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A novel foraging algorithm for swarm robotics based on virtual pheromones and neural network

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ABSTRACT

Swarm robotics is an emerging interdisciplinary field that has many potential real-world applications. Swarm robotics aims to produce robust, scalable, and flexible self-organizing behaviors through local interactions from a large number of simple robots. In this paper, a novel pheromone model of swarm foraging behavior is developed based on a neural network. The output of a single neuron corresponds to the density of a pheromone, which diffuses to neighboring neurons through their local connections. A neural network is updated based on the proposed evaporation model. Neural networks can often mimic the dynamics and features of pheromones. Therefore, in this work, we develop an optimization method to determine the key parameters of cooperative foraging based on mathematical modeling. The differential equation variables represent the number of foraging robots assigned different tasks. The solutions of the differential equations represent the dynamics of the foraging behavior. The key parameters that affect task allocation are determined to make optimal decision rules. Simulation experiments are conducted under different foraging scenarios. The experimental results demonstrate the effectiveness of the proposed pheromone model.

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1. Introduction

Swarm intelligence is a discipline inspired by nature, especially social insects. This discipline focuses on the collective behavior of social swarms [1]. The desired swarm behavior emerges from a set of simple rules and the local interactions of a large number of homogeneous and simple individual robots. The self-organizing coordination mechanisms of social insects have been effectively implemented in swarm robotic systems [2–4]. The application of swarm intelligence in robotics is known as swarm robotics, which has been successfully applied to different fields, such as self-driving, delivery robots, autonomous agricultural robots and automated warehouses [reviewed in 5].

Swarm robotics are a relatively new approach to designing robust, scalable, and flexible collective behaviors in which swarm intelligence techniques are applied. Many different schemes for emerging collective behaviors have been proposed during recent years, such as fully distributed architecture (ALLIANCE) [6], parallel multi-agent architecture [7], task-oriented hierarchical control architecture [8], neural-endocrine architecture [9], cooperative architecture [10], and modular multi-agent architecture [11]. To date, a complete theoretical framework that constructs a control architecture for group behavior does not fully exist. In recent years, nature-inspired metaheuristic algorithms have been applied to swarm robotics applications. The most well-known swarm-based algorithms are: particle swarm optimization [12], ant colony optimization, bee algorithm [13], and fish-swarm algorithm [14]. The remarkable success of using social animal behavior to model emerging collective behaviors provides a best-known paradigm for swarm robotics. In addition, macroscopic modeling has been available to understand the individual robot characteristics and gain insight into the design and analysis of swarm robotics behaviors [15–18]. Mathematical models are typically abstract versions of swarm robotics and are usually based on Markov processes. In practical implementations, thoughtful work must be performed to overcome the limitations of the models.

Although some emerging behavior models have been implemented in some swarm robotics platforms, the dynamic real-time control of a swarm robotic system is still considered challenging. Swarm foraging behavior is a classical benchmark problem in swarm robotics. The biggest challenge is to develop a self-organizing search and collection algorithm for swarm robotic foraging behaviors. This work targets two main contributions:

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to propose a novel neural network-based pheromone model of swarm foraging behavior and to study the optimization method for key parameters of cooperative swarm foraging with mathematical modeling. In this paper, a novel pheromone model of swarm foraging behavior is developed based on a neural network. If the foraging robots secretes pheromones, a corresponding neuron output will increase. The output will diffuse to neighboring neurons through local connections. Therefore, the output of the neural network will be updated based on the proposed pheromone evaporation model. The evolution of the neural network can mimic the features of pheromones. A parameter optimization algorithm, based on differential equations, is proposed in this work. The key variables of a set of rate equations are indexed by the number of foraging robots assigned to different tasks. Theoretical analysis shows that the waiting time of scouting robots to deliver food items is a critical parameter that affect the cooperation rate. We determine the optimal parameters of cooperative foraging to make the optimal control strategy. In addition, we present various scenarios that verify the effectiveness of the proposed pheromone model for cooperative swarm foraging.

The remainder of this work is organized as follows. The most relevant literature describing swarm foraging robotics are reviewed in Section 2. Section 3 proposes a novel foraging algorithm and an optimization method to find the cooperation rate. Section 4 describes the simulation experiments run for different foraging scenarios, lists the performance metrics, and begins the analysis of the results. The results are discussed and analyzed further in Section 5. Finally, some concluding remarks and future work are provided in Section 6.

2. Related works

Swarm robotics systems coordinate the behaviors of large numbers of simple mobile robots to emerge desired collective behaviors. The robots must avoid collisions and perform a set of tasks based on constraints of system. Therefore, communication and cooperation are the most challenging problems when training swarm robotics.

2.1. Foraging in swarm robotics

Swarm foraging behaviors are part of the set of functions swarm robotics possess that are inspired by social insects. As in a foraging ecosystem, robots search and collect food items in a shared environment. In general, foraging is self-organized by local and stochastic decisions of the individual team members. Pang et al. [19] proposed a dynamic response threshold model to perform foraging in a self-organized manner. The amount of food items in a nesting site was considered as the stimulus to individual robots and the threshold can be computed dynamically according to the number of resting robots. Brutschy et al. [20] presented a self-organized method for foraging of the individuals in swarm robotics systems. The proposed method was based on the delay of robots working on one subtask while waiting for another subtask. Nedjah et al. [21] proposed a distributed control algorithm of foraging for swarm robotic systems inspired by particle swarm optimization. The algorithm that each robot must run periodically to control the underlying decisions or actions. The diversity between these foraging behaviors makes them difficult to carry out on real robot. Therefore, most studies were carried out though simulation platform. The typical experimental platforms for swarm robotics include some multi-agent based platforms like Netlogo [22] and Starlogo [23], robotics based platforms like Swarmanoid [24] and ARGoS [25], real swarm robotic systems like Robotarium Swarm Robotics Testbed [26] and Kilobot Swarm [27].

In swarm robotics systems, a large number of simple robots interact with each other and with their environment. The desired collective behaviors emerge with the cooperation among robots. Therefore, the tasks must be allocated to a set of robots in a group if a special task cannot be performed by a single robot. Significant attention has recently been devoted to task allocation in swarm robotics [28]. Some mechanisms of task allocation have recently been proposed [19,29–31]. Depending on the style of communication, the task allocation can be divided into two classes, implicit and explicit. The complex swarm behaviors emerge through relatively simple individual rules. All robots have a set of decision-making mechanisms to realize their collective behaviors. Swarm robots collaboratively work together towards a common goal (e.g., foraging behavior), resulting in common resource competition. Therefore, conflict resolution for swarm foraging behavior is a challenging problem in swarm robotics, which has been widely studied recently [32–34].

2.2. Pheromone communication in swarm robotics

In swarm robotic systems, a large group of simple individuals cooperate with each other to complete complex tasks. The cooperation strategies of the individual robots are conducted via implicit or explicit communication, depending on the size and capabilities of the robots. The individuals in social insect societies mainly change the shared environment by depositing pheromones to emerging swarm behaviors, which is called stigmergy. Swarm robotic systems mostly rely only on the local information, and exchange information implicitly to mimic natural swarms. Schroeder et al. [35] proposed a Keller–Segel model for chemotaxis to develop a virtual-pheromone-based method of area coverage. Several control rules for efficient area coverage were conducted and inspired by the swarm behaviors of ant colonies. Kuyucu et al. [36] proposed a simple and efficient way to coordinate a large number of homogeneous robots in unknown environments. A guided probabilistic exploration is performed using random movement and pheromone-based stigmergic guidance in an unknown environment. Wei et al. [37] developed a communication system comprised of chemoemitter and chemoreceiver modules. The system communicates by producing volatile pheromone components and decodes the transmitted information via sensors.

Although the pheromone can work well in social insects, creating artificial pheromones is not easy in swarm robotic system; the system cannot replicate all the aspects of pheromones in nature. The main question is how and what chemicals can be released by the real robots, and how to describe the diffusion and evaporation in the exploration and transportation of swarm foraging [38]. A practical solution for the communication problem in swarm robotics is to use virtual pheromones. A stimergy field is typically found in swarm foraging, which corresponds to the shared environment. Robots can access the data of the pheromone field via an indirect communication among the individuals [39]. The most common modes for exchanging messages between robots in a swarm are bluetooth, wireless LAN and infrared [40–42].

2.3. Neural network architecture of swarm robotics

In swarm robotics systems, the complex swarm behaviors emerge from simple interaction rules. However, designing relatively simple individual rules to produce a large set of complex swarm behavior is extremely difficult. Programming emerging swarm behaviors still has no formal or precise architecture in swarm robotics. Neural networks and evolutionary techniques have been widely used to design individual rules of swarm robotic systems [43]. To establish the relationship between the cognitive

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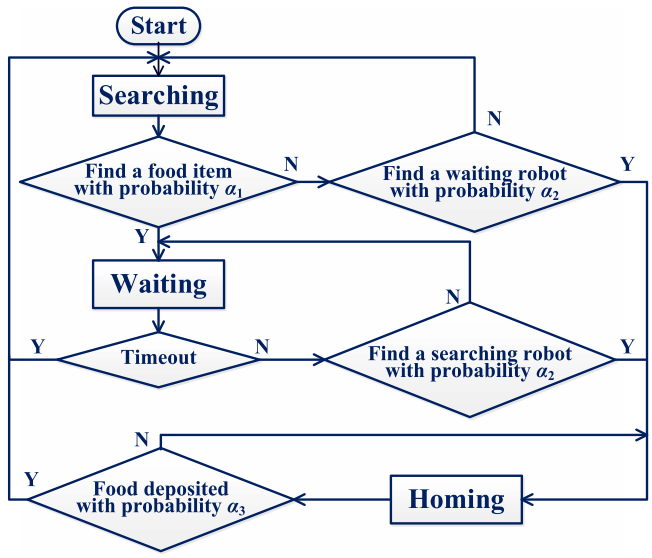

Fig. 1. The flowchart of cooperative foraging behavior (task). The cooperative foraging system consists of several different kinds of basic behavior: searching, waiting and homing. The terms α_1, α_2, and α_3 are the transition probabilities based on basic behaviors.

complexity and the simple rules, some neural network architectures have been proposed for swarm robotics [44]. Generally, the simple neural networks are evolved to develop rules specifying interactions between the swarm. Although evolutionary swarm robotics is an effective approach to develop robust collective behaviors, this evolution has a high computational cost.

To overcome the computational cost problem, the neural network method is combined with pheromones communication to developing emerging collective behaviors. In swarm robotics based on neural networks and pheromone communication, the inputs are made up of discrete pheromone sources, while the outputs are the robots' actions; therefore, the optimization weights are determined by the distribution of pheromone sources and the desired behaviors. The neural network-based model mainly includes Probabilistic Neural Networks, Multilayer Perception Neural Networks, Self-organizing Neural Networks, and Spiking Neural Networks [45]. Neural network models extract complex cognitive features from sensors to produce desired behaviors. Stigmergic communication is predominant in swarm robotics. However, in some cases, direct communication can also be observed. Sun et al. [46] designed a neural network controller that models the direct communication of swarm robots, whose behavior model is more effective to a fast reaction in exploration.

3. The proposed methods

In this section, we propose a foraging algorithm based on a neural network. Section 3.1 depicts the swarm mission. Section 3.2 addresses the proposed pheromone model based on a neural network. Section 3.3 describes the optimization method that determines cooperation rate.

3.1. Swarm missions

In a swarm foraging system, a group of identical reactive robots interact implicitly with each other in a shared environment. The motivation of these foraging robots is to search and deliver food items cooperatively. Object transportation is a challenging task [47]. Therefore, in this work, a swarm foraging system is simplified to consider a single food item cooperatively delivered by two robots.

In the initial stage, all foraging robots are in the nesting site without any prior knowledge about the tasks. Then, they search for food items randomly. The range at which robots can detect waiting robots or food items is 10 grid units. Once one scouting robot discovers a food item, it will wait for another robot to cooperate with it until the next time period τ. If there are no other robots who detect the waiting robot within the given time, the robot will give up the current food item and randomly search for another food item again. When a searching robot detects a waiting robot, the two foraging robots will deliver the food item cooperatively and become homing robots. After the food item is deposited in the nesting site, the homing robots will search for food items again. The flowchart of the cooperative foraging task is see Fig. 1.

The finite state machine model of the cooperative foraging behavior is established to develop a set of strategies within the task allocation. The model, which consists of a series of coupled rate equations, combines different states by transition rates. Each state corresponds to a special task. The cooperative foraging system consists of several basic behaviors: searching, waiting and homing. The state transitions of foraging robots with a special probability are shown in Fig. 1.

Searching: The scouting robots execute a random walk, at a fixed speed, to inspect the unknown environment. When a robot discovers a food item with its sensors, it will wait for another searching robot to cooperate with it.

Waiting: If the food source comes into the detection area, the scouting robots will stop searching and stay near the food item. Cooperation can be achieved when another scouting robot discovers the waiting robot and delivers the food item to the nesting site.

Homing: Any two robots who find the same food item will return home, with the collected food item, via a pheromone trail and will deposit more pheromones to increase the pheromone quantity over the current position. The robots interact indirectly, within the shared environment, to exchange the information.

3.2. Pheromones model based on a neural network

The collective behavior of swarm robotic systems emerges from the interactions between individuals and with the environment. Swarm robotics can be defined as a horde of mobile robots mimicking social insects or animals, such as ants, bees and other social animals. Social insects have developed many

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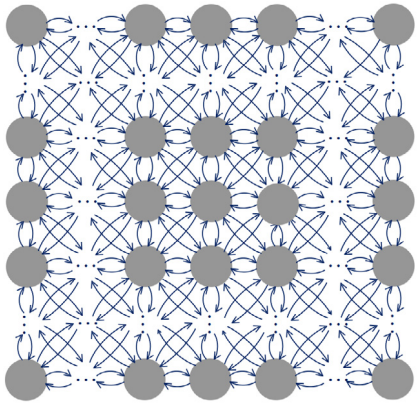

Fig. 2. Network neighborhood. The neural network has a single layer, which corresponds to the discretized grid environment. Each neuron corresponds to a unique position in the workspace.

ways to communicate with each other. For example, individuals in ant societies (colonies) release pheromones to coordinate the complex behaviors needed while foraging.

3.2.1. Pheromone diffusion model

Ants commonly use a pheromone trail to mark their foraging paths [48]. Some ants carrying food items will lay down a trail of attractive pheromones to help other ants find the food source. The pheromones propagate and evaporate quickly. Meanwhile, ants continuously renew the trail of pheromones to maintain the foraging paths. Therefore, the pheromones will be distributed in the work space while foraging.

In this work, a new pheromone diffusion model is developed based on a neural network that imitates the physical pheromones of ants. A dynamic wave expansion neural network (DWENN) is used to model pheromone diffusion. Neural network systems have a set of neurons with local area connections [49–51]. The topological structure corresponds to the robot's work space. The local connection of the immediate neighbors of the ith neuron is shown in Fig. 2.

When a robot secretes a pheromone in a certain position, the corresponding neuron will have a positive external input. The output of the neuron will diffuse via the immediate neighboring neurons. The pheromone diffusion model is defined as

$$x_i\,(t+1) = f\left(\sum_{j=1}^{8} w_{ij}x_j(t) + I_i(t)\right) \tag{1}$$

where $x_i(t+1)$ is the output of the ith neuron at time $t+1$, $x_j(t)$ is the output of the immediate neighboring neurons of the ith neuron at time t, w_{ij} is the connection weight from the ith neuron to the jth neuron, and $I_i(t)$ is the input of the ith neuron at time t. The connection weight matrix $\boldsymbol{W}$ is calculated by

$$w_{ij} = \begin{cases} e^{-\eta|i-j|^2} & \text{if } |i-j| \le 1 \\ 0 & \text{if } |i-j| > 1, \end{cases} \tag{2}$$

where $|i-j|$ is the Euclidean distance between the i -th and jth neurons and η is a real positive number. The external input $I_i(t)$ depends on the pheromones at a pre-defined position. When a scouting ant discovers a food item, it will try to bring it back to the nesting site while laying down an attractive pheromone $P_a$on the ground. The other ants will be attracted to the food source because of the pheromone trail. Once an exploring ant finds an obstacle, it will release a repellent pheromone P_o. When the ants walk randomly and explore their environment, they will release a repellent pheromone P_e to avoid other ants re-exploring the same area. The external input $I_i(t)$ is defined as

$$I_i(t) = \begin{cases} P_a & \text{Homing on } x_i(t) \\ P_o & \text{Avoiding Obstacle on } x_i(t) \\ P_e & \text{Walking Randomly on } x_i(t) \\ 0 & \text{Moving } \textit{along} \text{ Previous Trail} \end{cases} \tag{3}$$

where P_a is a positive minor constant, P_o and P_e are both negative constants. Once an exploring ant finds an obstacle, it will release a repellent pheromone P_o. When the ants walk randomly and explore the environment they will release a repellent pheromone P_e to avoid other ants re-exploring the same area. The absolute value of P_o is large enough to guide the ants to avoid obstacles. The absolute value of P_e is a minor constant. If there is new food source appearance the ants can explore the area with the evaporation of repellent pheromone P_e. When the homing robots return to the nest and become searching robots. They will walk randomly with probability r, which is exploration rate, a minor constant. The searching robots from homing state will move along the previous trail with probability 1-r. The transfer function $f(\cdot)$ is defined as

$$f(x) = \frac{1}{1+e^{-x}}. \tag{4}$$

3.2.2. Pheromone evaporation model

In the pheromone field, the update of the pheromone values undergoes two stages. After the foraging ants lay down pheromone trails, the trails will begin to evaporate. Evaporation reduces the pheromone density to ensure the scouting ants can explore new areas in the workspace. The evaporation of the pheromones is updated by

$$x_i'(t+1) = (1-\rho)\,x_i(t) + f\Big(\sum_{j=1}^{8} w_{ij}\Delta x_j(t)\Big) \tag{5}$$

where $x_i(t+1)$ and $x_i(t)$ are the density of the pheromones at time $t+1$ and t, at the position of the ith neuron, respectively. There term ρ is the evaporation rate, w_{ij} is the connection weight from the ith neuron to the jth neuron, $\Delta x_j(t)$ is the variations of the pheromones neighboring the ith neuron x_i, $f(\cdot)$ is the transfer function.

The output of neuron network represents the pheromone density. The output is positive when a robot secretes attractive pheromone, and negative when a robot lays down repellent pheromone on tails. The attractive trail pheromones guide the ant colony to find the food source. The repellent trail pheromones drive the colony to explore unknown territory and avoid obstacles. With the evaporation of pheromones on trails the absolute value of output keeps decreasing.

3.3. Optimization of cooperation rate

A differential equation approach has been widely used to describe the collective behaviors of multi-robot systems. The system behavior usually derived from the finite difference equation [52]. In the differential equations model, each dynamic variable corresponds to the average number of robots performing a special task. Let $N_s(t)$ denotes the number of searching robots at time t. $N_w(t)$ denotes the number of waiting robots who need to cooperate with other scouting robots. $N_h(t)$ denotes the number of homing robots who are delivering food items to the nesting site. $N_f(t)$ denotes the number of food items at time t. In the initial state of cooperative foraging, all robots begin at the nesting site to

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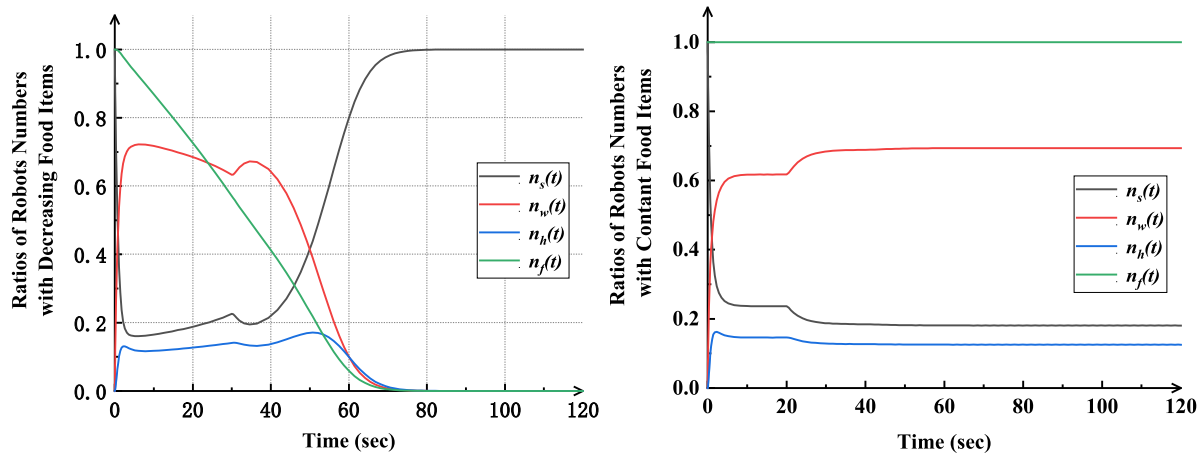

(a) Constant food items (b) Decreasing food items.

Fig. 3. The Solutions of the ratio equations, $n_s(t)$, $n_w(t)$, $n_h(t)$, and $n_f(t)$, are the ratios of the number of searching, waiting, homing robots, and food items at time t.

search for the food source. The differential equations models the dynamics of each variable as

$$\begin{aligned}\frac{dN_s(t)}{dt} &= -\alpha_1 N_s(t)\left(N_f(t) - N_w(t) - \frac{N_h(t)}{2}\right) \\ &\quad - \alpha_2 N_s(t) N_w(t) + 2\alpha_3 N_h(t) \\ &\quad + \alpha_2 N_s(t-\tau) N_w(t-\tau)\, \Gamma(t,\tau)\end{aligned}, \tag{6}$$

$$\begin{aligned}\frac{dN_w(t)}{dt} &= -\alpha_2 N_s(t-\tau) N_w(t-\tau)\, \Gamma(t,\tau) - \alpha_3 N_s(t) N_w(t) \\ &\quad + \alpha_1 N_s(t)\left(N_f(t) - N_w(t) - \frac{N_h(t)}{2}\right)\end{aligned}, \tag{7}$$

$$\frac{dN_h(t)}{dt} = -2\alpha_3 N_h(t) + \alpha_3 N_s(t) N_w(t) + \alpha_2 N_s(t) N_w(t), \tag{8}$$

$$\frac{dN_f(t)}{dt} = -\alpha_3 N_h(t) + u(t). \tag{9}$$

The first two terms of Eq. (6) account for the reduction of the number searching robots; this reduction can be due to finding food source or waiting too long. The third term accounts for the number of searching robots that have transitioned from the homing state after a successful foraging task. The fourth term accounts for the number of searching robots that have transitioned from the waiting state. These robots fail to cooperate with other robots within the waiting time. The last two terms result in an increase in the quantity of searching robots. The first term of Eq. (7) is the number of waiting robots which fail to cooperate. The second term is the number of waiting robots which cooperate successfully. The third term is the number of waiting robots that find the undetected food source. The first term of Eq. (8) is the number of homing robots that perform a successful foraging task. The second term is the number of homing robots that transition from searching to waiting states when the cooperation is completed. The first term of Eq. (9) is the number of food items delivered to nesting sites. The second term is the production rate of new food items.

The system of Eqs. (6)–(9) can be rewritten in a dimensionless form using the ratios instead of the numbers of robots. The variable transformations are defined by $n_s(t) = N_s(t)/N_0$, $n_w(t) = N_w(t)/N_0$, $n_h(t) = N_h(t)/N_0$ and $n_f(t) = N_f(t)/N_{f0}$ such that N_0 and N_{f0} are the initial number of the searching robots and food items, respectively. The corresponding ratio equations in dimensionless form are given as

$$\begin{aligned}\frac{dn_s(t)}{dt} &= -\alpha_1 n_s(t)\left(n_f(t) - n_w(t) - \frac{n_h(t)}{2}\right) \\ &\quad - \alpha_2 n_s(t) n_w(t) + 2\alpha_3 n_h(t) \\ &\quad + \alpha_2 n_s(t-\tau)\, n_w(t-\tau)\, \gamma(t,\tau)\end{aligned} \tag{10}$$

$$\begin{aligned}\frac{dn_w(t)}{dt} &= -\alpha_2 n_s(t-\tau)\, n_w(t-\tau)\, \gamma(t,\tau) - \alpha_3 n_s(t) n_w(t) \\ &\quad + \alpha_1 n_s(t)\left(n_f(t) - n_w(t) - \frac{n_h(t)}{2}\right)\end{aligned} \tag{11}$$

$$\frac{dn_h(t)}{dt} = -2\alpha_3 n_h(t) + \alpha_3 n_s(t) n_w(t) + \alpha_2 n_s(t) n_w(t) \tag{12}$$

$$\frac{dn_f(t)}{dt} = -\alpha_3 n_h(t) + u(t) \tag{13}$$

where N_0 and N_{f0} are the initial number of searching robots and food items, respectively. The ratio model is initialized as follows $n_s(0)$=1, $n_f(0)$=1, $n_w(0)$=0, and $n_h(0)$=0. The detection probabilities (α_1, α_2, and α_3) range from 0 to 1, where γ is the likelihood that a cooperation during the time interval [t-τ, t] does not occur (failed cooperation event), which also ranges from 0 to 1.

In one scenario, the food items will disappear when they are delivered to the nesting site. Then, the numerical solutions of the ratio equations ($u(t)$=0) are see Fig. 3(a). At time t_0, at the beginning of a run, all robots begin to search for a food source. As more and more searching robots detect food items, they begin to wait for another robot's cooperation, or deliver the food items to the nesting site. The number of food items decrease continuously until they are depleted. Finally, all robots will search for food sources randomly in the workspace. Another scenario is when another food item appears as a food source when the food item is delivered to the nesting site. In this case, the steady state solution of the cooperative foraging system are shown in Fig. 3(b). The foraging system reaches a steady state after a period of transient oscillations. The foraging efficiency is fully-determined by the waiting time τ. The dependence foraging efficiency on τ can be obtained by the proposed criterion.

In a cooperative foraging system, a single food item must be delivered by two robots. When a scouting robot detects a food item, it will wait for another robot to cooperate with it. Therefore, the waiting time is the critical parameter of the system. The solutions depend on the waiting time because they satisfy the following equations when the system reaches steady state,

$$-\alpha_1 n_s\left(n_f - n_w - \frac{n_h}{2}\right) - \alpha_2 n_s n_w + 2\alpha_3 n_h + \alpha_2 n_s n_w \gamma = 0 \tag{14}$$

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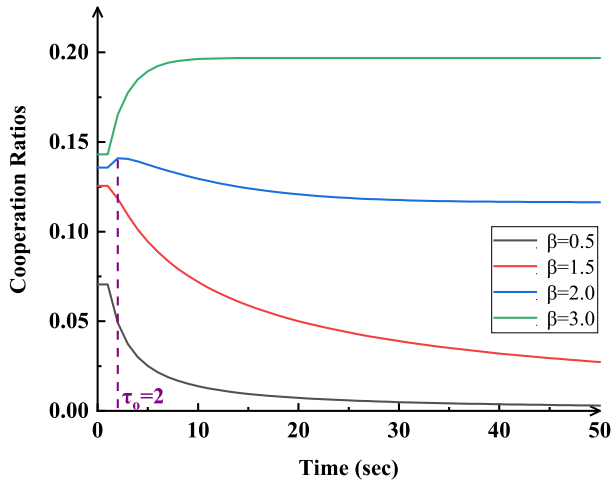

Fig. 4. The cooperation ratio of foraging system with different β value. β is the ratio of scouting robots and the amount of food items.

$$-\alpha_2 n_s n_w \gamma - \alpha_3 n_s n_w + \alpha_1 n_s \left(n_f - n_w - \frac{n_h}{2}\right) = 0 \tag{15}$$

$$-2\alpha_3 n_h + \alpha_3 n_s n_w + \alpha_2 n_s n_w = 0. \tag{16}$$

The waiting robots can complete the foraging task successfully through cooperative interaction. The cooperation ratio can be expressed by the following equation, in dimensionless form, based on the values of n_s and n_w,

$$R(t) = \alpha_2 n_s(t) n_w(t). \tag{17}$$

The cooperation ratio of a foraging system made up a set of foraging robots is shown in Fig. 4. The parameter β is the ratio of scouting robots to the amount of food items. If the quantity of searching robots is fewer or slightly greater than that of the food items, the waiting robots cannot obtain enough cooperation from their companions, e.g., β is equal to 0.5 or 1.5. The collaboration ratio will monotonically decrease as the waiting time goes by. When there are twice as many foraging robots as food items in the system the cooperation increases and then decreases after reaching a maximum as the waiting time goes by. If there are sufficient foraging robots in the system, e.g., β is equal to 3, the cooperation ratio will monotonically increase to reach the maximum because there are enough searching robots to cooperate with the waiting robots. Then, for a given number of robots, the cooperation ratio can be determined. Therefore, the robot waiting time has an optimal value. For the given n_s and n_w, the cooperation ratio reaches a maximum when n_s is equivalent to $n_w$based on Eq. (17). Therefore, the robot can choose a special subtask at a different time, e.g., searching, waiting, and homing. The foraging behavior of an ant colony works well with the highest efficiency when the optimal waiting time τ_o is equal to 2s.

4. Implementation

Two computer experiments were carried out with one and two food sources in a dynamic environment. The grid world is made up of 100 × 100 square lattices. Each grid item is sized within its assigned area (a square 5 *cm on a side)*. The output of the neurons at the boundaries of the domain are set to a negative constant. These boundaries are similar to obstacles in the area, e.g., areas with repellent pheromones. The maximum simulation time is 200 s in each foraging experiment. The size of the robot colony is 20, and the number of foraging robots is 10. There are no pheromones on the field at the beginning of a simulation. The initial output of the neural network is set to zero. The growth rate of fluctuation of the neural network output is 0.02. The evaporation rate of the output is 0.01. The sensing radius of each robot is 10 grip units, and the step size of each robot is 3 grip units.

4.1. Foraging algorithm based on virtual pheromones

When foraging begins, and starting at the nest site, the searching robots inspect the search space for a food source. There is no pheromone in the shared environment. The neural network output is initialized to zero. When exploring, the robots release repellent pheromones (negative) on the ground to repulse their mates from areas that were already visited. Once searching robots encounter a food source, the robots try to carry it and deposit attractive pheromones (positive) to attract their mates to the food source. The pheromones will gradually diffuse into the whole space and evaporate from the ground up. The waiting time of cooperative foraging is chosen based on the optimization method of the cooperation rate. The intensity of the pheromone trail will be reinforced successively. Eventually, all foraging robots will migrate toward the trail from the nest to the food source. The cooperative foraging behavior will emerge based on virtual pheromones. The foraging algorithm is as follows:

(1) **Initialize output of neural network to zero**

$x_i\,(t=0) = 0$

(2) **Foraging and until the food is consumed**

(3) **Exploring until finding the food source**
(4) Walk randomly/follow pheromone trails based on exploration rate ***r***
(5) Release repellent pheromone, and update the output of network:
$x_i\,(t+1) = f\left(\sum_{j=1}^{N} w_{ij} x_j(t) + I_i(t)\right)$, $N = 8$, $I_i(t) = P_o$ *or* P_e
(6) **Return to step (3)**
(7) **Waiting for the optimal waiting time**
(8) **Homing until arriving the nest site**
Follow pheromone trails
Release attractive pheromones, and update the output of network:
$x_i\,(t+1) = f\left(\sum_{j=1}^{N} w_{ij} x_j(t) + I_i(t)\right)$, $N = 8$, $I_i(t) = P_a$
(9) **Return to step (8)**
Pheromones evaporate from the ground: $x_i'\,(t+1) = (1-\rho)\,x_i(t) + f\left(\sum_{j=1}^{N} w_{ij} \Delta x_j(t)\right)$, $N = 8$

(10) **Return to step (2)**

4.2. The foraging with one food source

In this section we introduce the implementation of a single food source scenario. In the experiment, the ant nesting site is placed in the lower right corner of the world. The robots start from the nesting site to search for a food source, which is positioned at the lower left corner (see Fig. 5(a)). The gray rectangle obstacle is placed randomly, and can move freely. The repellent pheromones are then released by the scouting robots (green dots) according to Eq. (1) until gradually diffuse into the workspace. The space marked by the repellent pheromones is an area that has previously been explored. In response to the repellent pheromones, the scouting robots will strive to explore an unknown territory. Therefore, the scouting robots will find

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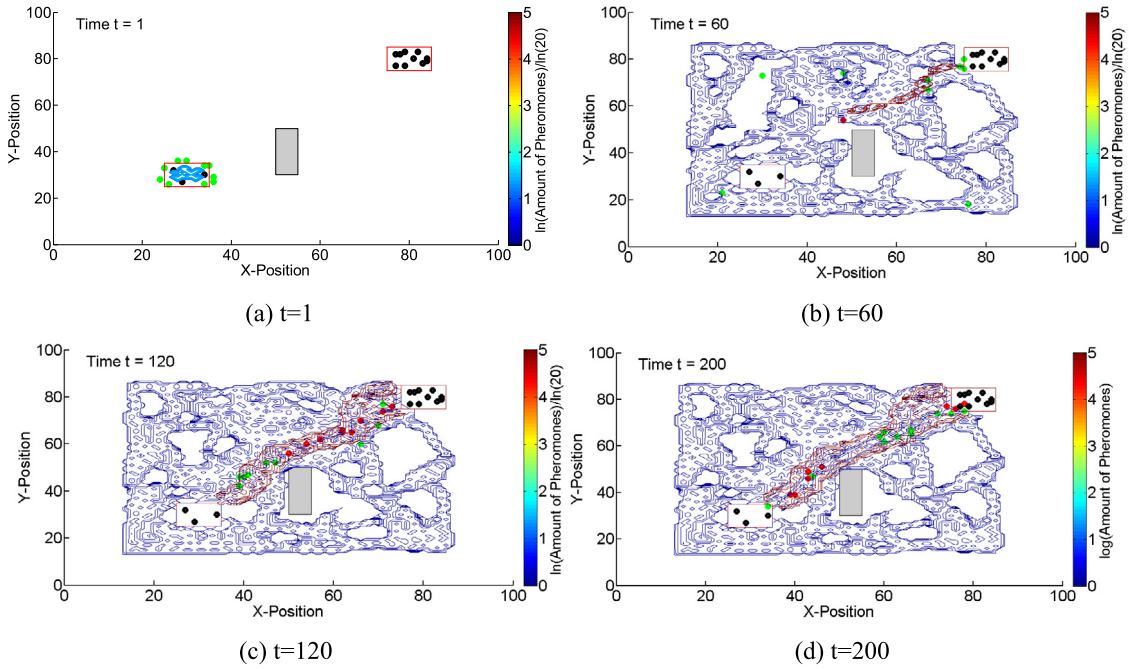

Fig. 5. Snapshots of pheromone distribution at different times with one food source, (a) Distribution of pheromone at time t=1, (b) Distribution of pheromone at time t=60, (c) Distribution of pheromone at time t=120, and (d) Distribution of pheromone at time t=200.

the food source effectively. The distribution of pheromones is see Fig. 5 at different times.

When the scouting robots discover the food source, they will pick-up the food items and bring them back to their nesting site. The homing robots (red dots) will lay down the attractive pheromones from the food source to the nesting site on the ground (see Fig. 5(b)). Likewise, the attractive pheromones diffuse into the workspace gradually. When the homing robots arrive at the nesting site, they are capable of recruiting other robots in the nesting site so they may scout the food source together. The pheromone trail attracts the other scouting robots (see Fig. 5(c)). The scouting robots follows this trail to find the food source and return to the nesting site. More and more homing robots release the attractive pheromones along the trail. The pheromone intensity of the trail will be reinforced by a large number of homing robots. Meanwhile, the pheromones will evaporate gradually. In the end, all robots scout the food source and return to the nesting site by traveling along the trail (see Fig. 5(d)).

4.3. Foraging with two food sources

To validate the effectiveness and reliability of the proposed pheromone model, another food source is introduced, that is positioned at the lower right corner (see Fig. 6(a)). After a period of foraging the scouting robots (green spots) find both food sources, and then carry the food items to home (see Fig. 6(b)). The homing robots (red spots) will lay down attractive pheromones to form a trail from each food source to the nesting site. Therefore, in the early stage of foraging, there are two trails in the workspace (see Fig. 6(c)). After a certain time (e.g. t=60), the gray rectangular obstacle moves upward 10 grid units. The distribution of pheromones will be updated continuously, and the foraging trail will be optimized (see Fig. 6(d)). More and more robots choose the shorter trail from the food source to the area where they can forage. The intensity of the attractive pheromones on the shorter trail will become stronger and stronger. Ultimately, all robots will follow the shorter trail so they may begin foraging faster; therefore, the robots ultimately give up on the longer trail. The pheromones outside of the shorter trail will slowly disappear with the evaporation.

4.4. Performance metrics

To test the proposed cooperative foraging algorithm, an optimal decision rule is obtained based on the optimal waiting time derived in Section 3.3. If finding the food source becomes too difficult, the searching robot must give up their current subtask to forage food items efficiently. The efficiency of the cooperative foraging system is optimized based on an optimized decision rule. Another important constraint to consider is the ability of foraging robots to determine the maximum number of food items a foraging robot can carry back to the nesting site.

In the cooperative foraging system, robots can obtain food items, but they also require energy and time to scout and deliver the food. The system's objective is to gain the best benefit at minimum cost during foraging. To determine the optimal decision rule, a robots' efficiency at the foraging task is defined as the ratio between the number of delivered food items and the foraging time. This is based on the optimal foraging theory defined as

$$E = \int n_f d(t), \tag{18}$$

where E is the robots' efficiency at the foraging task and $n_f(t)$ is the number of foraging food items at time t.

4.5. Result analysis

By analyzing the performance of the swarm foraging system, we can determine the optimal control strategy for individual robots. In this section, two foraging characteristics are introduced: foraging efficiency and coverage rate. A swarm's foraging efficiency can be evaluated approximately by calculating the total number of foraging food items and the total time in a given experimental implementation. Fig. 7 shows the number of foraging food items with different waiting times τ. At the beginning stage, all robots are searching for food sources. There are no food items that need to be delivered to the nest. The foraging curve levels off with a small slope and gradually increases as time goes on.

To calculate foraging efficiency, we will evaluate the line integral to determine a foraging curve. The area can be calculated

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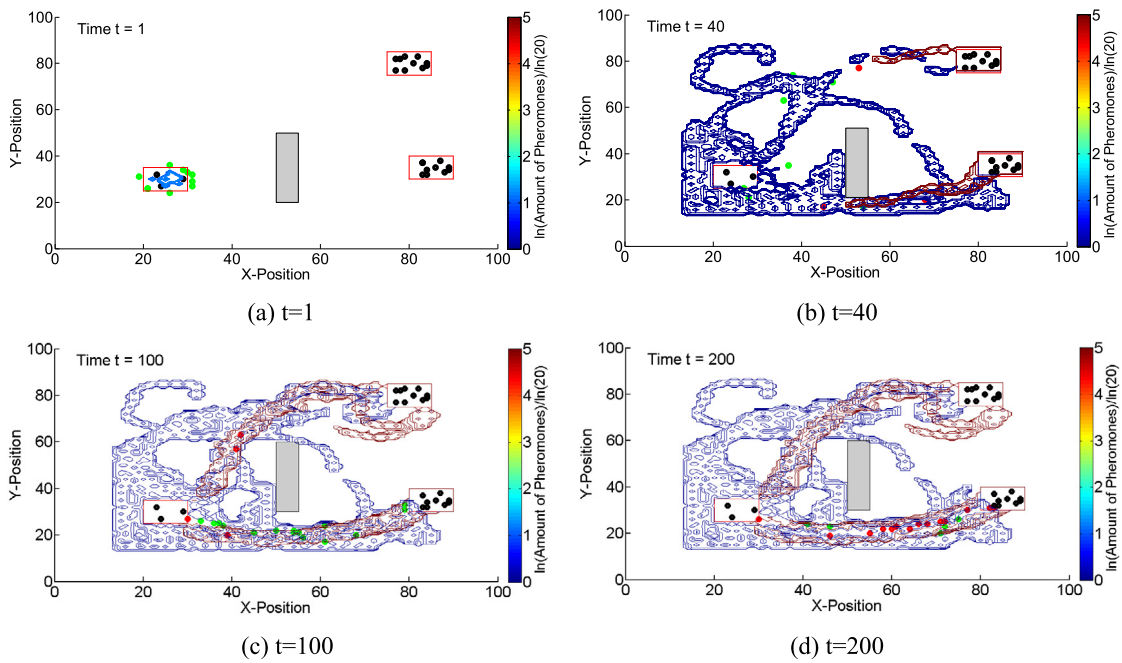

Fig. 6. Snapshots of pheromone distribution at different times with two food sources, (a) Distribution of pheromones at time t=1, (b) Distribution of pheromones at time t=40, (c) Distribution of pheromones at time t=100, and (d) Distribution of pheromones at time t=200.

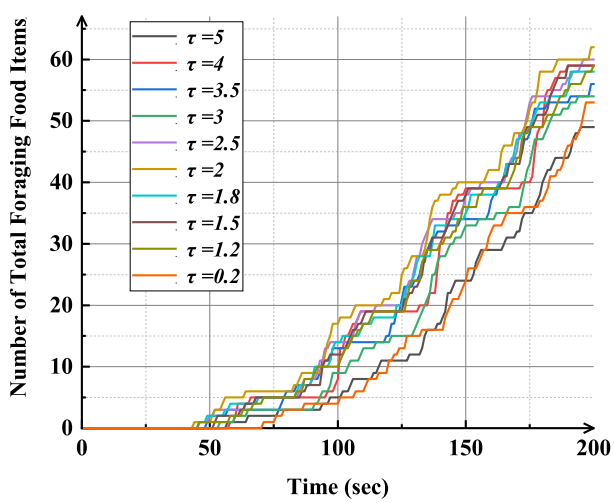

Fig. 7. Numbers of foraging food items with different waiting time τ, which is the waiting time for cooperation.

based on Eq. (18). The area indicates the average efficiency of foraging behavior. Fig. 8 shows that the average efficiency is 4272, which is equivalent to 2 s. A waiting time τ of 5 s and 0.2 s corresponds with an average efficiency of 2589 and 2600, respectively (Fig. 8(b) (c)). Fig. 8(d) shows the area of the foraging curve integral with various waiting times τ. This curve suggest that as the waiting time reaches 2 s, the system increases in average foraging efficiency. The experimental results are consistent with the theoretical analysis.

In a swarm foraging system, the robots do not know where the food items are located at the beginning of the operation. The robots initiate the roam and search tasks in the shared environment. When the searching robots discover a food source, they will travel home with the food items. Fig. 9(a) shows the average coverage of exploration. The optimal strategy for swarm foraging has been identified. The swarms perform efficiently when the waiting time is equal to 2 s. Foraging robots take more time to deliver food items and have a lower exploration coverage rate. The coverage rate of re-exploring area indicates the ratio of the region is explored many times compared to the entire workspace. Fig. 9(b) shows the coverage rate of repetition, which is an intermediate value of various different waiting times. This means the swarm robots perform the necessary search and deliver the food items efficiently.

To illustrate the advantage of our novel foraging algorithm for swarm robotics based on virtual pheromones, we do the next simulation under the same condition. The distribution patterns of food source is shown as Fig. 6(a). The pheromone will accumulate as the foraging task goes on. More and more robots forage food items along the pheromone trail. The probability of invalid searching will be reduced. The active walker model can be regarded as moving agents, which leave markings on the ground while moving. The movements of agents are subject to the sharing environment. They also change the environment locally by modifying the potential function. The agent moves from the position of higher potential to lower potential. The numbers of foraging food items with different algorithms show in Fig. 7. The neural network based algorithm has a higher foraging efficiency. Simulation demonstrates that the proposed novel algorithm can significantly improve the performance of foraging task (see Fig. 10).

5. Discussion

We have constructed and analyzed a novel pheromone-based cooperative foraging behavior model based on the wave expansion of neural networks. A neural network has a single layer that corresponds to the discretized grid environment. Each neuron is a label that identifies a unique position in the work space. When an ant lays down a pheromone at a specific position, the corresponding neuron is activated by an external input. Neural activities in the field propagate in waves from the neuron, where the activation is initiated. The output of the neuron represents the density of pheromones. The neural network mimics the inner workings of the pheromones. The proposed pheromone model

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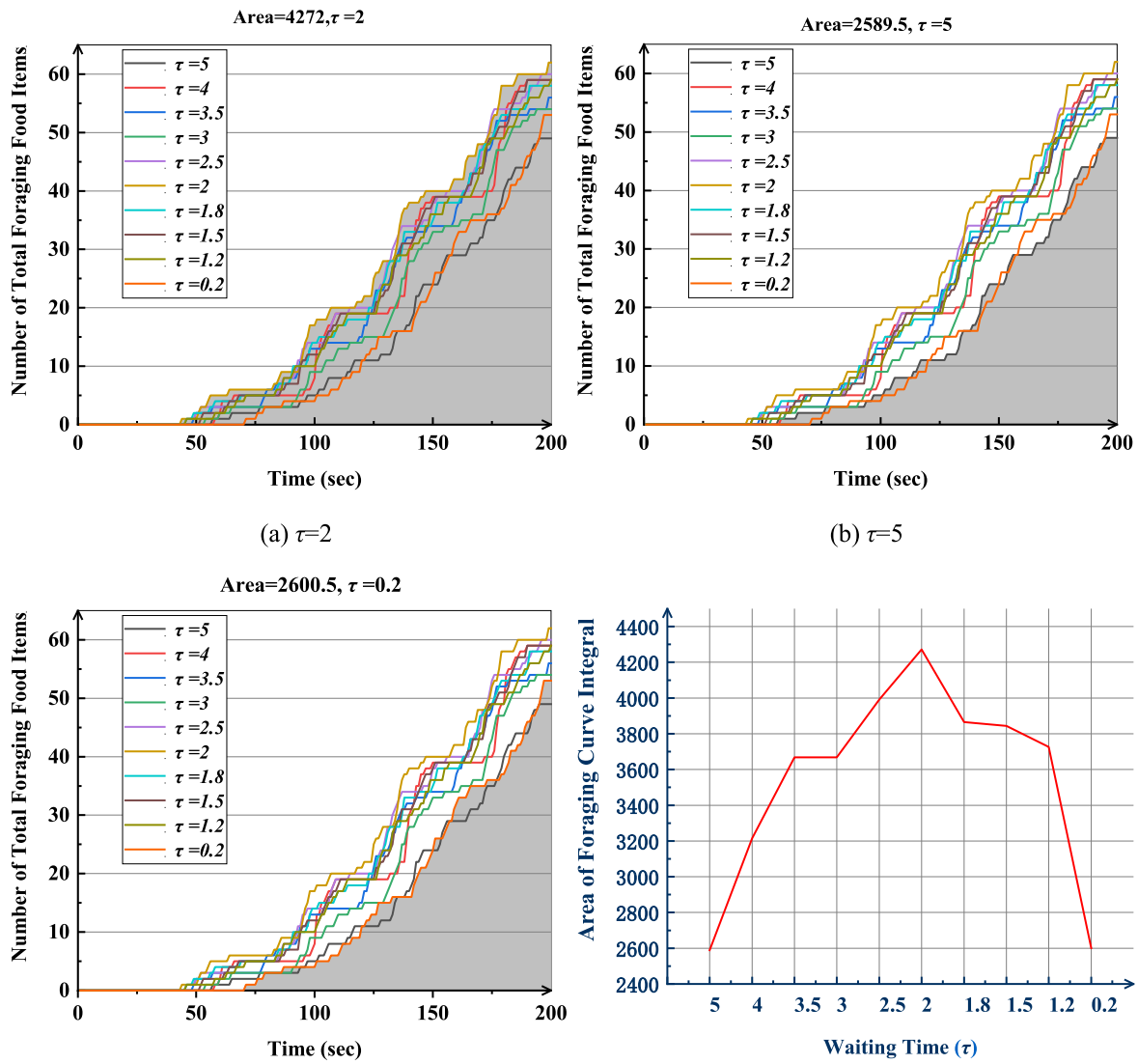
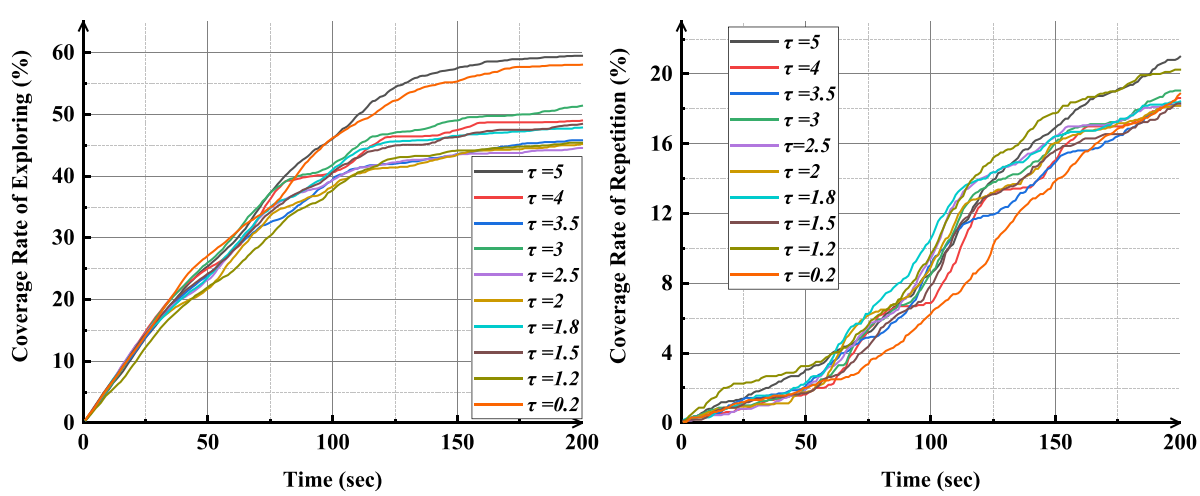


(a) τ=2 (b) τ=5

(c) τ=0.2 (d) Area of foraging curve integral with different τ

Fig. 8. Average efficiency for different waiting times τ, where τ is the waiting time for cooperation. The area indicates the average efficiency of foraging behavior.



(a) t=1 (b) t=60

Fig. 9. Coverage rate of exploring robots. τ is the waiting time for cooperation.

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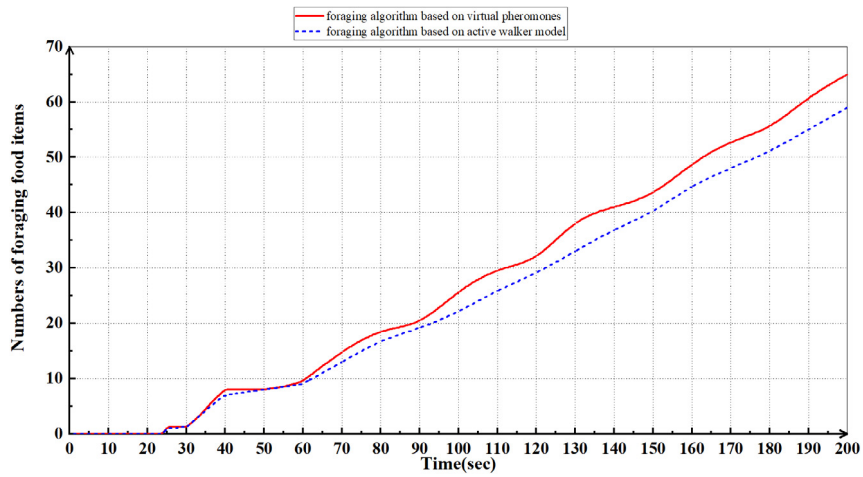

Fig. 10. Numbers of foraging food items with different algorithms.

is general. It easily transforms to other swarm robotic systems, which use local observations to make decisions.

In this paper a mathematical method is used to analyze the optimal parameters of collective behavior. A mathematical model is developed that governs the dynamics of a set (swarm) of average robots with different behaviors. We made a few simplifying assumptions in the proposed method. First, swarm robots are largely independent of each other and the state transition rates of probability were obtained from experiences. Second, we assumed that a single food item must be delivered by two foraging robots cooperatively. So, this is a specialized case of swarm foraging. To consider more general cases, we design a more complex cooperation strategy. In these general cases, a foraging system considers additional states that describe additional behaviors. This means that the coupled rate equations are associated to the number of robots that are cooperating.

The mathematical model is developed based on stochastic processes. A probabilistic model governs the evolution of the swarm's behaviors in time. Therefore, the solutions of the mathematical model describe the average collective behaviors over many simulations or experimental implementations. The analytical results show that the stochastic model agrees with the experimental results. In our simplified case, we obtain the analytical solution of the swarm foraging system. However, swarm foraging behaviors are usually too complex to develop an exact model. The implementation of a neural network model requires a very sophisticated methodology that can model extremely complex systems. At present, complex deep neural networks are reasonably expected to provide a practical control architecture for swarm robotics systems.

Finally, our proposed algorithm, based on neural networks, was implemented with smaller swarm sizes. The spatial distribution of food items affects the foraging rate. If there are obstacles or even mobile obstacles in the shared environment, the foraging robots will stay in obstacle-avoidance mode for a longer period. Additional difficulties may arise due to an increase in colony size, a change in food distribution, and a change in avoidance time. Some of the challenges of a swarm robotic system include: detection areas overlapping, spatial interference, and obstacle avoidance. In addition, even if the exact controllers are executed in a standard hardware component of all the robots in the swarm, the robot systems are still heterogeneous because of the inherent difference between individual robots. The parameters distributions and system noise should be considered to exactly describe the complex heterogeneous systems in practical applications.

6. Conclusions and future works

In this paper a novel pheromone model of swarm foraging behavior is developed based on a neural network. A dynamic wave expansion neural network (DWENN) is used to model pheromone diffusion. The neurons of the neural network correspond to different positions in a pre-defined workspace. When the robots release pheromones into their environment, the corresponding neurons (units) will receive an external input. The pheromones will diffuse through the local connections between neurons. The pheromone is also updated based on the proposed pheromone evaporation model. An optimization method is developed to choose the key parameters of the cooperative foraging task. The differential equations represent the evolution of the transition between different tasks of foraging robots. Each variable corresponds to the number of robots given a special task. The cooperation rate is formulated to evaluate the performance of the foraging behavior. The key parameter that affects foraging performance is analyzed via a task allocation model. The optimal parameters are found to determine the optimal control strategy of the cooperative foraging system. Two simulated experiments have been performed that consider a variety of food sources, cooperative foraging techniques, and pre-selected performance metrics.

The results reported in this paper suggest several future research directions. For instance, foraging behaviors can be very complex, depending on the system constraints considered; Thus, the minimum number of homing robots required to deliver a food item back to the nesting site needs to be found. Additionally, the time needed for the robots to wait for cooperation or travel from the nesting site to the food source are other constraints that need to be found. In future work, the task allocation model will have more identified constraints (for the cooperative foraging system).

In the proposed cooperative foraging algorithm, future work will also involve a survey of evaporation, diffusion, and noise. The magnitude of noise can impact another important performance metric, the percent of area covered. Noise can drive the scouting robots to find the area surrounded by the explored area to detect new food sources. The impact of noise on performance can be investigated for a combination of diffusion and evaporation. In addition, the cooperation rate varies with both evaporation rate and diffusion rates for a special noise value. The interaction of noise, diffusion and evaporation will be examined further in future work.

Swarm robotics has many potential applications due to its inherent robustness, scalability and flexibility. Swarm foraging is

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a widely used benchmark testbed for swarm algorithms; these foraging tasks can be tuned to improve the performance of swarm robotics systems. Future work will also include experimenting on real swarm robotic platforms to improve the proposed algorithms.

Declaration of competing interest

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2020.106156.

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