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Cooperative acceleration of task performance: Foraging behavior of interacting multi-robots system

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Abstract

We study the effectiveness of cooperative behavior in a society of interacting agents. After reviewing the problem and defining the concept of swarm intelligence, we examine collective behavior of many-body active clusters through a task to gather pucks in the field. In this study, we used a robot with a simple structure which has a driving system and the simplest interacting means; a light and some sensors. The effectiveness of group behavior was studied under various (homogeneous, localized) puck distributions with real experiment, simulation, and analysis. To evaluate the efficiency of group behavior, we examined the scaling relation between the task completion time and the number of robots, and the relation between the interaction period and the efficiency of group. We found that a cooperation between agents by a simple interaction is very efficient in enhancing the performance of the group compared with independent individuals.

Keywords: Cooperative behavior; Multi-robots; Swarm intelligence

1. Introduction

Many kinds of fish and birds live in a group [1]. Social insects such as ants and bees establish well-ordered societies even in the absence of particular intelligence of the individuals [2]. Multi-cellular living beings are founded on cooperations of cells. In these cases, each element does a simple task by responding to local conditions without any central control. But the whole system exhibits complex functions. It is interesting to study the mechanism that a cooperation by many simple elements creates qualitatively new behaviors. Many researchers have studied such systems, e.g. the collective behavior of ants [3–6] and the collective motions of animal clusters [7,8] have been explained by mathematical models. Experimental studies have also been performed to realize such systems artificially by using a distributed robotic system.

Since Walter [9] showed the complex behavior of two robots which had a simple interaction, some experimental studies have been made by using a group of autonomous robots [10–12]. It was discussed that even a robot which was composed of simple interactions between each part and the external coped with the environment just like having an intelligence [13,14]. But there are few researchers to understand their behaviors quantitatively. The purpose of our study is to investigate the collective behavior and the efficiency of active elements which have the simple architecture

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when they act as a group. To investigate the effectiveness of swarm, we picked up a task to collect pucks distributed in the field by interacting robots. This task looks like the foraging behavior of ants, but the movement and interaction of elements are more simplified than ants. It is known that ants follows instantaneous pheromone gradient (osmotorotaxis). The fundamental osmotorotaxic information is measured by the difference in pheromone concentration between the two antennae. This sensor information is translated to a response in motion. In our experiment, each robot usually moves straight in a finite field. When a robot encounters a puck, it emits light to broadcast its location to other robots and carries a puck to their home. The other robots follow the gradient of the light field. This simplification enables us to analyze their behavior quantitatively.

In Section 2, we define the effectiveness of cooperative behavior. It is called swarm intelligence. The efficiency of interacting elements is confirmed by both experiment and computer simulation in Sections 3 and 4, and their behavior is studied analytically in Section 5.

2. Collective behavior and swarm intelligence

Collective behavior and effectiveness of distributed autonomous elements have been studied in many different disciplines: behavioral ecology [3,4], nonlinear science [5,6], artificial intelligence, and robotics [11,12]. The behavior that emerges by interacting elements is called "swarm intelligence" [15,16]. The system is composed of N autonomous units that act asynchronously in an environment. Beni claimed that the swarm intelligence is a function which emerges from interactions among N units only when N exceeds a critical number N_c. The definition of swarm intelligence by Beni is represented in Fig. 1(a). The relation between the number of elements N and the amount of useful work W has a nonlinear feature due to the presence of a critical number in N. Here it is possible to generalize this definition. In case that the relation between N and W (N–W characteristics) is nonlinear, the system should be included as "swarm intelligent systems". Let $W(N)$ denote the amount of work achieved by N interacting agents, and $W_0(N)$ denote the work achieved by N independent agents. Emergence of swarm intelligence is defined as $W(N) > W_0(N)$, i.e., the work performed by a system of N interacting agents is larger than the plain sum of N individuals without interaction. So the possible relation between the number of elements and the amount of work drawn such as in Fig. 1(b) would also be considered as the swarm intelligence. For many kinds of tasks, $W_0(N)$ is simply proportional to N. The swarm intelligent system should have nonlinear characteristic in $W(N)$. In the case of Fig. 1(a), the presence of the critical number in N may come from nonlinear bifurcation or from phase transition-like phenomena. In such a case an assembly of independent elements does not exhibit effective works (order), implying $W_0(N) = 0$ for all N. Therefore we insist that in both cases nonlinearity in N–W characteristics is essential for the effectiveness of collective behavior.

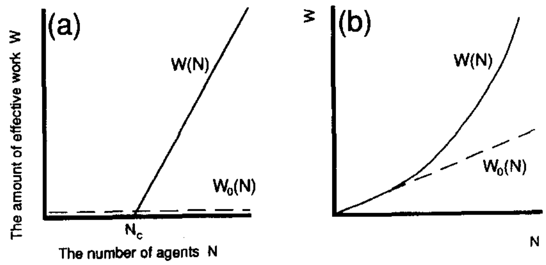


Fig. 1. Concept of swarm intelligence. (a) Beni's definition. The system composed of N units emerges a function only when N exceeds a critical number N_c. (b) Generalized definition. Emergence of swarm intelligence is defined as $W(N) > W_0(N)$. Here $W(N)$ denotes the amount of work achieved by N interacting agents, and $W_0(N)$ denotes the work achieved by N independent agents.

3. Experiment

In this study, we assumed a simple interaction between each robot, and performed experiments with real robots. The shape of robot that was used in this experiment is shown in Fig. 2. Its size was 9.6 cm width × 6 cm length ×15 cm height. It is driven by a pair of DC motors. It has two fixed arms and mechanical

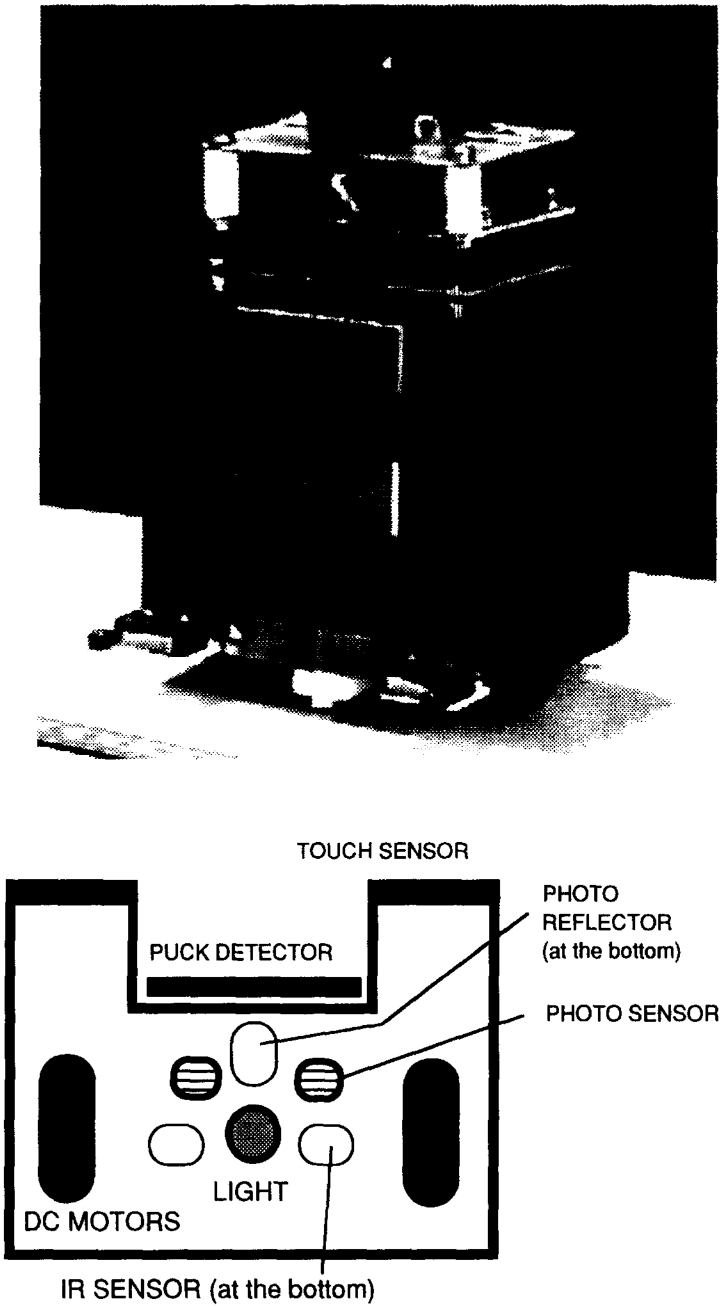


Fig. 2. The figure of the robot used in this study: above: Photograph of robot; bottom: schematic drawing of the robot.

switches equipped at the tip of each arm. They are used as touch sensors to avoid colliding with boundary walls and other robots. When the switch is turned on, the motor on the opposite side rotates in reverse: if the left switch touches something, the right motor rotates in reverse. The period that the motor rotates in reverse is constant and the robot turns about 60° for this period. As a result, the robot can avoid colliding with

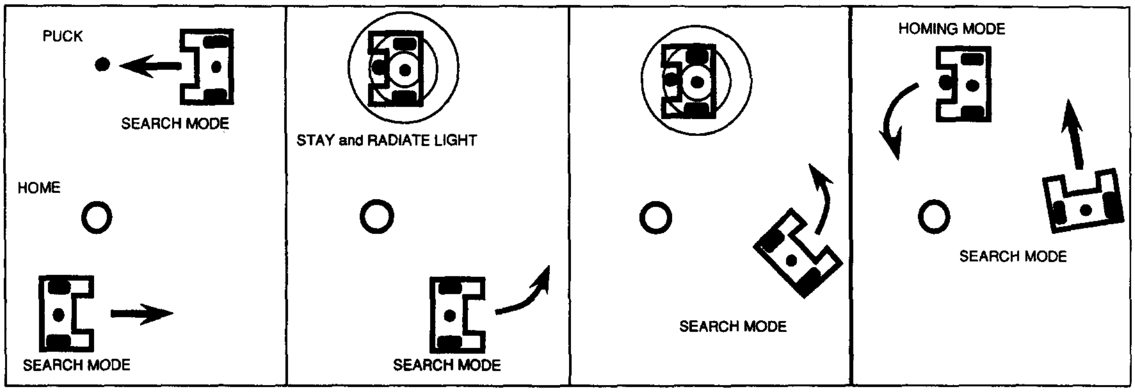


Fig. 3. Example of movement. A robot which meets a puck radiates light for a short period. After that, it moves to home which radiates IR. Another robot which has no puck reacts to the light.

boundary walls and other robots. A light on the top is used to indicate its place with regard to other robots. The robot has a pair of photo sensors and a pair of IR sensors. The photo sensors are used to find out other robots and the IR sensors are used to lead the robot to the center of the field [17]. A photo reflector at the bottom is used to recognize the color of the field.

Each robot has two modes: searching mode and homing mode. In searching mode, each robot moves straight unless it meets a puck, other robots and wall. When the robot encounters a puck, robot stays there and turns on its light for a short period. We call this "interaction period". Other robots which have no puck react to this light and turn their directions toward the light by using a pair of photo sensors. Thus the robot follows the gradient of light field.

After the interaction period, the robot which has a puck turns off its light and changes its mode to homing mode. In homing mode, the robot moves toward the IR-LED array at the center of the field using their two IR sensors. When it knows that it has arrived home by using the photo reflector, it changes the direction randomly, and again searches for pucks. Fig. 3 shows an example of their movement.

The field for this experiment was 190×190 cm and its surface was black. The boundary had a wall. There was a white square and IR-LED array at the center of the field. We will call this square "Home". The total amount of pucks used in this experiment was 32. The size of a puck was $4 \times 4 \times 4$ cm. Various kinds of distribution are possible. We chose two types of distribution in this experiment: the homogeneous field and the localized field (Fig. 4). The interaction periods were 0 s (no interaction) and 30 s. Fig. 5 shows a photograph of the experiment.

At the start of experiment, the robots were placed in the center of the field, each pointing to a different direction. The experiment continued until all pucks were collected to the home. Fig. 6 shows a temporal evolution of collected pucks. Each plot is the average of three trials. In case that pucks were distributed homogeneously, it takes much time to complete the task when there is an interaction (Fig. 6(a)). On the other hand, in case that pucks were distributed locally, all pucks were collected faster when there is an interaction (Figs. 6(b) and (c)) also show that increasing the number of robots was effective.

4. Simulation

To confirm the effectiveness of the collective behavior of robots in various situations, we simulated their movements by a computer simulation.

The state variables of a robot are the position vector $\boldsymbol{r}$, and its heading direction θ. The internal states of a robot are classified into two main states: searching and homing mode; and two substates: avoiding

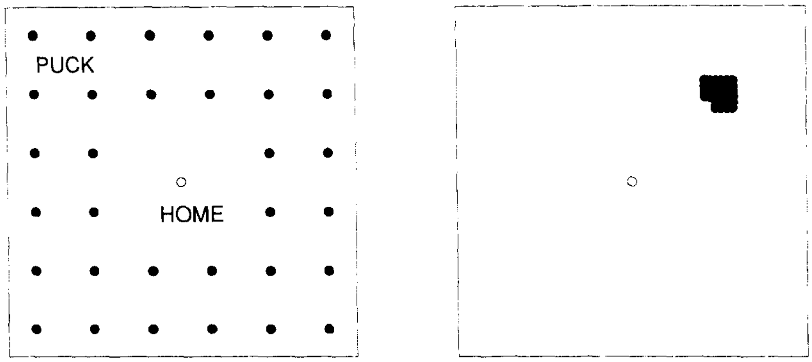


Fig. 4. The distribution of pucks which were used in this experiment: a homogeneous field and a localized field. Total amount of pucks were 32.

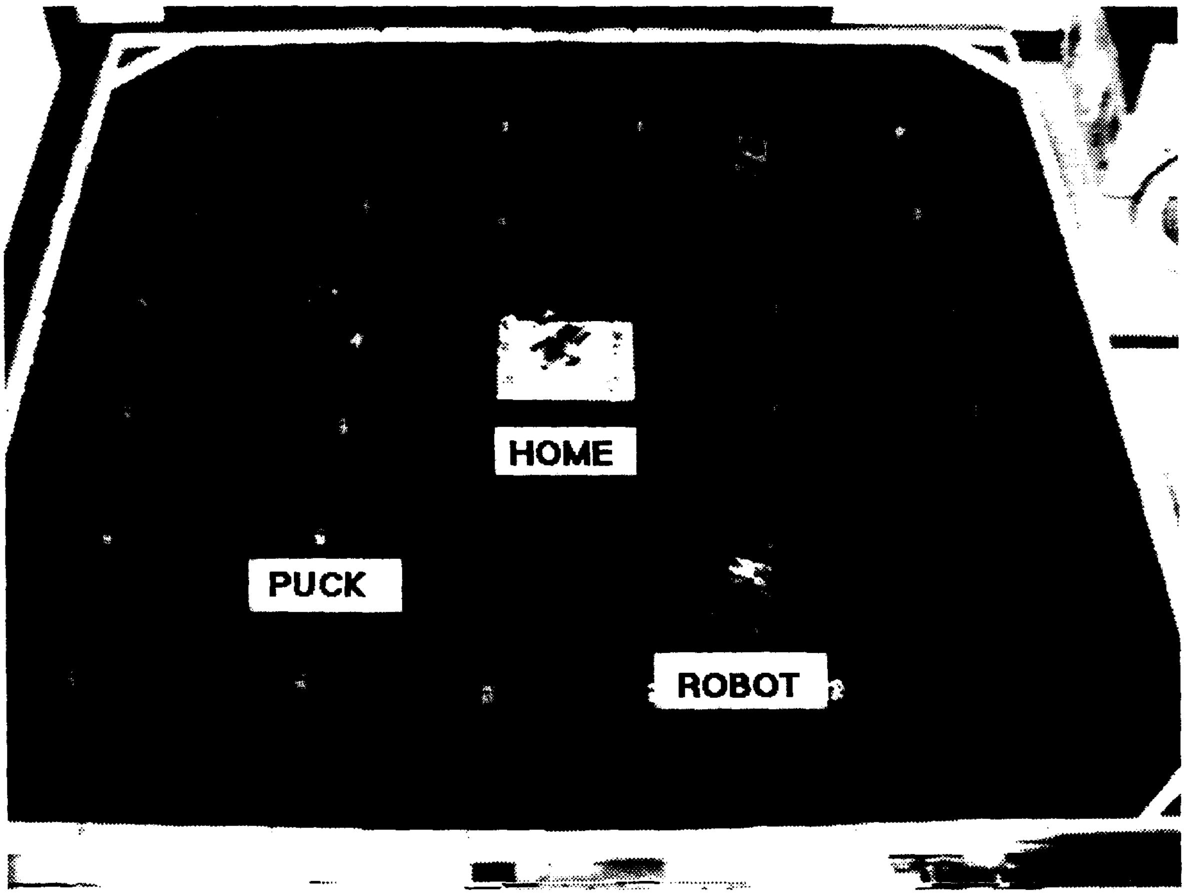


Fig. 5. The photograph of experiment. There is a home at the center of field. It always radiates IR. As robots recognize their existences by lights, the experiments were made in the dark room.

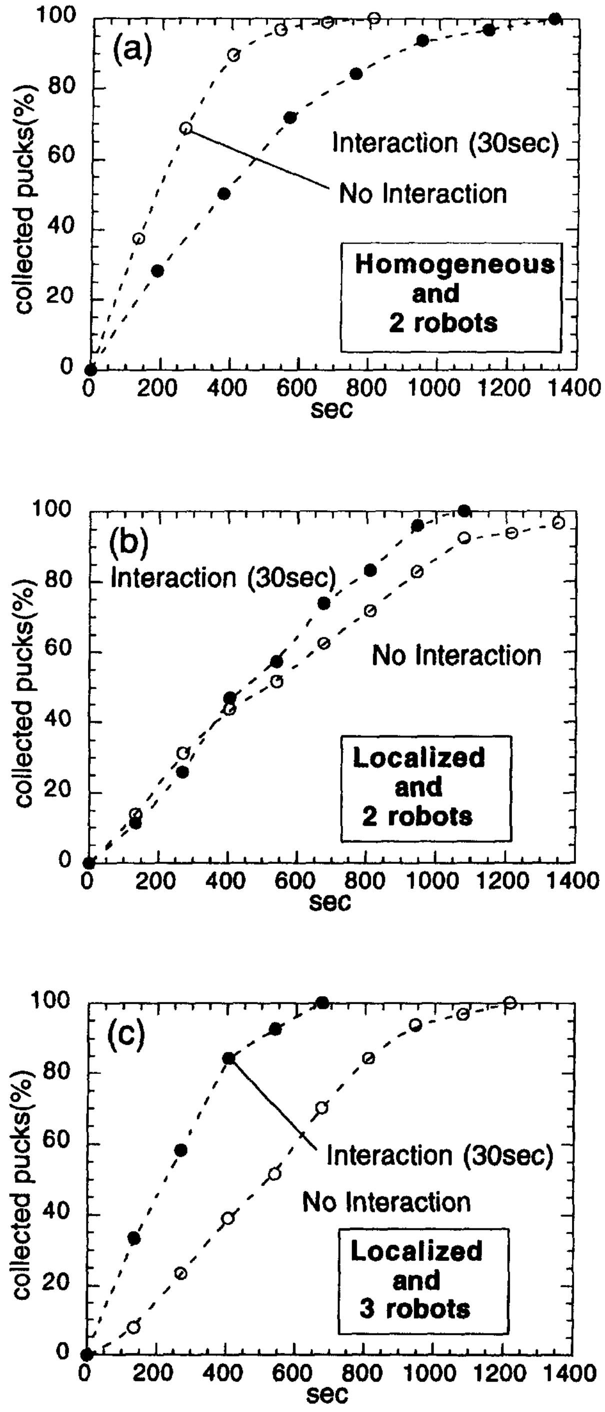


Fig. 6. Temporal evolution of collected pucks for experiments. In case that pucks were distributed homogeneously, no interaction is more effective. But in case that the distribution was localized, robots collect pucks effectively under the interaction.

and following state. The transitions between different states are initiated by sensor inputs. Therefore the next state of the robot is determined by its present state and sensor inputs. Each robot moves in its heading direction with a constant speed unless it is changing heading directions. Heading changes occur only in the beginning of each state.

On computer simulation, we assumed three types of distributions of pucks: homogeneous, localized in 25% area of the field and localized in 1% area of the field (Fig. 7). The total amount of pucks was 60. As an initial condition, the robots were placed in the center of the field, each pointing to a different direction. It was assumed that the shape of robot was circular and its diameter was 10 cm. When it collided with other robots and walls, it turned about 60° like a real robot. We took into account noise of sensory input and the environment in real experiment. Thus the heading dynamics is defined as, $\theta_{n+1} = \theta_n \pm 60 + \Delta\theta$, where $\Delta\theta$ is a random variable uniformly distributed within (−5, +5) degrees. The sign of the second term in the left hand side is uniquely determined by whether the left or right sensor detected signal. Fig. 8 shows the trajectories of robots. It shows the trajectories by five robots until 90% of all pucks were collected. In field 1, we know that the work without interaction was finished faster because the density of plots are low (Fig. 8(a)). In case that there are interactions, we observe many circular patterns (Fig. 8(b)). This is because the robots which have no puck were attracted and went round a robot which encountered a puck. In field 3, the density of plots are high under no interaction (Fig. 8(c)). The probability to meet pucks was low because the pucks were placed locally. So it took much time until the task was finished. On the other hand, we know that the futile movements were reduced by the interactions (Fig. 8(d)).

Fig. 9 shows the temporal evolution of puck collection in the case of five robots. Each plots are the average of 20 trials. The interaction periods were 0 and 100 s. We know that the interaction is not effective in field 1, but is effective in fields 2 and 3. These results are essentially the same as the experiment. We know that the temporal evolution of puck collection is well

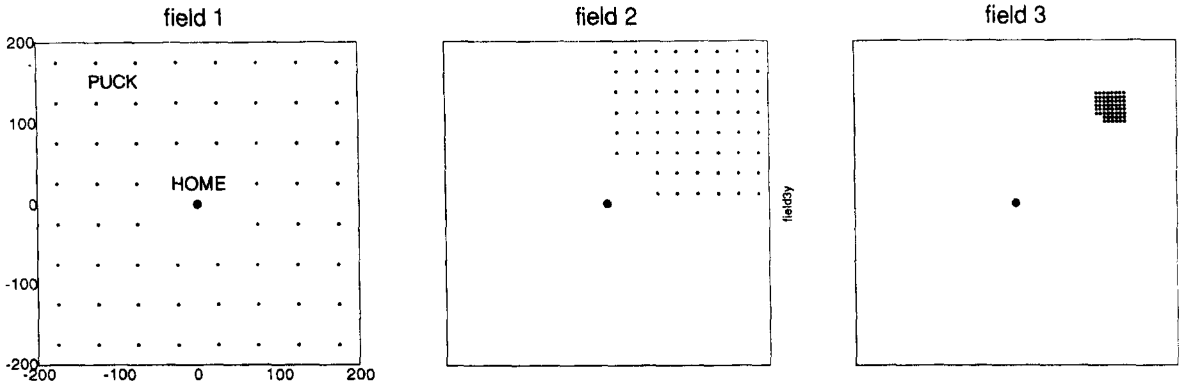


Fig. 7. The fields which were used in computer simulation. Field 1: homogeneous; field 2: localized in 25% area of the field; field 3: localized in 1% area of the field.

fitted by an exponential function in field 1, while by a linear function in fields 2 and 3.

We measure the task completion time from these figures. But the dispersion of the task completion time is large in each case. We define the completion time T such that 90% of all pucks were collected to home in this study. Fig. 10 shows the relation between the number of robots N and the task completion time T.

Fig. 10(a) shows the task completion time T as a function of N in log–log plot for robots without interaction and Fig. 10(b) shows the case with interaction. Note that the task completion time T and the number of robots N have power law relation in this figure:

$$T \sim N^{\beta}.$$

The exponent β depends on the interaction period. The relation between interaction period and exponent β is shown in Fig. 11. $\beta = -1$ (dashed line in this figure) means that the completion time and the number of robots are inversely proportional which is expected if each robot works independently. If the exponent β is less than -1, it implies that the group is more effective for the task.

Here, we chose a specific initial condition of robots. We also simulated the case that the robots were placed randomly in space. Also it was confirmed that the task completion time and the number of robots have power law relation. In this case, the exponent β was almost same but the coefficient was different.

5. Discussion

We showed the relation between the number of robots and the efficiency of group through the task to gather pucks in the field. If there is no interaction between each robot, their working ability is in proportion to a number of robots. But if there are interactions, their efficiency as a group depends on the puck distribution. In case of the field which is extremely localized, robots can improve their working ability due to their interactions.

If we assume the amount of work per unit time, i.e., $1/T$, we obtain the relation shown in Fig. 12. This figure implies that our system emerges the swarm intelligence which is generalized in this study.

Fig. 11 shows the power law exponents change from -1 to -1.8 as a function of the interaction period. We evaluate these results by an analytic approach. The rate equation for the task accomplishment can be written as

$$\frac{\partial P}{\partial t} = \begin{cases} -\{\text{finding rate}\} \times \{\text{transporting rate}\}, & (1) \\ -f(P, N)N, & (2) \end{cases}$$

where P is the total amount of the pucks that remained in the field, and N is the number of robots. The rate of change in P is a multiple of two factors: the rate of finding pucks in the searching mode, $f(P, N)$, and the transporting rate of pucks under the homing mode. $f(P, N)$ is a function of P, N, and the spatial distribution of pucks. The transporting

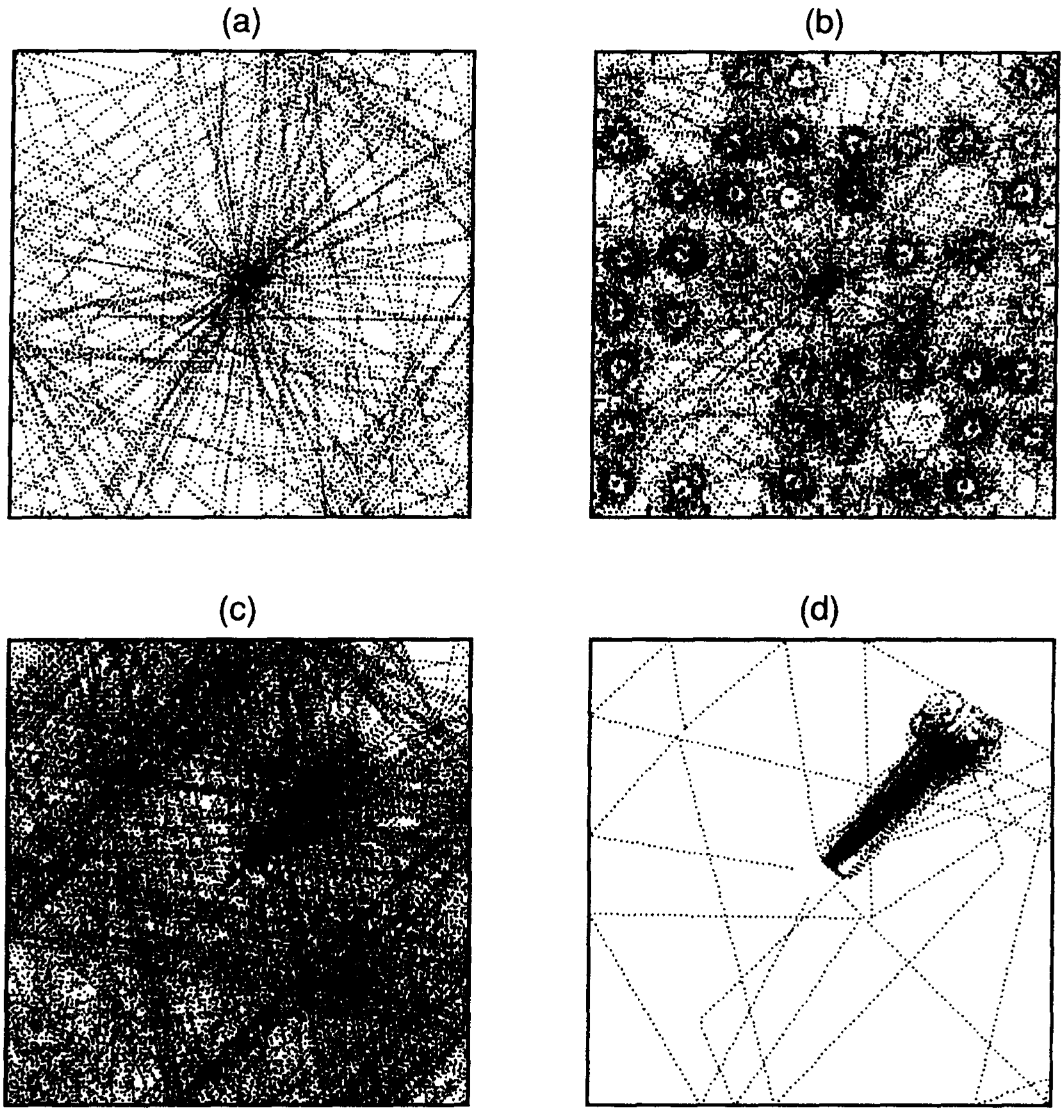


Fig. 8. The trajectories of five robots: (a) the case of no interaction in field 1; (b) the case of 100 s interaction in field 1; (c) the case of no interaction in field 3; (d) the case of 100 s interaction in field 3.

rate is proportional to the number of robots N as a first approximation providing that each robot takes the same time for homing without interfering with others. If the interference between homing robots is not negligible, the transporting rate becomes $N(1-\alpha N)$ where α is a constant describing the interference effect.

We assume that the trajectory of each robot is ergodic in the field in the searching mode. This assumption is approximately satisfied by the chaotic billiard like motion of robots by collision processes.

5.1. In case that there is no interaction between each robot

When the pucks are distributed uniformly in the field, the probability that a robot finds a puck is proportional to the density of pucks, thus $f(P, N) = P/S$,

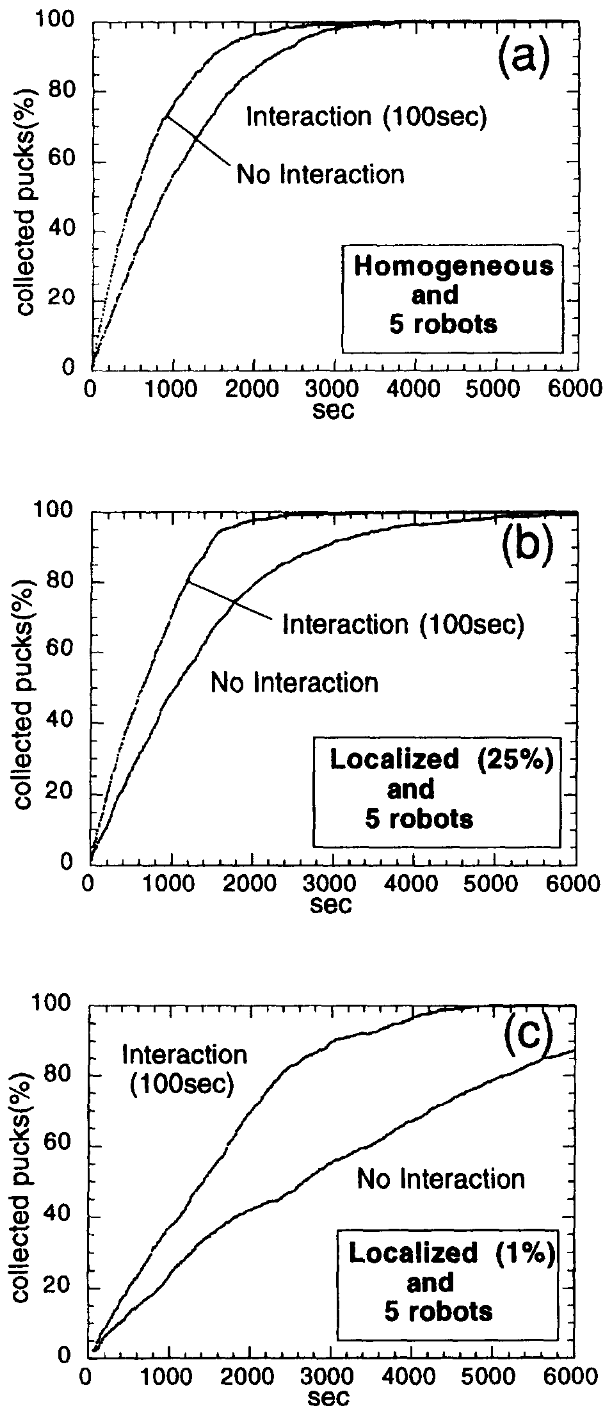


Fig. 9. Temporal evolution of collected pucks for computer simulation. Each plot is the average of 20 trials. The results are same as the experiment essentially.

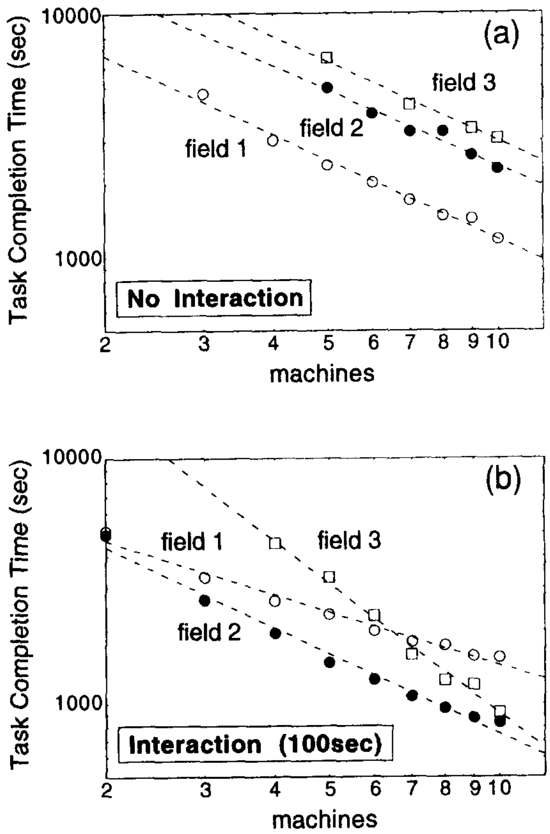


Fig. 10. Relation between the number of robots and the task completion time: (a) the result for robots without interaction; (b) the result for the case with interaction.

where S is the area of the field. The rate equation becomes

$$\frac{\partial P}{\partial t} = -c\frac{NP}{S}, \tag{3}$$

where c is a constant independent of P and N. The solution of Eq. (3) is $P = P_0 \exp(-c(N/S)t)$, where P_0 is the initial amount of pucks. The vertical axis of Figs. 4–7 should be compared with $P_0 - P$.

For the localized distribution, we assume that the field is divided into many small subspaces with area a and all pucks are located in one of the subspaces. The probability that a robot finds a puck is $f(P, N) = a/S$. It reads

$$\frac{\partial P}{\partial t} = -c'\frac{N}{S}, \tag{4}$$

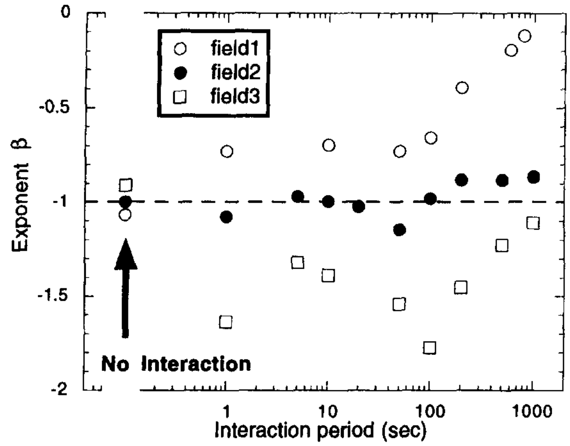


Fig. 11. The relation between interaction period and exponent of the power law. In this figure, exponent -1 means that the completion time and the number of machines are inversely proportional. The case that the exponent is less than -1 implies that the group is more effective for the task.

where c' is a constant determined by a and c. The solution is $P = P_0 - c'(N/S)t$. In this case, the amount of pucks decreases linearly in time. In both cases, the completion time T is inversely proportional to N. These analytical estimates agree well with the experiments and numerical simulations.

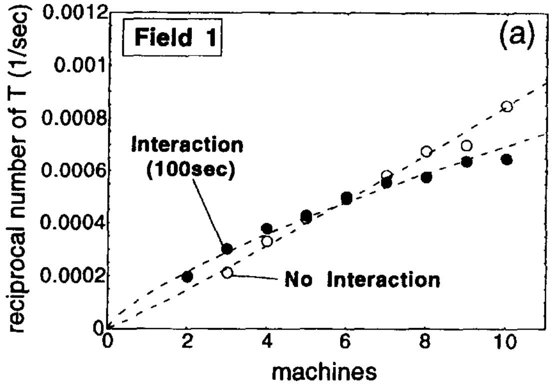
5.2. *In case that there is an interaction between each robot*

For the homogeneous distribution, the efficiency of group is worse because the attraction by the other robot interferes with searching. Therefore the finding rate can be written as $f(P/N) = P/S - \gamma N$ as a first approximation, where γ is a constant. In this case the interaction makes worse the efficiency.

For the localized distribution, once a robot finds a puck all robots find the position of pucks. As a result, N pucks are found at once. Therefore the finding rate is $f(P, N) = a(N/S)$. The rate equation is

$$\frac{\partial P}{\partial t} = -c''\frac{N^2}{S}. \tag{5}$$

The amount of remaining pucks decreases linearly in time as in Eq. (4). However, the completion time T decreases much faster than the independent case as N increases.



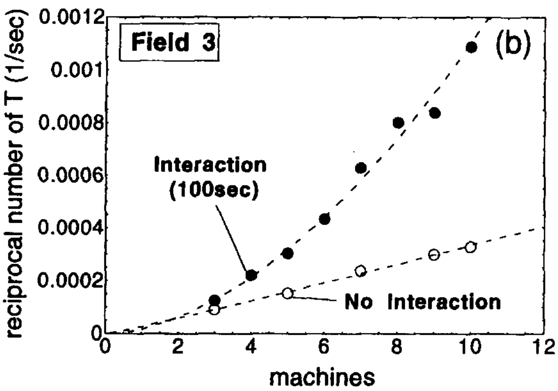


Fig. 12. The relation between the number of robots and the amount of work per unit time: (a) in case of field 1; (b) in case of field 3.

It is shown that the interaction between robots improves the group efficiency if the pucks are localized in the field. From Eq. (4), the exponent β is -1 when the robots are independent, on the other hand from Eq. (5), β is -2 when they interact idealistically. Therefore we expect that the exponent β takes a value between -1 and -2 in the real experiments depending on the detailed interacting process such as the interaction range and period.

5.3. *Phase transition like behavior*

In Sections 3 and 4, we showed the example of swarm intelligence defined generally. This system did not have the critical number which was defined by Beni. Here, we also show an example where this

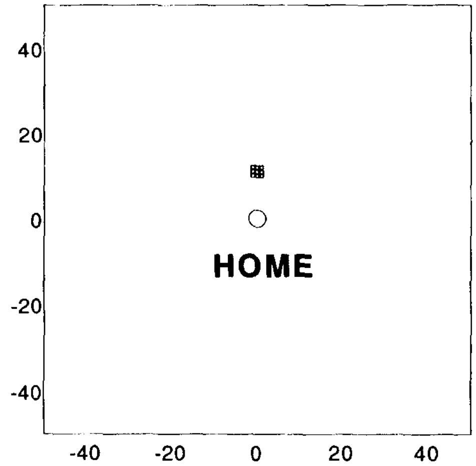
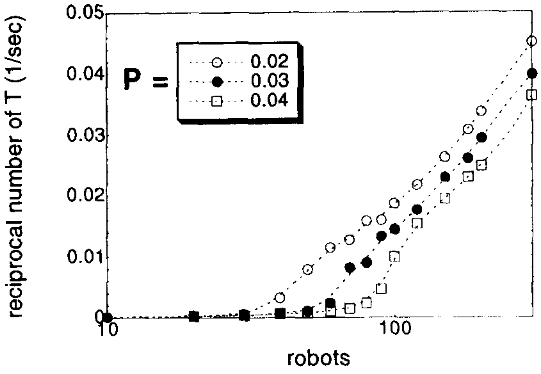
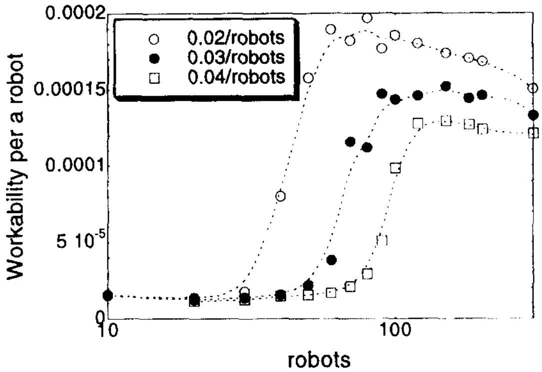


Fig. 13. The field used in Section 5.3. Pucks were placed locally and the number of pucks was infinite.



(a)



(b)

Fig. 14. The result for the case that there was a finite interaction distance between robots. Here T was defined as the time in which 500 pucks were collected to the home. (a) The relation between the number of robots and the amount of work per unit time. (b) The relation between the number of robots and workability per a robot.

system would have a critical number under a simple assumption:

(1) the sensitivity of photo sensors is finite. It means that the distance at which the robots would catch the other robots' signals is finite.

(2) the field is sufficiently large. This assumption implies the collision of robots would be ignored.

The condition of simulation was as follows: The field used in this simulation was 100×100 (Fig. 13). Infinite pucks were placed locally. A completion time T was defined as the time in which 500 pucks were collected to the home. The behavior of each robot was almost the same as described in Section 4, but the velocity of each robot was 10 times faster and their collisions were ignored. The intensity of light on each robot was 1 and it decayed by the inverse power law of the distance. P denoted the sensitivity of each robot. If the intensity of light caught by a robot exceeded P, the robot could recognize and move to the light. Here the interaction distance is finite, instead of infinite as was in Sections 3 and 4.

The result is shown in Fig. 14. Fig. 14(a) shows the relation between the number of robots and the reciprocal number of T. Fig. 14(b) shows the relation between the number of robots and the work load per robot. We notice that there is a critical number of robots. Strictly, the critical value is not the number of robots, but the density of robots. Increasing the density causes a phase transition on the effectiveness of puck collection.

6. Conclusion

We studied the swarm intelligence through the task to gather pucks in the field. In this study, the definition of swarm intelligence was generalized at first and it was confirmed by real robot system and simulation. If there is no interaction between each robot, their working ability is in proportion to a number of robots. In other words (completion time) $\cdot$ (number of robots) $=$ constant. But if there is the interaction, the efficiency of group depends on both the distribution of pucks and interaction time. In case of homogeneous field, the longer the interaction period is, the worse the efficiency of group is. When pucks are localized, there is an optimum interaction duration. Here we can find out the swarm intelligence emerged by their interactions. However, a long interaction period lowers the effectiveness. It is because the interaction period prevents robots to carry pucks.

We evaluated the efficiency of the group quantitatively. The power law exponent for task completion time as a function of number of robots changes from -1 to -1.8 by changing the interaction period. Analytically, we can obtain that it changes from -1 to -2.

We also showed phase transition-like behavior in this system by assuming a finite interaction between robots, where the workability of the group increased drastically when the density of robots exceeded the critical value.

This phenomenon corresponds to swarm intelligence as defined by Beni, showing that generalized swarm intelligence emerges in this collecting system. Simple interaction improves the efficiency of the whole society drastically as the number of elements is increased, and as a result, we can realize a swarm intelligence in such a simple system.

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