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Designing pheromone communication in swarm robotics: Group foraging behavior mediated by chemical substance

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Abstract In swarm robotics, communication among the robots is essential. Inspired by biological swarms using pheromones, we propose the use of chemical compounds to realize group foraging behavior in robot swarms. We designed a fully autonomous robot, and then created a swarm using ethanol as the trail pheromone allowing the robots to communicate with one another indirectly via pheromone trails. Our group recruitment and cooperative transport algorithms provide the robots with the required swarm behavior. We conducted both simulations and experiments with real robot swarms, and analyzed the data statistically to investigate any changes caused by pheromone communication in the performance of the swarm in solving foraging recruitment and cooperative transport tasks. The results show that the robots can communicate using pheromone trails, and that the improvement due to pheromone communication may be non-linear, depending on the size of the robot swarm.

Keywords Swarm robotics · Social insects · Pheromone communication

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1 Introduction

1.1 Chemical substance as a medium for robot communication

The introduction of chemical signals between robots is a challenging topic in swarm robotics. Swarm robotics studies typically deal with huge numbers of robots, and communications among them definitely play an important role. When designing a swarm system, researchers therefore have to deal with the issue of communication. A typical means of communication is the use of telecommunication media, where each robot has a wireless device using radio waves or light to exchange messages directly with other robots. Most swarm robotics systems make use of such media. An alternative method is to use chemically based media, inspired by biological communication using pheromones. A chemically based medium has the following characteristics: (a) Evaporation: Volatile pheromones evaporate and disappear from their original location at normal temperatures. (b) Diffusion: Pheromones can diffuse forming a gradient of their density. This gradient can provide information for other organisms. (c) Locality: Pheromone communication depends on local environmental conditions (e.g., direction of the wind, humidity, and temperature). (d) Reactivity: Because the chemical features of a pheromone can change over time due to reactions with the environment, a chemical medium has the potential to enrich the information of the environment. These characteristics raise the possibility of indirect, time-delayed, "anonymous" communication between swarm members. This type of communication is in stark contrast with that using telecommunication media, where an information receiver can easily identify its sender. Moreover, in the context of swarm intelligence, the information itself can be collective; that is, many senders can over time transmit information to one receiver at a certain future time. It is also worth noting that anonymity and collectiveness form the basis of social insect collective behaviors known as stigmergy (Grasse 1959). Such communication would be easier to implement using chemically based media.

In this paper, we focus on the characteristics of chemically based media mentioned above and implement them in a robot swarm. Our system is based on the well-known algorithm of Ant Colony Optimization (ACO) (Dorigo et al. 1996). In our experiments with real robots, ethanol is used as the chemical medium, and each robot has ethanol sensors and an ethanol pump that can release ethanol on the floor. Using these devices, we show that the robots can solve collective tasks more efficiently using chemical communication.

1.2 Related works

Cooperative object transport described in this paper is closely related to two major tasks in the study of swarm robotics: group foraging and cooperative manipulation. In group foraging, robots search and collect objects distributed in the environment. They can improve their performance through cooperation, especially when the distribution of the objects is inhomogeneous (Balch and Arkin 1994; Balch 1999; Hamann and Worn 2007). In cooperative manipulation, a group of robots cooperate to carry an object. As the object is generally too heavy to be carried by a single robot, coordination is required to manage its transport correctly. This task is known as "box-pushing" (Kube and Zhang 1993; Donald et al. 1994; Mataric et al. 1995; Kube and Bonabeau 2000).

Another important aspect studied in this paper is indirect, time-delayed, "anonymous" communication as opposed to direct, instantaneous, "signed" communication. Methods for the former can be further classified depending on the type of communication media used, that is, either physical or chemical. Regarding physical media, Steels (1990) and

Beckers et al. (1994) demonstrated a simple algorithm enabling a swarm of robots to gather objects efficiently using indirect communication via location of the objects themselves. Physical objects, which served as the medium for communication, can contain additional information to support robot navigation. Kurabayashi and Asama (2000) developed a portable device, called the Intelligent Data Carrier (IDC), which stores information, allows wireless communication with robots, and can be dispersed in unknown environments to facilitate communication between the robots. Ichikawa and Hara (1996) proposed utilizing the robots themselves as landmarks for other robots. Nouyan et al. (2008, 2009) showed that a group of robots coordinately formed a chain connecting two places, which served as navigation information for other robots.

As for chemically based media, there are two approaches to incorporate these in swarm robotics: the first is to emulate chemical substances, and the other is to introduce real chemical substances. Because real chemicals and their detectors are usually difficult to deal with, emulation of chemical substances has been used in previous studies. Russell (1997) proposed a robot system comprising a heater and thermometers, with residual heat on the floor considered as the pheromone. Sugawara et al. (2004) proposed a virtual environment comprising a projector and a CCD camera, in which diffusion and evaporation of chemical substances were calculated by a host computer and projected on the floor as colored images. Garnier et al. (2007) applied a similar system for path selection.

The use of real chemical substances in swarm robotics was introduced by Hayes et al. (2002), who developed a distributed robot system using odor sensors, and demonstrated successful cooperative localization of the source of the odor. Purnamadjaja and Russell (2007) developed a robot system with a gas diffuser and odor sensors, and demonstrated that chemical signals can be utilized for aggregation behavior. Fujisawa et al. (2008b) used ethanol and alcohol sensors as a trail pheromone system, similar to social insect group foraging, and demonstrated that the robots successfully located prey and then linked their nest and the prey using a pheromone trail. The research documented in this paper extends this system.

2 Forager recruitment facilitated by pheromone communication

2.1 The recruitment algorithm

The algorithm presented here was originally proposed by Fujisawa et al. (2009, 2008b, a, 2007), who simplified the algorithm of Kurumatani (2000) for a single robot attracting other robots. For the sake of clarity, we describe the algorithm in greater detail here. The experimental environment is set as a bounded two-dimensional field, including one or more robots, a food source, and a nest. The algorithm assumes that each robot can detect the direction of the nest from any location in the environment, which, based on the observation that some ant workers use a solar compass (Holldobler and Wilson 1990), we feel is a reasonable assumption.

The algorithm is described by the deterministic finite automaton shown in Fig. 1. In the algorithm, we define three states $S_i (i = 1, 2, 3)$, five perceptual cues (stimuli) $P_{ij} (ij = 12, 13, 21, 31, 32)$, and three effector cues (actions) $E_i (i = 1, 2, 3)$. As shown in Fig. 1, a robot in state S_i takes action E_i. If a robot in state S_i detects perceptual cue P_{ij}, then it changes its state to S_j.

Details of the states of the robot (S_i) and associated effector cues (E_i) are given below: S_1 is the state of searching without any information about the location of food. The robot takes

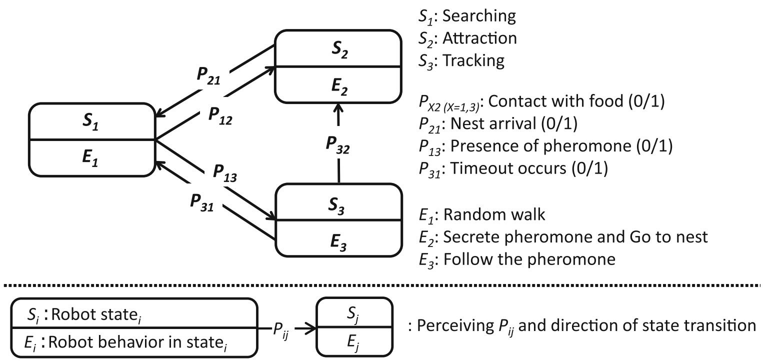

Fig. 1 State transition rule for foraging using pheromone communication

action E_1, a random walk in search of food in the environment. S_2, attraction, is the state of recruitment, where the robot already knows the location of the food source. The robot takes action E_2, secreting pheromone while moving in the direction of the nest. This action serves as the behavior to recruit other robots and requires a priori information about the direction of the nest as mentioned above. S_3 is the tracking state, where the robot has information only about the direction in which it should proceed. This information is provided as a pheromone trail and indirectly indicates the location of the food. The robot then takes action E_3 following the pheromone path toward the food. This action also requires a priori information about the direction to the nest. As for perceptual cues (P_{ij}), $P_{12,32}$ denotes contact with food, P_{21} is arrival at the nest, P_{13} is detection of pheromone, and P_{31} is the perception of losing the pheromone trail, which occurs t s after the robot actually loses perception of the pheromone trail.

We distinguish the following two categories of action E_2: "laying down" as the action occurring after a robot in state S_1 perceives cue P_{12}, and "reinforcing" as the action occurring after a robot in state S_3 perceives cue P_{32}. In other words, "laying down" pheromone results from a transition from state S_1 to S_2, and requires no communication with other robots, whereas "reinforcing" the pheromone trail is the result of a transition from state S_3 to S_2 induced by the trail collectively made by other robots, and can be viewed as an indirect, or stigmergic communication among the robots. The occurrence of reinforcing indicates the establishment of pheromone communication; a robot obtains information from other robots indirectly via the pheromone in the environment, and subsequently reacts to this information. In this study, we regard the number of times that "reinforcing" occurs as a measure of the efficiency of pheromone communication, and the total number of "laying down" and "reinforcing" events as a measure of swarm performance (i.e., an indication of the number of food transport communications).

Kurumatani (2000) modeled the robot as a mass point, whereas we model our virtual robots as rigid body objects, and thus we need to consider dealing with collisions between robots. We propose action rules to handle potential collision situations detected by a robot as given in Table 1. Traffic jams on the pheromone trail are solved as follows. After a collision, robots take different actions, which we call "priority rules," depending on their internal state.

We define an order of priority where a robot in state S_2 has the highest priority: (1) S_2 (stopping and waiting to avoid another robot), (2) S_3 (acting according to the rules in Table 1 and tracking the pheromone trail), and (3) S_1 (avoiding other robots). After collision, the robot with the higher priority takes the action defined by the rules in Table 1, while the robot

Table 1 Action rules when a robot detects a collision

State of robot	Collision object	Action of robot after collision
S_1	Robot or wall	disengage from collision point and turn around
	Food	Lay down the pheromone trail
S_2	Robot	Halt temporarily
	Food or wall	(beyond the model's scope)
S_3	Robot or wall	Disengage from collision point
	Food	Lay down the pheromone trail

with the lower priority stops for a given time so as not to interfere with the behavior of the higher priority robot and then takes its action. We assume that the robot can detect the direction of the collision (from the front or back). When it detects a collision from the front, the robot reacts based on the priority rules described in Table 1. In the case of a collision from the back, the robot ignores the event. A detailed investigation of this collision processing in relation to swarm performance of real robots has been reported elsewhere (Fujisawa et al. 2012).

2.2 Simulation

2.2.1 Simulation settings

Robot and pheromone characteristics We set the shape of a virtual robot to be a cylinder, 150 mm in diameter, with a maximum speed of 100 mm/s. The robots can move within a bounded two-dimensional square environment. A grid with cells of size 10 mm × 10 mm is overlaid on the environment. Evaporation and diffusion of pheromone are modeled according to Nakamichi and Arita (2004). Pheromone evaporation is calculated by the following discrete equations:

$$F_\mathrm{p}(x, y, t) = \gamma_\mathrm{vap} F_\mathrm{p}(x, y, t-1) + \Delta F_\mathrm{p}(x, y, t), \tag{1}$$

where $F_\mathrm{p}(x, y, t)$ denotes the amount of pheromone at position (x, y) at time t, γ_vap is the coefficient of evaporation, and $\Delta F_\mathrm{p}(x, y, t)$ denotes the addition of pheromone defined as

$$\Delta F_\mathrm{p}(x, y, t) = \begin{cases} Q_\mathrm{p} & \text{if an } S_2 \text{ robot is on cell}(x, y) \\ 0 & \text{otherwise} \end{cases}, \tag{2}$$

where Q_p is the amount of pheromone added. Pheromone diffusion is calculated by the following equation:

$$\begin{aligned} A_\mathrm{p}(x, y, t) = {} & A_\mathrm{p}(x, y, t-1) + \gamma_\mathrm{dif}\{A_\mathrm{p}(x+1, y, t-1) \\ & + A_\mathrm{p}(x-1, y, t-1) + A_\mathrm{p}(x, y+1, t-1) + A_\mathrm{p}(x, y-1, t-1) \\ & - 5A_\mathrm{p}(x, y, t-1)\} + (1-\gamma_\mathrm{vap}) F_\mathrm{p}(x, y, t), \end{aligned} \tag{3}$$

where $A_\mathrm{p}(x, y, t)$ denotes diffusion in the atmosphere of the amount of pheromone at position (x, y) on the grid at time t. The second term on the right-hand side denotes flux in the amount of pheromone between neighboring cells where γ_dif is the coefficient of diffusion, while the third term gives the amount of pheromone evaporating from the ground. A robot located at position (x, y) on the grid can detect the diffused amount of pheromone denoted as $A_\mathrm{p}(x, y, t)$. This is a specification of the robots sensor. Figure 2 graphically illustrates the

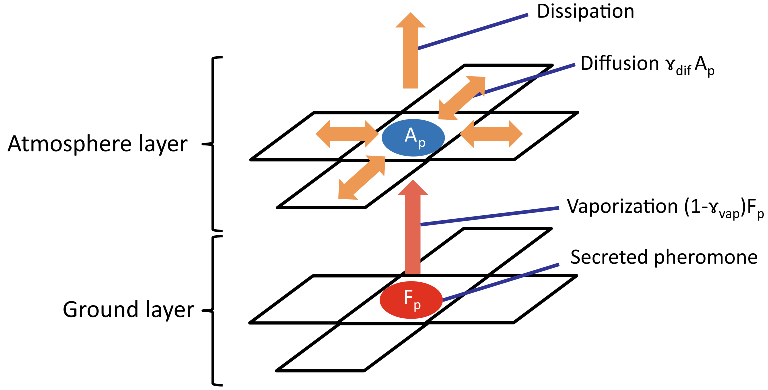

Fig. 2 Vaporization, diffusion, and dissipation in discrete space

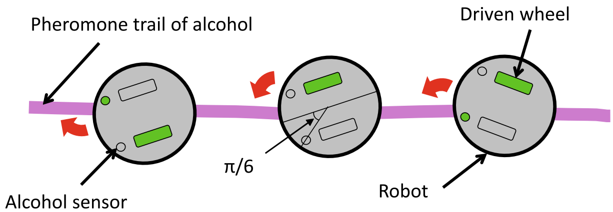

Fig. 3 Behavior on the pheromone trail

various pheromone calculations. The robot deposits pheromone on the ground, but detects it in atmosphere. This model is required for robot implementation.

Behavior of individual robots in each state A robot in state S_1 moves randomly in the environment in search of food. The robot can select one of four motions: moving forward, moving backward, turning right, and turning left. At each simulation step, the direction of the robot is determined probabilistically as follows: moving forward with probability 0.52, turning to the right with probability 0.16, turning to the left with probability 0.16, and moving backward with probability 0.16. A robot in state S_2 deposits pheromone on the ground. The robot then detects the direction of the nest and moves in that direction, secreting pheromone according to Eq. 2. A robot in state S_3 follows a pheromone trail. The mechanism of trail-following mimics real ant behavior: ants detect a pheromone trail through their two antennae. When an ant detects a trail through its left (right) antenna, it moves to the left (right) (Hangartner 1967). To mimic this feature, two pheromone sensors are located on the bottom of each virtual robot. As shown in Fig. 3, the position of the two sensors is set at an angle $\pi/6$ from the direction of movement, which is determined by the moving wheel on the same side as the sensor detecting the pheromone. The direction taken by the robots (see Sect. 2.1) is always toward the food, which is defined as the direction away from the nest.

Parameters In the simulation runs, the size of the environment was set to 1,800 mm $\times$ 1,800 mm. The nest and food, with a radius of 600 and 160 mm, respectively, were located at opposite corners of the environment. Each simulation consisted of 12,000 steps, that is, 20 min with the simulation step set to 0.1 s. The parameters controlling pheromone evaporation and diffusion were set as γ_{vap}=0.999 and γ_{dif}=0.001, respectively. Each robot drops a set

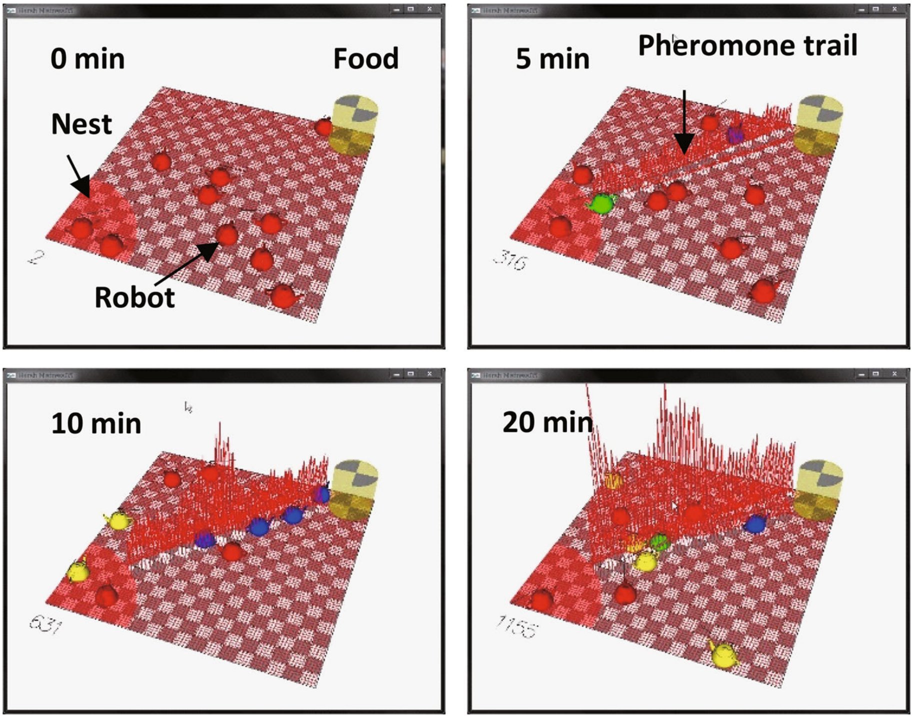

Fig. 4 Typical simulation results for ten robots, a food source, and a nest. Each robot is represented as a *colored teapot*, where *red*, *green*, and *blue teapots* denote S_1 (searching), S_2 (attraction), and S_3 (tracking) robots, respectively. A *yellow teapot* denotes a colliding robot

amount of pheromone (100) on a cell. A threshold of 68.67 was introduced to define the smallest amount of pheromone a robot could detect. This value was calculated so that a robot could detect the existence of pheromone for five minutes after a "laying down" event.

2.2.2 Simulation results

Ten independent simulations were executed, with the initial locations of the robots set randomly for each run. Figure 4 depicts a typical simulation result with ten robots. The amount of pheromone compound (A_p in Eq. 3) is indicated by thin red bars extending perpendicular to the environment. The robots had already formed a pheromone trail at $t = 5$ min, and the trail was reinforced at $t = 10$ min, as indicated by the height of the thin red bars. Finally, at $t = 20$ min, efficient pheromone communication was realized where the robots used the established pheromone trail laid down and reinforced by others.

Effect of the presence of pheromone communication Figure 5 shows the relationship between the robot swarm size (varying from 1 to 40) and the swarm performance, measured as the total number of "laying down" and "reinforcing" events (henceforth, referred to as pheromone secreting events) during the 20 min simulation. "With communication" means the sum of "laying down" and "reinforcing" events, and "without communication" means "laying down" events. An increase in robot swarm size leads to an increase in the number of reinforcing events, compared with the number of laying down events. Another finding is the diminishing

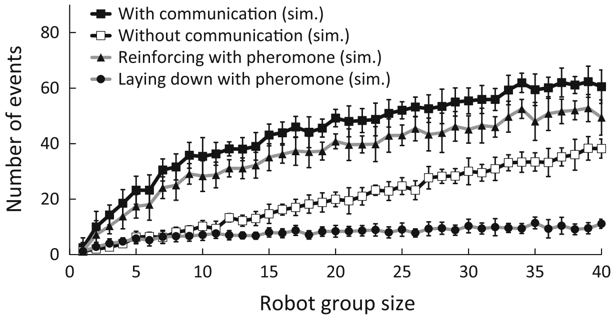

Fig. 5 Relationship between the robot swarm size and the total number of "laying down" and "reinforcing" events: The *gray line* with *black circles* indicates the number of laying down events, the *gray line* with *black triangles* indicates the number of reinforcing events, the *black line* with *black squares* indicates the number of foraging tasks with communication, while the *black line* with *white squares* indicates the number of foraging tasks without communication, where all values are averaged over ten simulation runs. (*Error bars* denote the standard deviation.)

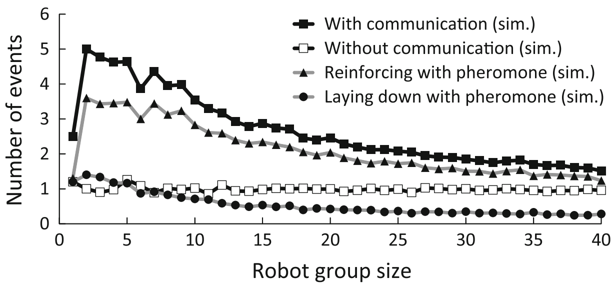

Fig. 6 Relationship between the robot swarm size (depicted on the *horizontal axis*) and the normalized number of "laying down" and "reinforcing" events per robot (depicted on the *vertical axis*)

returns of the number of reinforcing events; too many robots in the environment result in less effective pheromone communication. In other words, a relatively small robot swarm is sufficient to establish pheromone communication.

Figure 6 shows the performance per robot (i.e., the total number of pheromone secreting events divided by the robot swarm size), which indicates the contribution of a single robot to the swarm performance. The degree of pheromone communication, measured as the number of reinforcing events, decreases with an increasing robot swarm size. This result indicates that a high robot density reduces the effectiveness of pheromone communication. On the other hand, as shown by the results obtained, individual performance without communication is mostly constant irrespective of the swarm density.

Scalability of pheromone communication In the previous section, we tested the performance of the swarm through simulations, but the number of robots in the system and the size of the environment were too small to verify the scalability of the approach. Hence, we executed a simulation program with wider ranging parameters to assess the performance (i.e., the total number of pheromone secreting events) of the virtual swarm in relation to (1) the presence/absence of pheromone communication, (2) the number of robots, and (3) the size of the environment. The other conditions remained the same as in the previous simulations.

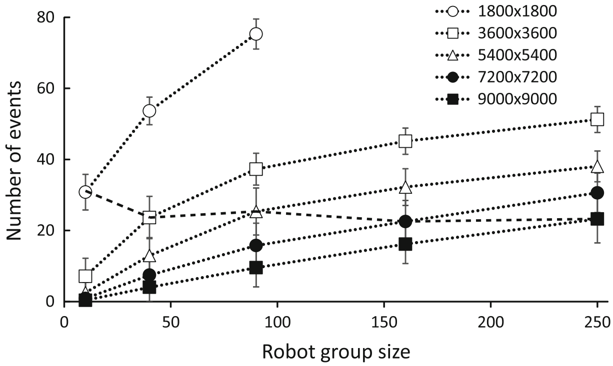

Fig. 7 Relationship between the robot swarm size and the total number of pheromone secreting events: The *blue*, *red*, *green*, *purple*, and *orange lines* indicate experimental environment sizes of 1,800 mm × 1,800 mm, 3,600 mm × 3,600 mm, 5,400 mm × 5,400 mm, 7,200 mm × 7,200 mm, and 9,000 mm × 9,000 mm, respectively. The *dashed line* indicates the same robot density across all the experimental environments. All values are averaged over 40 simulation runs, and *error bars* denote the standard deviation

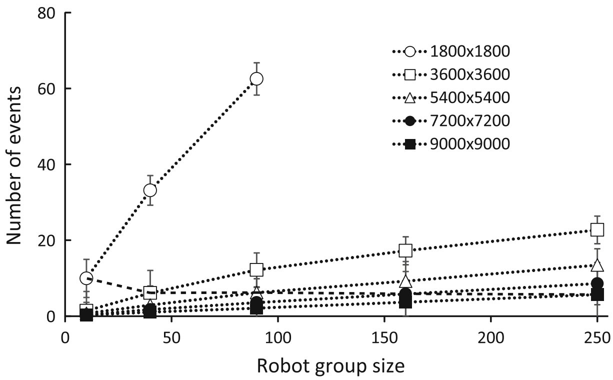

Fig. 8 Relationship between the robot swarm size and the total number of foraging without pheromone communication (i.e., the laying down events): the different colored lines have the same meanings as those in Fig. 7

Figures 7 and 8 show the performance of the simulated swarm with and without pheromone communication, respectively. The presence of pheromone communication improves the performance with the increase being statistically significant at the 0.1 % level (multiple regression, $slope = 14.58$, $p < 0.001$). Performance deteriorates with an increasing environment size ($slope = -6.441 \times 10^{-5}$, $p < 0.001$), while an increasing robot swarm size significantly increases the performance ($slope = 0.1677$, $p < 0.001$), thereby confirming the results presented in Sect. 2.2.2.

As a measure of scalability, we assessed the swarm performance with a constant robot density ($3.086/\mathrm{m}^2$, corresponding to ten robots in a 1,800 mm × 1,800 mm environment as shown in Fig. 4) by changing the field size (1,800 mm × 1,800 mm, 3,600 mm × 3,600 mm, 5,400 mm × 5,400 mm, 7,200 mm × 7,200 mm, and 9,000 mm × 9,000 mm) and the corresponding number of robots (10, 40, 90, 160, and 250) for communication both with and without pheromone. With the exception of the 1,800 mm × 1,800 mm environment with ten robots, which showed significantly higher performance (at the 0.1 % level) under

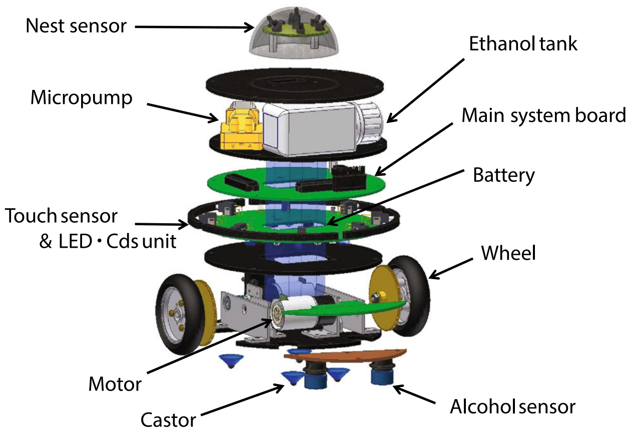

Fig. 9 Main components of ARGOS-01

both communication conditions (pairwise *t* tests, Benjamini–Hochberg adjusted for multiple comparisons, $p < 0.001$ for communication both with and without pheromone), swarm performance did not change significantly when varying the size of the environment and the number of robots ($p > 0.05$ for communication both with and without pheromone) (see Figs. 7 and 8, respectively). This result indicates scalability of swarm performance in environments larger than 3,600 mm × 3,600 mm. The exceptional performance in the 1,800 mm × 1,800 mm environment could be explained by the fact that the sizes of the food and nest were fixed. Thus, they decreased the effective size of the environment in which the robots moved and disproportionately increased the density of the robots in the 1,800 mm × 1,800 mm environment compared with the larger environments.

2.3 Experiment with real robots

2.3.1 Experimental setting

To validate the proposed swarm behavior algorithms and simulation results, we developed a robot called ARGOS-01 (*A*ntelligent *R*obot *G*roup *O*perating *S*ystem). In this study, we used ethanol (C_2H_5OH) as the pheromone. Since ethanol volatilizes at normal temperature, we expected that the characteristics of the chemical medium (see Sect. 1.1) would be similar to those of real pheromones.
Robot Figure 9 depicts our robot and its organization. The fully autonomous robot comprises three microcomputers and sensors as shown in Fig. 10. We used a programmable system-on-chip supplied by Cypress Semiconductor Corp. (San Jose, CA, USA). The microcomputers are connected to one another by an inter-integrated circuit (I^2C).

Specifications of the ARGOS-01 are as follows: body diameter, 150 mm; height, 195 mm; weight, 1.26 kg; and maximum speed, 0.1 m/s. The size and speed correspond to our simulation settings (see Sect. 2.2.1). The robot is equipped with two active wheels and four castors. The active wheels are controlled independently, so that the robot can move freely in any direction on a flat plane. A micro-pump and tank in the robot's third layer is used to drip ethanol for the pheromone trail. The robot is also provided with four sets of sensors to detect perceptual cues as shown in Fig. 1: (1) touch sensors and CdS (cadmium sulfide)

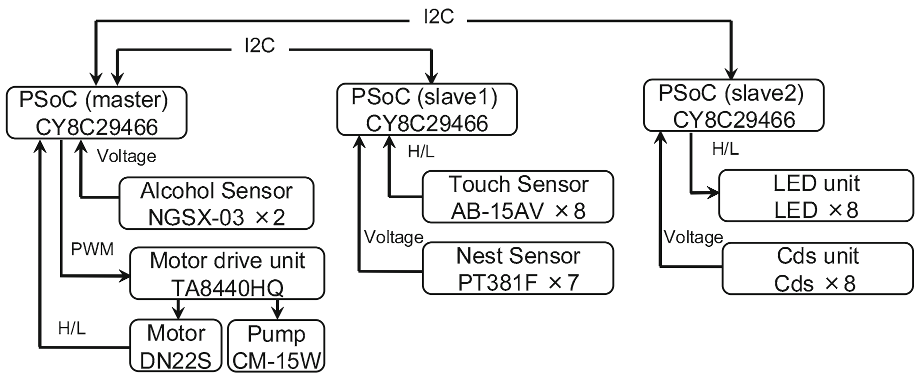

Fig. 10 System diagram of ARGOS-01

units to detect food ($P_{x2}, x = 1, 3$); a robot emits blue light so that other robots can detect it; (2) infrared phototransistors to detect the nest (P_{21}); using this sensor, the robot can detect the direction of the nest; (3) alcohol sensors to detect pheromone (P_{13}); and (4) an internal timer to detect when the time out occurs (P_{31}); if the robot loses track of the pheromone trail, then it starts the timer. After $t = 4$ s, the robot changes its internal state. The behavior of individual robots follows the algorithm given in Sect. 2.1.

A detailed description of each sensor is given below: Eight touch sensors are located on the second layer to detect collisions with other objects (other robots, food, and walls). In addition, eight LEDs and eight CdS units are located in the same place to detect light-emitting food. The CdS units are able to detect light-emitting food from a distance of 15 cm. Seven infrared phototransistors acting as nest sensors are located on the top layer to detect the direction and distance to the nest, and thus, its absolute position. Distance to the nest is measured by the voltage of the infrared phototransistors, which increases as the robot moves closer to the nest. The nest consists of electric infrared lamps indicating its position. Two alcohol sensors for detecting pheromone are located on the bottom of the robot, similar to the virtual robot (see Sect. 2.2.1), to trace the pheromone trail.

Parameters The size and location of the environment, nest, and food, and the duration of the experiment (20 min) were set to be the same as in the simulations (see Sect. 2.2.1). The robot swarm size varied as 1, 2, 3, 4, 7, and 10. A preliminary experiment showed that 40 v/v% (volume percent) had the highest swarm performance with a 5 min persistence duration of the pheromone on the ground, corresponding to that in our simulation study.

2.3.2 Experimental results

Swarm behavior At the start of each experiment, the robots were randomly placed in the environment. Each experiment was monitored using optical and infrared thermographic (IRM-320T) cameras. The thermographic images enabled visualization of the pheromone trail by taking advantage of the vaporization heat of ethanol. Repeated observations confirmed that the robots could communicate with one another as a swarm to form the pheromone trail. Figure 11 shows a typical result with four robots. A pheromone trail connecting the nest and food was formed 10 min after the onset of the experiment (Fig. 11b, b′). Subsequently, the trail was reinforced, as indicated by the lower temperature on the trail (Fig. 11c, c′).

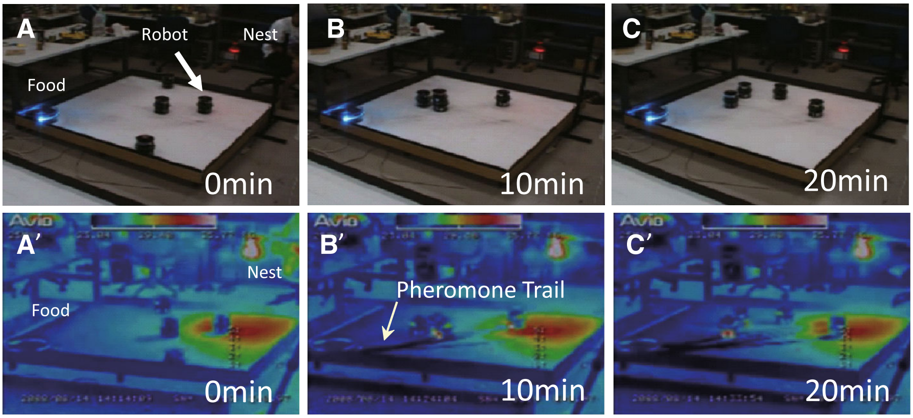

Fig. 11 Snapshots of the experimental results with four robots

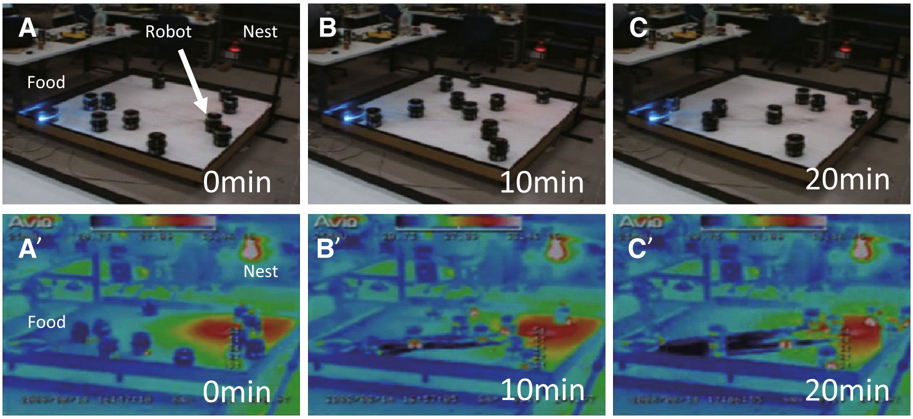

Fig. 12 Snapshots of the experimental results with ten robots

Figure 12 shows a typical result with ten robots. In this case, the pheromone trail was already present at $t = 10$ min (Fig. 12b, b′), indicating more efficient swarm behavior with the increased robot group size.

Effects of pheromone communication and robot swarm size Figure 13 shows the relationship between the presence/absence of pheromone communication and swarm performance, measured by the number of pheromone secreting events. Consistent with the simulation results, pheromone communication significantly improves swarm performance in real robot experiments (two-tailed Student's t test, $p < 0.001$).

Figure 14 (dotted line) shows the relationship between the robot swarm size and swarm performance in the presence of pheromone communication. An increased robot swarm size in a given environment significantly improves swarm performance (linear regression, $R^2 = 0.86$, F-test, $p < 0.001$). Diminishing returns with increased robot swarm size is observed, assessed by the number of "reinforcing" events. This pattern is consistent with that observed in our simulation results (Fig. 14). To improve the correspondence between the simulations and robot experiments in greater detail, we re-executed our simulation model with the radius

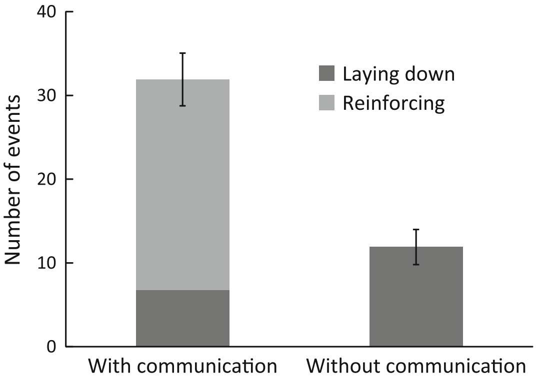

Fig. 13 Performance with and without pheromone communication: the *vertical axis* denotes the number of foraging (laying down and reinforcing). The *dark gray* and *light gray bars* indicate "laying down" and "reinforcing" events, respectively, while the *error bar* indicates standard deviation. Ten independent experiments were performed

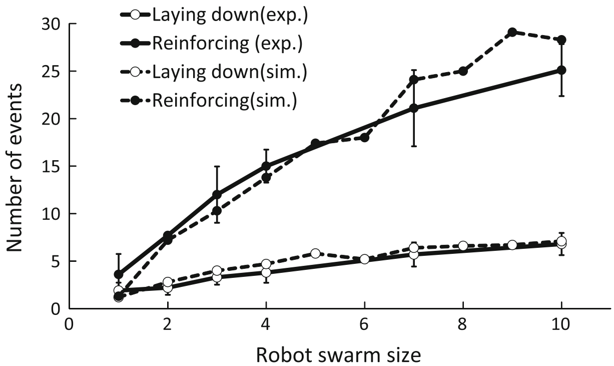

Fig. 14 Comparison of simulation and experimental results with the radius of the food set to 260 mm. The *red circles* indicate "laying down" events, and *blue circles* indicate "reinforcing" events. The *black* and *gray solid lines* indicate experiment results, and the *black* and *gray dashed lines* indicate simulation results. The plots show the average over ten independent experiments. (*Error bars* denote the standard deviation.)

of the food set to 260 mm instead of 160 mm. The modified food size in the simulations resulted in a wider trail, which more closely matched the real robot experiments with the size of the food set to 160 mm (Fig. 14). The improved match may result from the fact that, in the real robot experiments, food is detected by the robots via LED light, causing the effective size of the food to be greater than its actual size.

3 Application to cooperative transport

3.1 Swarm behavior algorithm for cooperative transport

In this section, we extend our swarm algorithm to realize cooperative transport. In our original algorithm (Fujisawa et al. 2007, 2008b, a, 2009), which was analyzed and integrated above, the focus was on pheromone communication. Having modified the algorithm (Fujisawa et al. 2010), here, we analyze its performance using real robots. The new algorithm is described by a deterministic finite automaton, in which robots are tasked with searching for food in a given environment and then transporting it to their nest, in a fully autonomous manner (Fig. 15). We defined six internal states, $S_i\,(i = 1, \ldots, 6)$; 14 perceptual cues (stim-

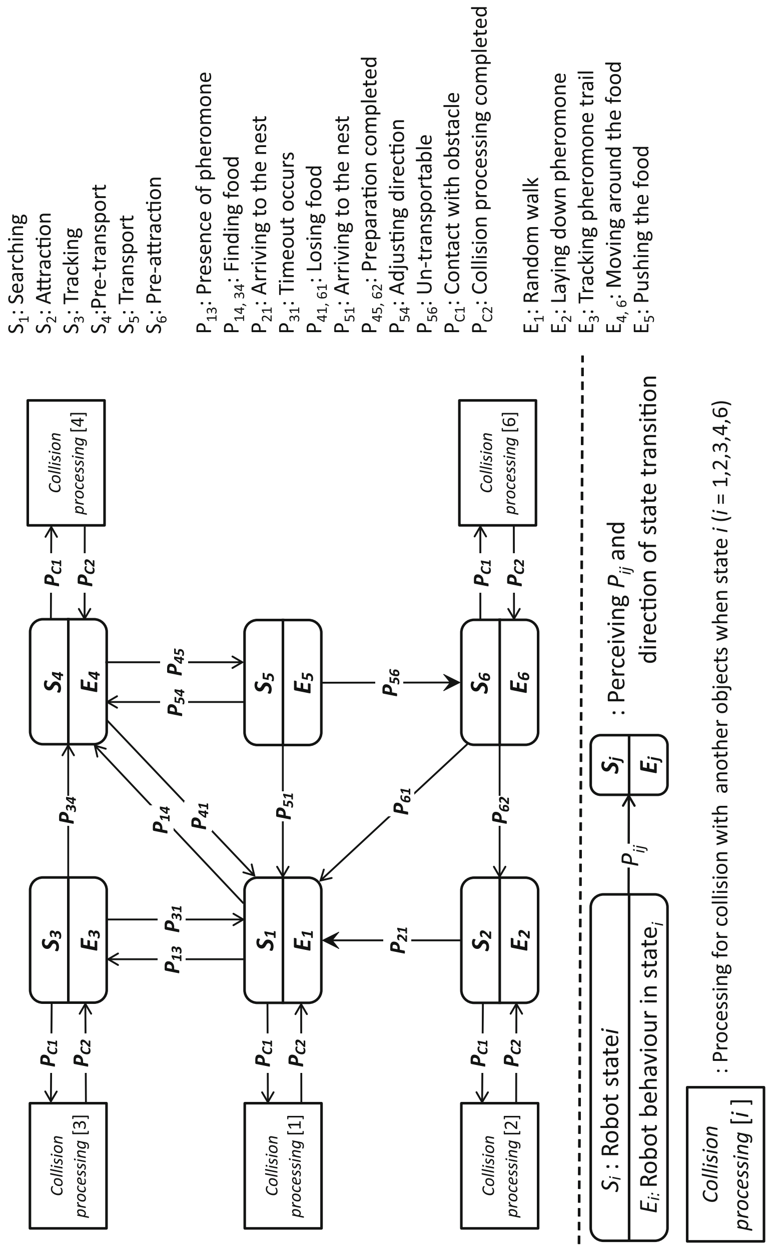

Fig. 15 State transition rule for cooperative transport using pheromone communication

uli), $P_{ij}(ij = 13, 14, 21, 31, 34, 41, 45, 51, 54, 56, 61, 62, C1, C2)$; and six effector cues (actions), $E_k(k = 1, \cdots, 6)$. We also assumed that there are sufficient robots in the environment, and that all robots can detect the direction of the nest (see Sect. 2). As shown in Fig. 15, a robot in state S_i takes action E_i. If the robot in state S_i detects perceptual cue P_{ij}, then it changes its state to S_j. Details of the internal states S_i of the robot, perceptual cues P_{ij}, and effector cues E_i are given below.

Table 2 Behavior selection using the algorithm for cooperative transport after a collision; the robots (S_5) transport the food by colliding with other robots or food. Thus, there is not "Collision Processing [5]"

Collision Processing	Contact position	Robot's behavior after making contact with another object
Collision Processing [1]	Front	On-site rotation after disengaging from contact point by moving backwards
	Back	On-site rotation after disengaging from contact point by moving forwards
Collision Processing [2]	Front	Stop on-site
	Back	Disengage from contact point by proceeding forwards
Collision Processing [3]	Entire circumference	Disengage from contact point by moving backwards
Collision Processing [4]	Front	Disengage from contact point by moving backwards
	Back	Disengage from contact point by proceeding forwards
Collision Processing [6]	Front	Disengage from contact point by moving backwards
	Back	Disengage from contact point by proceeding forwards

S_1, searching: the robot does not have any information about the food. S_2, attraction: the robot has information about the location of the food. S_3, tracking: the robot has direction information about the location of the food. S_4, pre-transport: the robot knows the location relationship between the food and the nest. When a robot finds food, in some cases, it cannot move the food. As each robot can only exert a pushing (not pulling) action, it needs to move around the food so that the food is between the robot and the nest. S_5, transport: the robot pushes the food. S_6, pre-attraction: if the food does not move, the robot moves around it once again to make its way back to the nest.

P_{21}, arriving at the nest; P_{13}, the presence of pheromone; P_{31}, timeout; $P_{14,34}$, finding food (the robot "finds food when it makes contact with the food); $P_{41,61}$, losing food; $P_{45,62}$, preparation completed (the food is located between the robot and the nest); P_{51}, arriving to the nest; P_{54}, adjusting direction during transport (to keep pushing the food towards the nest); P_{56}, detecting the impossibility of transport; P_{C1}, contact with an obstacle (a wall or another robot); P_{C2}, collision processing completed.

E_1, random walk; E_2, laying down pheromone (secreting pheromone while moving toward the nest); E_3, tracking a pheromone trail; E_4, moving around the food (to ensure the food is between the robot and the nest); E_5, pushing the food; E_6, moving around the food (to return to the nest).

The robot perceives the existence of an obstacle through physical contact with it and acts according to the collision algorithm given in Table 2. We improved our previous collision algorithm (Fujisawa et al. 2009) to prevent traffic jams on the pheromone trail. In addition, as the robots always make contact with one another during cooperative transport, collision processing is not executed in state S_5. Thus, there is no collision processing in state S_5.

3.2 Robot transport experiment

3.2.1 Experimental settings

Robot and food item The basic setup of the robots was the same as in Sect. 2.3.1. By applying the proposed swarm behavior algorithm to the robot system, we verified the effectiveness

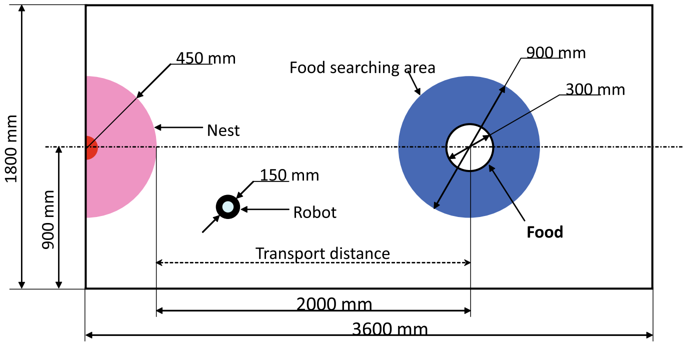

Fig. 16 Plane view of experimental environment

of pheromone communication in cooperative transport. For this purpose, we equipped each robot with a mechanism for searching for food. Light was emitted by each circular food item so that a robot could detect its existence using light sensors when arriving within the "detection area." The robot then made contact with the food. Since this study focused on cooperative transport by a robot swarm, the weight of the food was heavy enough so that it could not be moved by a single robot.

Parameters Figure 16 shows the experimental environment: a 3,600 mm × 1,800 mm 2D flat plane surrounded by walls. The diameters of the food and the nest were 300 mm and 900 mm, respectively. The "detection area" around the food was set as a circle with radius 450 mm with the food at its center. The weight of the food was set to 3.58 kg, requiring the cooperation of at least three robots to move it. The distance from the food to the nest was 2,000 mm. We defined the time limit for a robot to recognize cue P_{56} (impossible to transport food) as 20 s after starting to push the food. We also set a minimum threshold value for pheromone detection above which the alcohol sensor detected the pheromone (100 % ethanol[1]) trail. This meant that a robot was able to detect the trail for 5 min after the pheromone was laid down.

In each experiment, the robots were provided with enough ethanol so that each was able to lay down five pheromone trails. Once a robot had emptied its ethanol tank, it was replaced by a spare robot to allow the experiment to continue until the task was completed. The task was considered completed once the robots had successfully transported the food to the nest.

3.2.2 Experimental results

Figure 17 shows sequential snapshots of the transport experiment with ten robots. A, B, and C are normal camera images, while a′, b′, and c′ are thermographic images showing the pheromone trail. As early as 10 min from the onset of the experiment, the robots formed a pheromone trail, which was effective in recruiting other robots to the food source. Using a combined effort, the robots succeeded in transporting the food to the nest after 20 min. The results clearly show that the robots achieved cooperative transport, and that our new swarm algorithm works effectively.

[1] We needed 5 min duration time of pheromone trail, and found that the robot lays down a few times in preliminary experiment. Therefore, we used 100v/v% ethanol which does not require sensitive micro-pump setting.

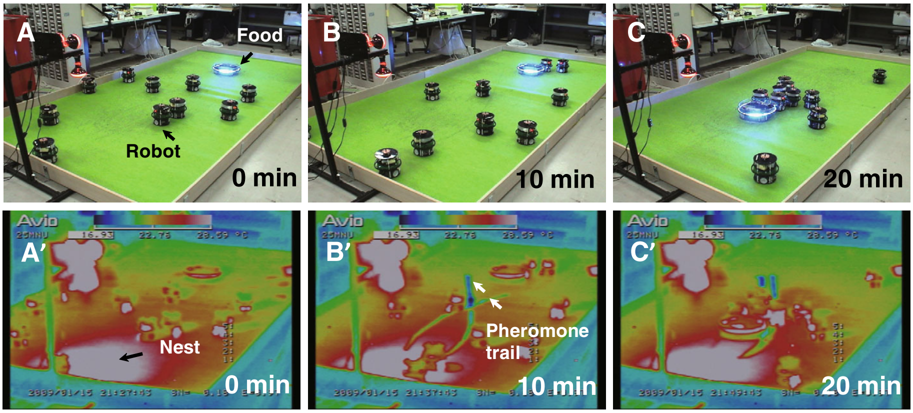

Fig. 17 Snapshots of experimental results with ten robots using pheromone communication (**a**, **b**, **c** captured by digital camera, **a**′, **b**′, **c**′ captured by thermography)

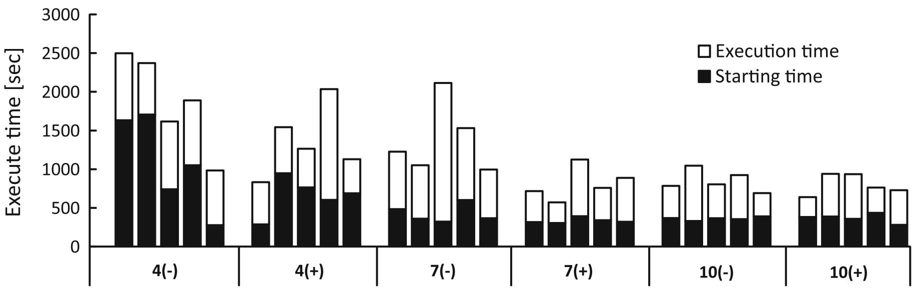

Fig. 18 Experimental results showing duration of preparation for transport (*black bars*) and actual transport (*white bars*) with and without pheromones

Effects of pheromone communication and robot swarm size Previously, we performed an experiment to determine whether pheromone communication resulted in more effective cooperative transport (Fujisawa et al. 2010). Figure 18 shows the relationship between the absence/presence of pheromone communication, the robot swarm size (4, 7, and 10), and the total time taken for cooperative transport, with five replicates shown separately for clarity. The results were analyzed statistically using R 3.0.1 (R Core Team 2013). The difference in total time was statistically significant (Kruskal–Wallis test, $p = 0.002$) for the six levels (defined by the absence(−)/presence(+) of pheromone for each robot swarm size (4, 7, and 10), hereafter referred to as 4(−), 4(+), 7(−), 7(+), 10(−), and 10(+), respectively). Pairwise comparisons revealed that the major difference lay between levels 4(−), 4(+), 7(−) and 7(+), 10(−), 10(+) (Wilcoxon signed-rank tests with Benjamini–Hochberg adjustment of p-values, all $p \leq 0.05$ between these two sets of levels). In other words, the presence of pheromone was effective only for the robot swarm size of 7, while an increasing robot swarm size required a shorter time for cooperative transport.

The total time depicted is the sum of the time taken before the transport starts (starting time) and the time for execution of the transport (execution time). The difference in starting time was not statistically significant across the six levels ($p = 0.1$), indicating that the starting time was not affected by the presence of pheromone or by the robot swarm size. The difference in execution time was significantly different for the six levels ($p = 0.006$), although pairwise comparisons revealed non-significant differences among the levels (i.e., $p > 0.05$), possibly due to the small sample sizes. These analyses suggest that the effect of pheromone communication was effective only with an intermediate robot swarm size (i.e., a comparison between 7(−) and 7(+)) that the effect of pheromone communication was mainly on the execution time, and that an increasing robot swarm size tended to require a shorter execution time, irrespective of the presence of pheromone. The performance of cooperative transport is affected by complex factors, such as effective search, effective recruitment to the food, and a continuous supply of more robots than the minimum number of robots that can collectively push the food. Because the algorithm is sufficiently complex to simulate, the underlying mechanism still remains unexplored. A more detailed observation will evaluate the relative importance of these factors in future studies.

With only four robots in the environment, we observed a marked difference in performance with and without pheromone communication. Without using pheromones for communication, the robots took a great deal of time before starting to push the food, as they depended entirely on random walking to congregate at the food. With pheromone communication, the robots were attracted to the food source, and they began transporting the food more quickly. However, there is no clear effect of the use of pheromone communication on solving the given task with ten robots in the environment for the same reason as mentioned above.

4 Discussion and conclusion

In this study, we realized cooperative behavior of a swarm of robots coordinated by a chemical substance acting as pheromone, in both simulations and real robot experiments. Compared with the previous studies on swarm robots with pheromone communication, our system does not require external control to effect communication between robots, and thus can be seen as a completely autonomous system.

In the foraging recruitment experiment (Sect. 2), the robots indirectly communicated using pheromone trails resulting in improved recruitment performance compared with that without pheromone. Simulations with increasing robot swarm and environment sizes showed that our system is scalable. At the same time, however, an increased robot swarm size resulted in diminishing returns in overall performance (Fig. 5), which led to a reduction in individual performance (Fig. 6). The diminishing returns phenomenon has been reported as a general characteristic of swarm robots and could be attributed to overcrowding (Krieger et al. 2000). In the context of pheromone-communicating robots, Sugawara et al. (2004) reported a similar phenomenon.

In the cooperative transport experiment (Sect. 3), the robots were successful in transporting a food item cooperatively, but a formal statistical analysis revealed that the contribution of pheromone communication to the task depended on robot swarm size, that is, the presence of pheromone significantly improved the performance only with an intermediate swarm size of seven robots for a particular environment size. When setting complex tasks for pheromone-communicating robots, we have to consider the non-linear effects of various parameters on their performance in solving the task. Such non-linear effects in pheromone communication systems could also be a source of the emergence of complex “swarm intelligence,” which deserves further investigation.

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References

Balch, T. (1999). The impact of diversity on performance in multi-robot foraging. In *Proceedings of the Third Annual Conference on Autonomous Agents, ACM* (pp. 92–99).

Balch, T., & Arkin, R. (1994). Communication in reactive multiagent robotic systems. *Autonomous Robots*, *1*(1), 27–52.

Beckers, R., Holland, O., & Deneubourg, J. L. (1994). From local actions to global tasks: Stigmergy and collective robotics. In R. Brooks & P. Maes (Eds.), *Artificial life IV*. Cambridge, MA: MIT Press.

Donald, B., Jennings, J., & Rus, D. (1994) Analyzing teams of cooperating mobile robots. In *Proceedings of the 1994 IEEE International Conference on Robotics and Automation, IEEE* (pp. 1896–1903).

Dorigo, M., Maniezzo, V., & Colorni, A. (1996). Ant system: optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, *26*(1), 29–41.

Fujisawa, R., Imamura, H., Hashimoto, T., & Matsuno, F. (2007) Swarm intelligence of multi-robot using pheromone trail. In *Proceedings of the 2nd Internal Symposium on Mobiligence* (pp. 203–206).

Fujisawa, R., Dobata, S., Kubota, D., Imamura, H., & Matsuno, F. (2008a). Dependency by concentration of pheromone trail for multiple robots. In *Proceedings of Sixth International Conference on Ant Colony Optimization and Swarm Intelligence, LNCS 5217, Springer* (pp. 283–290).

Fujisawa, R., Imamura, H., Hashimoto, T., & Matsuno, F. (2008b). Communication using pheromone field for multiple robots. In *Proceedings of the IEEE/RSJ 2008 International Conference on Intelligent Robots and Systems, IEEE* (pp. 1391–1396).

Fujisawa, R., Imamura, H., Hashimoto, T., & Matsuno, F. (2009). Development of multi-robots communicating by pheromone trail. *IPSJ Transactions on Mathematical Modeling and its Applications*, *2*(2), 81–90. In Japanese.

Fujisawa, R., Imamura, H., & Matsuno, F. (2010) Cooperative transportation by swarm robots using pheromone communication. In *Proceedings of the 10th International Symposium on Distributed Autonomous Robotics Systems (DARS2010), Springer*.

Fujisawa, R., Dobata, S., Sasaki, Y., Takisawa, R., & Matsuno, F. (2012). Collision-induced "priority rule" governs efficiency of pheromone-communicating swarm robots. In *Proceedings of Eighth International Conference on Ant Colony Optimization and Swarm Intelligence, LNCS 7461, Springer* (pp. 228–235).

Garnier, S., Tâche, F., Combe, M., Grimal, A., & Theraulaz, G. (2007). Alice in pheromone land: An experimental setup for the study of ant-like robots. In: *Swarm Intelligence Symposium, SIS 2007, IEEE* (pp. 37–44).

Grassé, P. P. (1959). La reconstruction du nid et les coordinations inter-individuelles chez Bellicositermes Natalensis et Cubitermes sp. La théorie de la stigmergie: Essaid'interpretation du comportement de termites constructeurs. *Insectes Sociaux*, *6*(1), 41–80.

Hamann, H., & Wörn, H. (2007). An analytical and spatial model of foraging in a swarm of robots. In E. Şahin, W. M. Spears & A.F.T. Winfield (Eds.), *Swarm Robotics, LNCS 4433* (pp. 43–55). Berlin: Springer.

Hangartner, W. (1967). Spezifität und Inaktivierung des Spurpheromons von Lasium fulginosus Latr. und Orientierung der Arbeiterinnen im Duftfeld. *Zeitschrift für Vergleichende Physiologie*, *57*, 103–136.

Hayes, A., Martinoli, A., & Goodman, R. (2002). Distributed odor source localization. *IEEE Sensors Journal*, *2*(3), 260–271.

Hölldobler, B., & Wilson, E. (1990). *The ants*. Cambridge, MA: The Belknap Press of Harvard University Press.

Ichikawa, S., & Hara, F. (1996). Experimental characteristics of multiple-robots behaviors in communication network expansion and object-fetching. In *Proceedings of the 3rd International Symposium Distributed Autonomous Robotic System, Springer* (pp. 183–194).

Krieger, M., Billeter, J., & Keller, L. (2000). Ant-like task allocation and recruitment in cooperative robots. *Nature*, *406*(6799), 992–995.

Kube, C., & Zhang, H. (1993). Collective robotics: From social insects to robots. *Adaptive Behavior*, *2*(2), 189–218.

Kube, C., & Bonabeau, E. (2000). Cooperative transport by ants and robots. *Robotics and Autonomous Systems*, *30*(1), 85–101.

Kurabayashi, D., & Asama, H. (2000). Knowledge sharing and cooperation of autonomous robots by intelligent data carrier system. In *Proceedings of the 2000 IEEE International Conference on Robotics and Automation, IEEE* (Vol. 1, pp. 464–469).

Kurumatani, K. (2000). Macro-model generation for emergent cooperative behaviors in ant colony's foraging (1)—a simple model case. *Journal of the Japanese Society for Artificial Intelligence*, *15*(5), 829–837. (In Japanese).

Matarić, M., Nilsson, M., & Simsarin, K. (1995). Cooperative multi-robot box-pushing. In *IEEE/RSJ International Conference on Intelligent Robots and Systems 95'. Human Robot Interaction and Cooperative Robots', Proceedings of the 1995, IEEE* (Vol. 3, pp. 556–561).

Nakamichi, Y., & Arita, T. (2004). An evolutionary simulation of the origin of pheromone communication. In *ISPJ Symposium Series, Information Processing Society of Japan* (Vol. 2004, pp. 51–58).

Nouyan, S., Campo, A., & Dorigo, M. (2008). Path formation in a robot swarm. *Swarm Intelligence*, *2*(1), 1–23.

Nouyan, S., Groß, R., Bonani, M., Mondada, F., & Dorigo, M. (2009). Teamwork in self-organized robot colonies. *IEEE Transactions on Evolutionary Computation*, *13*(4), 695–711.

Purnamadjaja, A. H., & Russell, R. A. (2007). Guiding robots' behaviors using pheromone communication. *Autonomous Robots*, *23*(2), 113–130.

R Core Team: R. (2013). A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Retrieved August 20, 2014 from http://www.R-project.org/.

Russell, R. (1997). Heat trails as short-lived navigational markers for mobile robots. In *Proceedings of the 1997 IEEE International Conference on Robotics and Automation, IEEE* (Vol. 4, pp. 3534–3539).

Steels, L. (1990). Cooperation between distributed agents through self-organisation. In *Proceedings of the 1990 IEEE International Conference on Intelligent Robots and Systems, IEEE* (pp. 8–14).

Sugawara, K., Kazama, T., & Watanabe, T. (2004). Foraging behavior of interacting robots with virtual pheromone. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS2004), IEEE* (Vol. 3, pp. 3074–3079).