatory networks in gram-negative bacteria. *Current Opinion in Microbiology*, 4(2), 186–193.
- Wohlgemuth, S., Ronacher, B., & Wehner, R. (2001). Ant odometry in the third dimension. *Nature*, 411(6839), 795–798.
- Wystrach, A., Mangan, M., & Webb, B. (2015). Optimal cue integration in ants. In *Proceedings of the Royal Society B* (Vol. 282, No. 1816). The Royal Society. <https://doi.org/10.1098/rspb.2015.1484>.