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Paper

Local communication of multiple mobile robots: design of group behavior for efficient communication

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Abstract—A novel design method of robot behavior is discussed to realize efficient local communication for cooperation of multiple mobile robots. Local communication is now increasingly utilized in cooperative many-robot systems because of its advantages of load distribution and simple implementation. In its usage, the design of each robot's behavior is a very important issue since it has a significant effect upon the communication efficiency in a collective manner. In this study, we introduce a simple group behavior and analyze how it improves the performance of local communication among many mobile robots. The performance is evaluated using the information transmission time that plays a crucial part in effective cooperation. Next, the optimal group size is analytically derived by minimizing the transmission time. The effectiveness of the analytical design method is verified by computer simulations of many-robot communication.

1. INTRODUCTION

The cooperation of mobile robots is being brought into use to execute sophisticated and complex tasks thanks to recent progress in this field. It is clear that the cooperation requires communication among robots, such as task notification, and information exchange during task execution. Through such communication, information should be transmitted to necessary robots fast enough for efficient cooperation. A great deal of research has been conducted on mobile robot communication, which can be roughly classified into:

(1) Global communication with wide-area media [1–4].

(2) Local communication with limited capacity [5–7].

Global communication (1) works well for a system with about less than 10 robots. It is not, however, directly applicable to much greater numbers of robots because robots might receive too much unnecessary information beyond their information processing capacity.

For these reasons, we adopted local communication (2) to take account of the limit of communication capacity. Local communication has the following advantages in many-robot systems:

- Easy implementation using infrared device [7] or camera image [8].
- Load distribution and concurrency of communication which reduce excessive information processing.
- Robustness of the overall system against addition, removal, or breakdown of robots.

As this is human-like 'from-mouth-to-mouth' communication where robots communicate with others in a limited area, information is gradually diffused among robots.

In most of the cases, task information needs not be transmitted to all robots but to a certain portion of them since in many-robot systems tasks are usually performed locally and concurrently. For instance, we can know how many robots should be involved in such tasks as cooperative transportation or search using the information about the weight of the object to transport or the area to search. It is therefore essential to transmit information efficiently to the number of robots required for task execution.

The performance of local communication is greatly influenced by robots' behavior with respect to the environment and other robots. It is important to know this effect from the viewpoint of efficient information transmission to the desired number of robots. Many studies on robot behavior mentioned the communication among robots [9–14]. Most of them dealt with group behavior and showed by computer simulations that it improves the efficiency of such tasks as sample collecting or foraging. Communication can be regarded as a similar task in the sense that it is collection and transmission of information in place of objects; accordingly, group behavior is possibly effective in improving of the communication performance. Group behavior has also an advantage of a smooth shift from task searching to cooperation. However, few studies made clear the effect of group behavior on the efficiency of communication based on mathematical analysis. Moreover, there has been practically no research that analyzed appropriate group size.

This paper focuses on how group behavior improves the efficiency of local communication. We assume a general environment where events, the sources of information, take place randomly. A simple group behavior is introduced so that the information may be transmitted efficiently to necessary robots that deal with these events cooperatively. We will derive the optimal group size which gives the minimum transmission time through a series of analyses on the information diffusion. The analytical results allow us to design the robot behavior without executing time-consuming simulations of many robots. We also develop a self-organizing group formation algorithm.

2. FUNDAMENTAL ANALYSIS OF LOCAL COMMUNICATION

This section presents the formulation of information diffusion in a simple case where each robot moves randomly. We give a brief overview of the previous research [14]. This methodology of analysis will be extended to communication among robot groups in the next section.

2.1. Communication model

As mentioned previously, we employ a simplified model as briefly described below (Fig. 1):

- **Local Communication**. Information is transmitted among robots within a limited communication area in the form of *packet*. A packet can contain information of multiple events.
- **Events**. *Events* take place randomly in the environment. The events correspond to the sources of information.
- **Motion of Robots**. Each robot moves randomly.

Any communication medium which has a limited communicating range is involved in this model. Besides the examples such as infrared [7, 15] and image [8] media mentioned in Section 1, the analysis can be applied to radio communication for planetary exploring robots [9] or mine-sweeping [12] robots which should cover a very large area.

'Events' represent tasks such as cooperative transportation and search, or faults and emergencies to be detected by surveillance robots which:

- Are given at any point of the environment at any time.
- Should be executed or recovered by cooperation of multiple robots.

The information about an event should be transmitted from the detector robot to necessary numbers of robots so that the event is duly dealt with.

Concerning the robot movement, we adopt random motion as a simple fundamental movement which can cover a relatively wide area.

Time t is counted up from 0 after an event occurs, while the event remains detectable to robots. The information about an event obtained by a robot is spread to other robots by random motion and local communication (we call this *information diffusion*) as shown in Fig. 1.

Robots which have already obtained the information are called *I-Robots* (informed robots), and those without information are referred to as *N-Robots*. The ratio $r(t)$ of

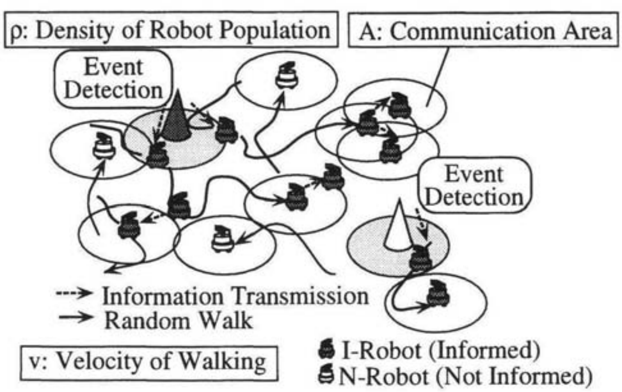


Figure 1. Information transmission by local communication.

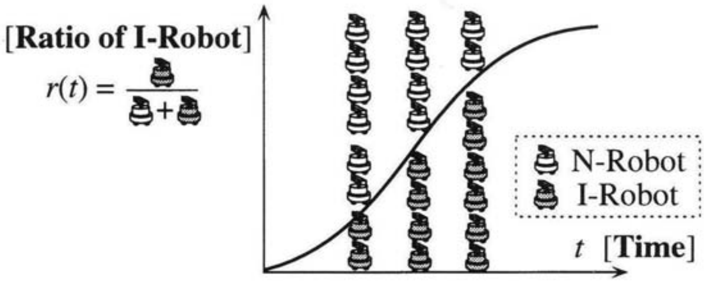


Figure 2. Information diffusion among robots.

I-Robots to all robots increases by information diffusion as Fig. 2 illustrates. Given that a packet can include information of multiple events, information of each different event is diffused independently.

The following are variables of the model (Fig. 1):

$r(t)$ ratio of I-Robots at time t to all robots in the environment;
R, A, ϕ radius, communication area and visual angle;
v velocity of robot motion;
ρ, ρ_{ev} density of robot population and events;
n_{e} number of robots to which the information should be transmitted.

The goal of this section is to represent the ratio of I-Robots $r(t)$ in terms of parameters ρ, v, A and time t. First, a differential equation of $r(t)$ is derived and then we show this differential equation can be approximated by a logistic equation.

2.2. *Formulation of information diffusion*

Robots change their state from N-Robot to I-Robot by obtaining the information of a specific event. The increment of $r(t)$ per time Δt, $\Delta r(t)$, corresponds to the ratio of these newly generated I-Robots at time t. We define the *information acquisition probability* $P(t)$ as the probability that a robot obtains information at time t. Then $\Delta r(t)$ is proportional to the product of $P(t)$ and the percentage of N-Robots $1 - r(t)$.

$P(t)$ is computed as the probability that a robot finds at least one I-Robot or the event in its communication area. We can derive $P(t)$ using Poisson distribution with mean $\rho A r(t)$ and $\rho_{\mathrm{ev}} A$ on the ground that it describes the spatial distribution of randomly moving robots.

$$P(t) = 1 - e^{-\rho A r(t)}\, e^{-\rho_{\mathrm{ev}} A}. \tag{1}$$

The differential equation of $r(t)$, which we call the *equation of information diffusion*, is derived as follows:

$$\frac{\mathrm{d}r(t)}{\mathrm{d}t} = \beta(v)\{1 - r(t)\}\{1 - e^{-\rho A r(t)} e^{-\rho_{\mathrm{ev}} A}\}, \tag{2}$$

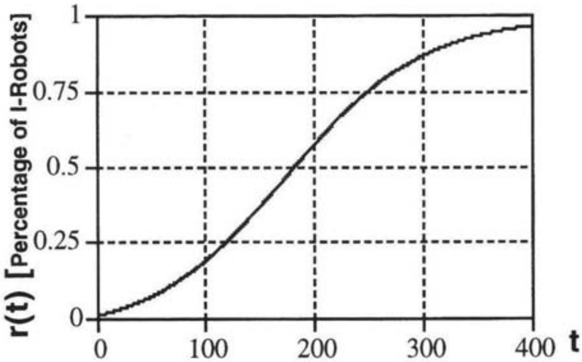


Figure 3. Logistic function [$\beta(v) = 0.01$, $\rho = 0.1$, $\rho_{ev} = 0.005$, $R_c = 1.0$].

where $\beta(v)$ is a coefficient that stands for the effect of robot motion [14, 15].

When ρA, the mean number of robots in communication area, is small enough (say $\rho A < 0.5$), the equation of information diffusion (2) can be rewritten as (3) using linear approximation of the exponential function.

$$\frac{\mathrm{d}r(t)}{\mathrm{d}t} = \{ar(t) + b\}\{1 - r(t)\},$$
$$a = \beta(v)\rho A, \quad b = \beta(v)\rho_{ev} A. \tag{3}$$

Equation (3) is an extended form of *logistic equation*, which is often utilized to model growth curve or diffusion of infection. The solution $r(t)$ of (3) can be analytically obtained as a logistic function like Fig. 3.

This simplified analytical result allows us to calculate easily the diffusion time required so that the information is diffused up to certain percentage [14].

3. FORMULATION OF INFORMATION DIFFUSION BY GROUP BEHAVIOR

We are now ready to analyze the information diffusion among mobile robots behaving as groups. We will first formulate the information diffusion among robot groups and secondly the diffusion within a group in the form of differential equations.

3.1. Model of grouping behavior

We noted earlier that group behavior is expected to improve the communication performance as reported in previous research. We therefore introduce group behavior in local communication so that the information is transmitted more efficiently to the number of robots necessary for event handling.

A line-up motion is chosen among various forms of group behavior since it can be easily implemented using only local communication and has an advantage in sweeping a large area.

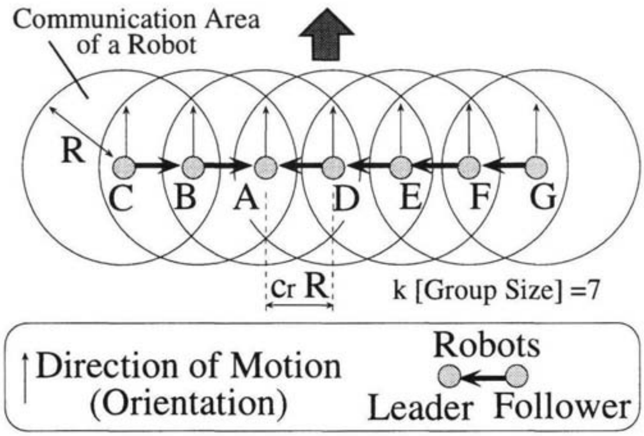


Figure 4. Model of group behavior.

For simplicity, we assume that the visible angle of robots is 360 deg and that robots move straightforward in the environment. The group behavior is illustrated in Fig. 4 and defined as follows:

- Robots move in line formation keeping their orientation vertical to the formation line.
- A robot looks at only one robot on either side to keep the same orientation. We call following and followed robots *followers* and *leaders*, respectively. In Fig. 4, robot B is the follower of A and the leader of C.
- A group is formed by robots connected by the leader–follower relationship. Consequently, there exists only one robot moving independently without a leader (robot A in Fig. 4).
- The *group size* is defined as the number of robots k in the group. The relative distance between two adjacent robots is $c_r R_c$, where c_r ($c_r < 1$) is the ratio of following distance to communication radius R_c.
- The group size k is uniform in the system.
- Groups are supposed to be already formed at the initial state. The group formation behavior will be discussed later in Section 6.

The group behavior above can be realized without any central coordinators. In the following analyses, we consider the environment where events occur randomly.

3.2. Information diffusion among groups

The analytical procedures in Section 2 will be applied to the lined-up robot groups. A robot group can be modeled as one robot with an augmented communication area like a line segment as illustrated in Fig. 5. Communication between two robot groups becomes possible when they overlap.

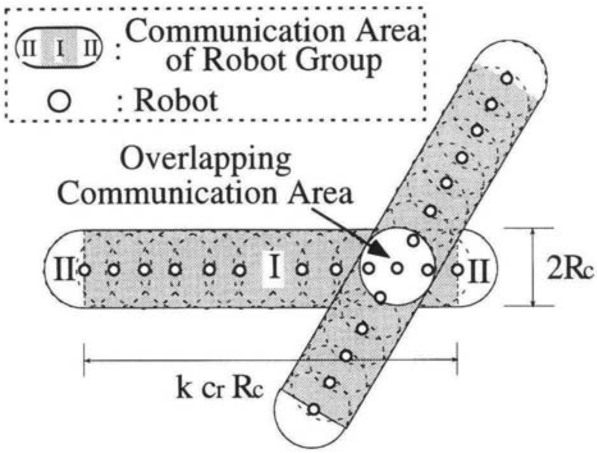


Figure 5. Communication area of robot groups.

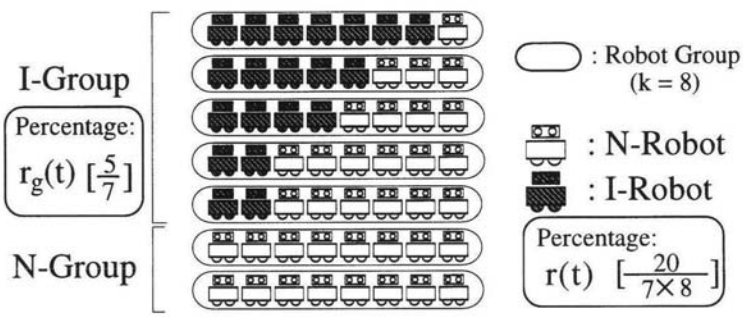


Figure 6. The diffusion process within robot groups.

The communication area A_g of a robot group can be obtained as the sum of areas I and II in Fig. 5. We can roughly estimate A_g as follows:

$$A_g = R_c^2\big(2c_r(k-1)+\pi\big), \qquad \rho_g = \frac{k}{A_g}, \tag{4}$$

where ρ_g denotes the density of robots inside the group.

We refer to groups including at least one I-Robot as *I-Groups*. In contrast, *N-Groups* are groups without any I-Robots. We define $r_g(t)$ as the ratio of I-Groups to all groups in the environment. This $r_g(t)$ describes how information is diffused among robot groups. Recall that $r(t)$ denotes the percentage of I-Robots to all robots.

Figure 6 shows the diffusion process among groups when there are seven groups with size $k = 8$. In this example, $r_g(t) = 5/7$ since five groups out of seven include at least one I-Robot and $r(t) = 20/(7 \times 8)$, from the existence of 20 I-Robots in total.

Using the notations above, we will apply the methodology in Section 2.2 to derive differential equations concerning $r_g(t)$ in the following analysis.

Let us now consider the information acquisition probability $P_{\mathrm{g}}(t)$ for robot groups which denotes the probability that at least one robot in the group can obtain the information from other overlapping groups, if any. We need first to know the mean number of I-Robots in the overlapping area in Fig. 5 in order to calculate $P_{\mathrm{g}}(t)$ based on Poison distribution. Since the area can be approximated by a robot's communication area A as shown in Fig. 5 and the density of groups in the environment is ρ/k, we obtain the average number of I-Robot in the overlapping area as $(\rho/k)A_{\mathrm{g}}\rho_{\mathrm{g}}Ar(t)$.

The equation of information diffusion between robot groups is derived by applying the following substitution to equations (1) and (2).

$\rho Ar(t) \leftarrow \frac{\rho}{k} A_{\mathrm{g}}\rho_{\mathrm{g}}Ar(t)$	Average number of I-Robots in the communication area,
$\rho_{\mathrm{ev}}A \leftarrow \rho_{\mathrm{ev}}A_{\mathrm{g}}$	Average number of events in the communication area.

Consequently, we obtain

$$P_{\mathrm{g}}(t) = 1 - e^{-\frac{\rho}{k}A_{\mathrm{g}}\rho_{\mathrm{g}}Ar(t)}e^{-\rho_{\mathrm{ev}}A_{\mathrm{g}}}, \tag{5}$$

$$\frac{\mathrm{d}r_{\mathrm{g}}(t)}{\mathrm{d}t} = \beta_{\mathrm{g}}(v)\{1 - r_{\mathrm{g}}(t)\}\left\{1 - e^{-\frac{\rho}{k}A_{\mathrm{g}}\rho_{\mathrm{g}}Ar(t)}e^{-\rho_{\mathrm{ev}}A_{\mathrm{g}}}\right\}, \tag{6}$$

where $\beta_{\mathrm{g}}(v)$ is the coefficient equivalent to $\beta(v)$ in (2) which represents the effect of robot motion in the case of group behavior.

Please note that this is an extended form of equation of information diffusion (2). If we set

$$k = 1, \quad \beta_{\mathrm{g}}(v) = \beta(v), \quad r_{\mathrm{g}}(t) = r(t),$$

then (6) is reduced into the same formula as (2).

3.3. Information diffusion within a group

The index of diffusion $r(t)$ should be derived in such a way that the diffusion within a group is taken into account. Figure 6 tells us that $r(t)$ is smaller than $r_{\mathrm{g}}(t)$ and increases to get closer to $r_{\mathrm{g}}(t)$.

The percentage of N-Robots in a group at time t is given by $1 - (r(t)/r_{\mathrm{g}}(t))$. The average number α of robots found in the communication area of each robot is calculated as:

$$\alpha = 1 \cdot \frac{2}{k} + 2 \cdot \frac{k-2}{k} \quad (k \geqslant 2).$$

The proportion α of N-Robots out of $1 - (r(t)/r_{\mathrm{g}}(t))$ in a group get the information at time t, then the differential equation of $r(t)$ is:

$$\frac{\mathrm{d}r(t)}{\mathrm{d}t} = r_{\mathrm{g}}(t)\frac{\alpha}{k}\left\{1 - \frac{r(t)}{r_{\mathrm{g}}(t)}\right\}. \tag{8}$$

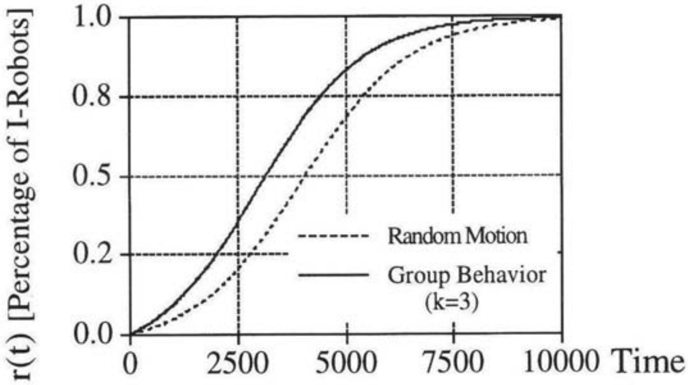


Figure 7. Information diffusion by group behavior.

Table 1.
Parameters of the robot system

ρ	(density of robot population)	0.024
v	(velocity of motion)	0.2
ρ_{ev}	(density of event)	0.001
R_c	(radius of communication area)	1.0
c_r	(ratio of following distance)	0.8

Equations (6) and (8) express the information diffusion among robot groups. Since they are nonlinear simultaneous differential equations, we compute the diffusion process $r(t)$ using such a numerical computation as the Runge–Kutta method. Figure 7 shows the information diffusion process for group size $k = 3$ calculated from (6) and (8) using the parameters in Table 1. For comparison, diffusion by random motion is plotted together. We can see that the group behavior makes the diffusion more rapid than individual random motion, so the transmission time is reduced. This clearly demonstrates the efficiency of communication is improved by the introduced group behavior.

4. DERIVATION OF OPTIMAL GROUP SIZE

Group behavior has such advantages as fast detection of events and smooth shift to cooperation phase from event search. Nevertheless, too large or too small group size may delay the information diffusion and then lower the communication efficiency.

It is hence important to determine the optimal group size in accordance with the given number of robots to transmit the information to.

We refer to the number of robots required for cooperative task execution as n_e. We will first analyze the diffusion time that elapses until general n robots acquire the information and then derive the optimal group size k_{opt} that minimizes the diffusion time to n_e robots.

4.1. Calculation of diffusion time

What we have formulated so far is the diffusion process (graph A in Fig. 8). Let us consider T_a and T_b representing the diffusion time among groups and within a group, respectively. As the graph (B) in Fig. 8 shows, T_a is the time period required for the transmission to the first robot in the $i+1$th group after the diffusion to i groups (which means diffusion up to $r(t) = i \times (k/N)$, where N is the total number of robots). T_b is given as $T_b = k/\alpha$ using α in (7).

Now let $T(n,k)$ denote the diffusion time to n robots with group size k. The graph of $T(n,k)$ looks like the graph (B) in Fig. 8, as T_a is much greater than T_b except for very congested environments.

We can compute numerically the diffusion time as $t = p^{-1}(x)$ from $x = r(t)$ given in (6) and (8). The number of group i of which all the component robots are I-Robots is calculated as $i = [n/k] + 1$. Thus $T(n,k)$ is given as:

$$T(n,k) = \begin{cases} p^{-1}\left(\dfrac{n}{N}\right) & (n \bmod k = 0) \\ p^{-1}\left(\dfrac{ki}{N}\right) - \dfrac{T_b}{k}(ki - n) & (n \bmod k \neq 0), \end{cases} \tag{9}$$

where $[a]$ represents the maximum integer which does not exceed a.

Figure 9 shows calculated diffusion time $T(n,k)$ versus given robot number n for different group size k.

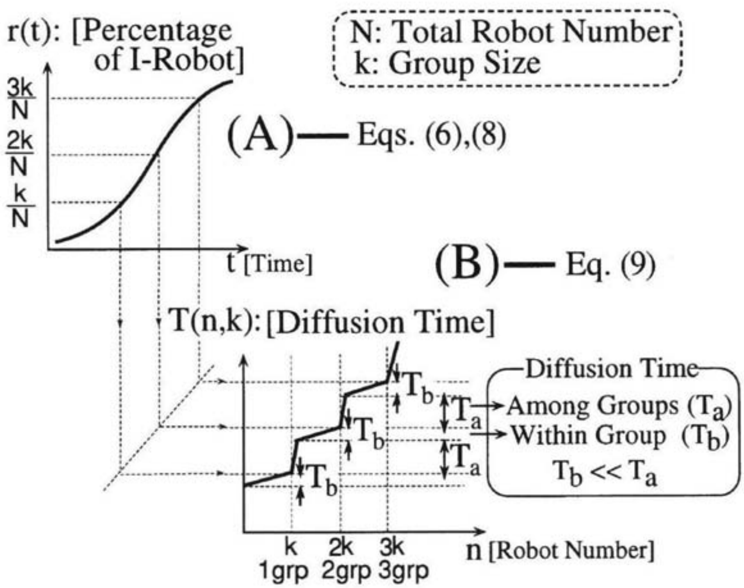


Figure 8. Calculation of diffusion time.

4.2. *Optimal group size for constant n_e*

Figure 10 shows $T(n_e, k)$ with respect to group size k when $n_e = 6$. It is calculated from (9) using the parameters in Table 1. In Fig. 10, $T(n_e, k)$ takes the minimum value at $k = 6$ $(= n_e)$, which is the optimal group size k_{opt}. For other values of n_e as well, the following formula holds true in general:

$$k_{opt} = n_e. \tag{10}$$

For further analysis, see Appendix.

4.3. *Optimal group size for stochastically distributed n_e*

It is possible that the number of robots n_e required for tasks should vary according to the content of each event handling. For instance, the area to sweep or the weight of

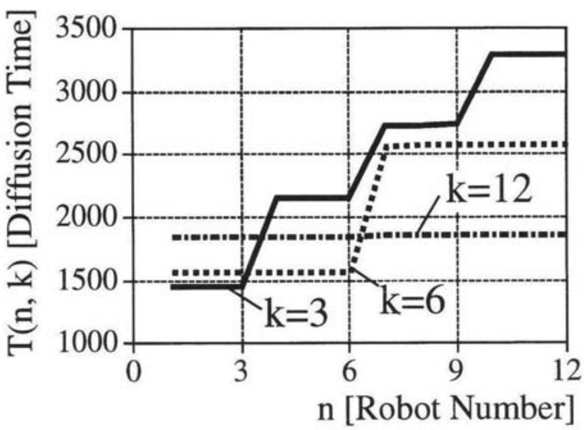


Figure 9. Calculated diffusion time by group behavior.

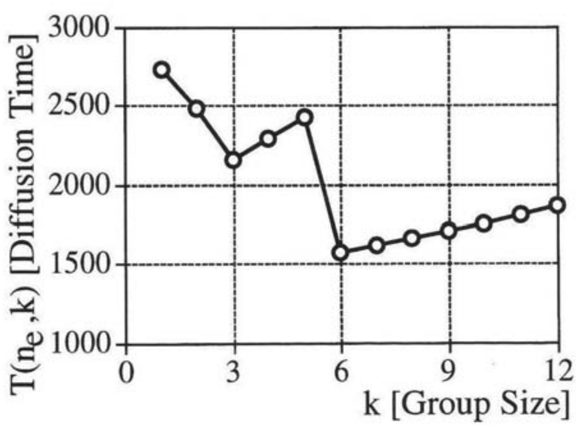


Figure 10. Diffusion time by different group size ($n_e = 6$).

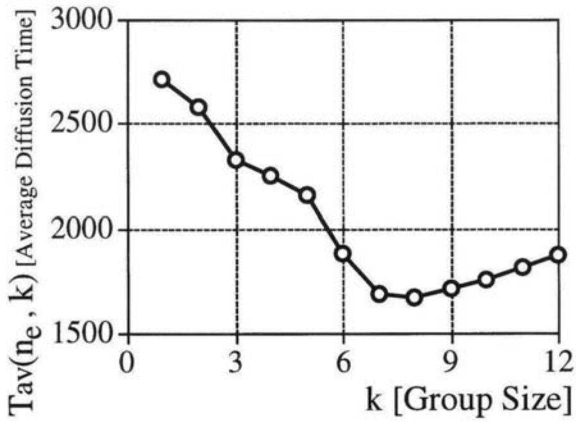


Figure 11. Average diffusion time T_{av} ($n_e = 6.0$, $\sigma = 1.0$).

the object to transport may change from task to task. Let us now turn to the analysis of the optimal group size when the probability $p(n_e, i)$ that the task requires i robots is given by certain stochastic distribution with mean n_e.

The average diffusion time $T_{av}(n_e, k)$ with group size k is computed using (9) as:

$$T_{av}(n_e, k) = \sum_{i=1}^{N} p(n_e, i)T(i, k). \tag{11}$$

Thus the optimal group size k_{opt} is obtained as the value of k minimizing $T_{av}(n_e, k)$.

Suppose a case that the stochastic distribution $p(n_e, i)$ is described by normal distribution $\varphi(n_e, i, \sigma)$ with mean n_e and standard deviation σ. Figure 11 indicates the relationship between $T_{av}(n_e, k)$ and group size k for $n_e = 6.0$, $\sigma = 1.0$ with other parameters the same as those in Fig. 10.

We obtain $k_{opt} = 8$ ($\neq n_e$) unlike the case of constant n_e in Section 4.2. In general, k_{opt} increases as σ becomes large because the gradient of $T(n_e, k)$ with constant n_e is larger for $k < k_{opt}$ than for $k > k_{opt}$ as seen in Fig. 10.

5. SIMULATIONS FOR ANALYSIS VERIFICATION

We implemented robots' group behavior in an environment shown in Fig. 12 and simulated the information diffusion among robots to verify the effectiveness of the analysis.

Groups are supposed to be already formed in the initial state and the simulation starts when events take place at time 0. See Section 6 for the group formation algorithm. The parameters of simulations are the same as those in Table 1. We use a simple collision avoidance method with which robots repulse when they approach in certain proximity, e.g. 10% of communication radius R_c. The modeling with Poisson distribution remains valid even using this avoidance behavior, as it is applied only when robots get very close.

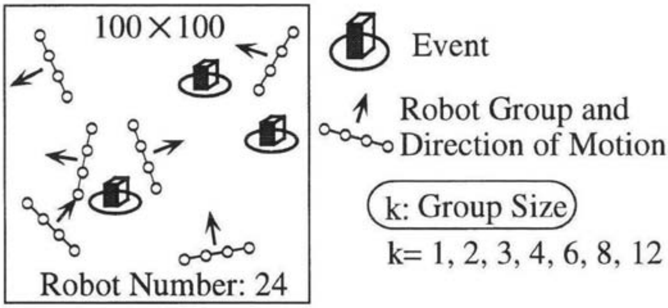


Figure 12. Simulation environment.

Twenty simulations have been undertaken to obtain the average characteristics of information diffusion. Simulation results are compared with theoretical values as to the diffusion process and the optimal group size.

5.1. Equations of information diffusion

Simulation results of diffusion process $r(t)$ are compared with theoretical values obtained using the equations of information diffusion (6) and (8). Figures 13 and 14 show the results for group size $k = 3$ and 6, respectively.

Theoretical values indicate more rapid diffusion than simulations, with maximum 10% of modeling error. It is due to the overestimated communication area of group A_g approximated by a rectangle. In spite of the error, the theoretical values correspond well to the simulation results with different group size k; it follows that the derived differential equations effectively model the information diffusion of robots.

5.2. Diffusion time and optimal group size

Simulation results of diffusion time $T(n, k)$ with different group size k are plotted in Fig. 15 in terms of robot number n. The theoretical values in Fig. 9 are in good agreement with simulation results within the observed modeling error in Section 5.1.

The relationship between $T(n_e, k)$ and group size k for constant desired robot number $n_e = 6$ is shown in Fig. 16. The cases of $k = \{1, 2, 3, 4, 6, 12\}$ are simulated as uniform group sizes over the environment. In Fig. 16, the theoretical values model the simulation results within the modeling error. The optimal group size k_{opt} which minimizes $T(n_e, k)$ equals n_e as we have shown in the analysis. For stochastically distributed n_e also, analytically predicted k_{opt} fits the simulation in Fig. 17.

We have seen so far that the analysis models the actual information diffusion by group behavior with good accuracy. Especially, the analysis of optimal group size provides a meaningful guideline on the design of robot behavior according to the number of robots to transmit the event information. These research results allow us to design the behavior without doing time-consuming simulations of many robots.

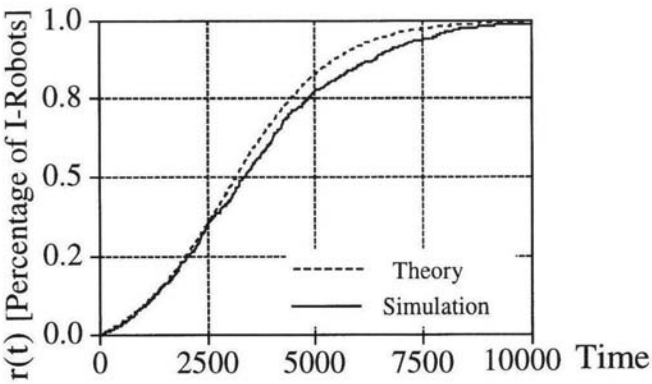


Figure 13. Simulation results of diffusion process ($k = 3$).

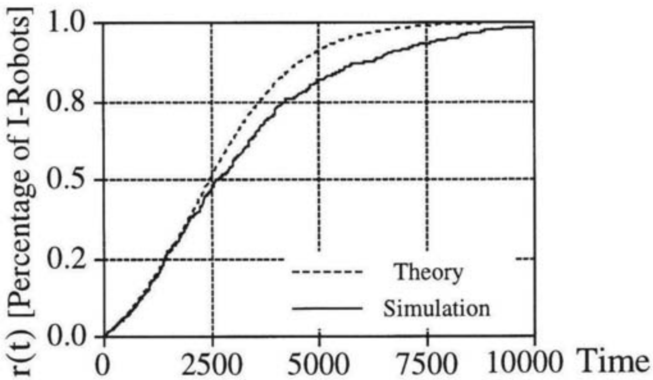


Figure 14. Simulation results of diffusion process ($k = 6$).

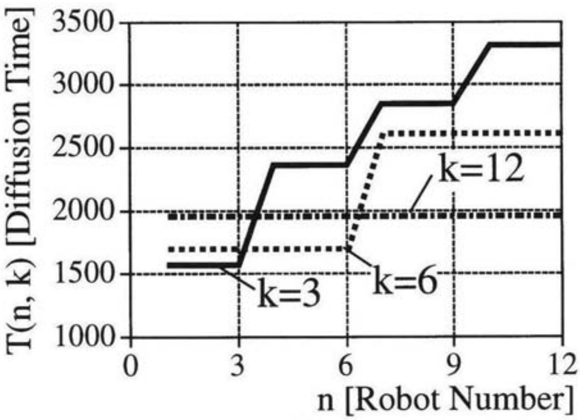


Figure 15. Diffusion time by group behavior.

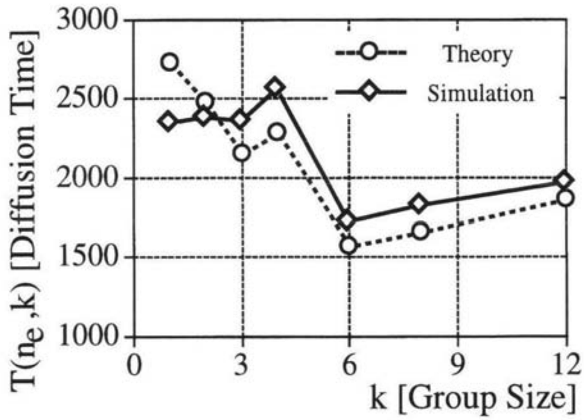


Figure 16. Diffusion time by different group size ($n_e = 6$).

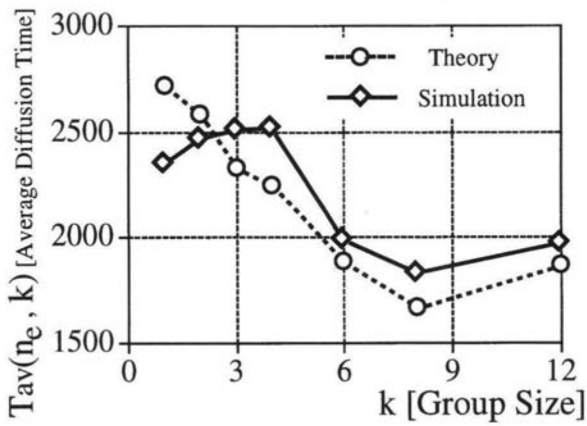


Figure 17. Average diffusion time T_{av} ($n_e = 6.0$, $\sigma = 1.0$).

6. REALIZATION OF GROUP FORMATION

The analyses in Section 3 were made on the assumption that robot groups have been already formed in advance. However, this formation must be done in a decentralized manner in distributed mobile robotic systems. This section presents a formation algorithm that allows robots to form line-up groups using only local communication.

6.1. Algorithm for group formation

We introduce an algorithm for group formation which enables robots to make up groups in a decentralized way using local communication. Before describing the algorithm, the following are given as assumptions.

- Each robot has an identification number *ID*.
- Robots have such internal variables as desired group size k_d, current group size k_c and the identification number of the group ID_g.

- At the initial state:

  k_c and ID_g are set to 1 and its own ID, respectively;

  k_d is given to every robot in advance;

  robot moves randomly without leader.
- Robots can read other robots' internal variables (k_c, ID_g) only from its adjacent robots, i.e. their leader and followers.
- Only robots at the edge of a lined-up group can quit his group. When a robot enters another group, it is disposed between appropriate robots.

A simple algorithm is shown below for self-organization of robot group by local communication. When a robot X quits a group A and enters another group B, the group-formation procedures are as follows. $A \rightarrow ID$ means ID of robot or group A.

```
guit-group (A):
  reset X → k_c to 1;
  reset X → ID_g to X → ID;
  (the former adjacent robots of group A decrements k_c)
enter-group (B):
  read k_c and ID_g from the new adjacent robots;
  set incremented value to X → k_c;
  set X → ID_g to B → ID_g;
  (the new adjacent robots of group A increments k_c)
```

The following algorithm shows how a robot X at the edge of group A behaves when it encounters another robot Y of group B. We should notice that in a group there can be more robots than desired number k_d because of transmission delay within the group.

```
if Y → k_c < Y → k_d [k_d not achieved in group B]
  if X → k_c < X → k_d [k_d not achieved in group A]
    if X → k_c < Y → k_c [group A smaller than B]          Case 1
      X calls quit-group (A) and enter-group (B)
    else if X → k_c == Y → k_c [same group size]           Case 2
      X or Y calls quit-group () by probability 0.5
      enter-group () for the other group
  else if X → k_c > X → k_d [k_d surpassed in group A]     Case 3
    X calls quit-group (A) and enter-group (B)
```

In this algorithm, there are three cases where a robot quits its group as indicated in Fig. 18. There must be only one robot moving without leader in a group. The change of internal states such as ID_g or k_c is propagated inside the group. It is clear that the delay of information propagation becomes more important in a large group.

6.2. *Simulation of group formation*

We will show groups of desired size are formed using the explained algorithm by computer simulations. Simulations start from a initial state where all robots are randomly distributed in the environment. In simulations, $R_c = 1$ and $c_r = 0.8$ as

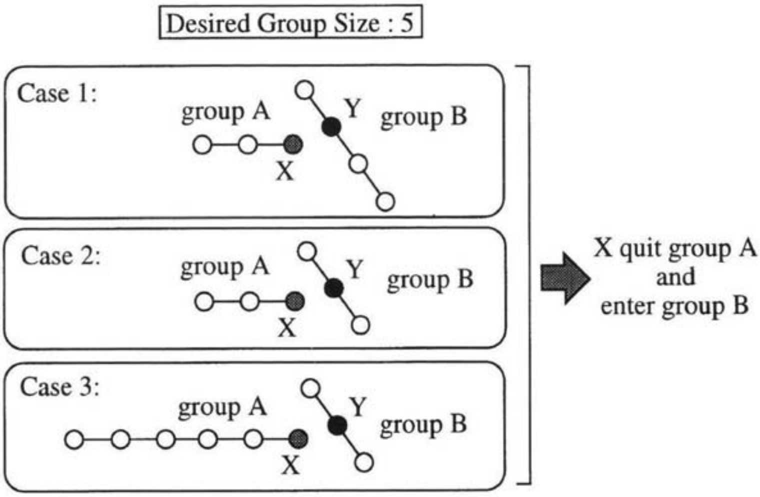
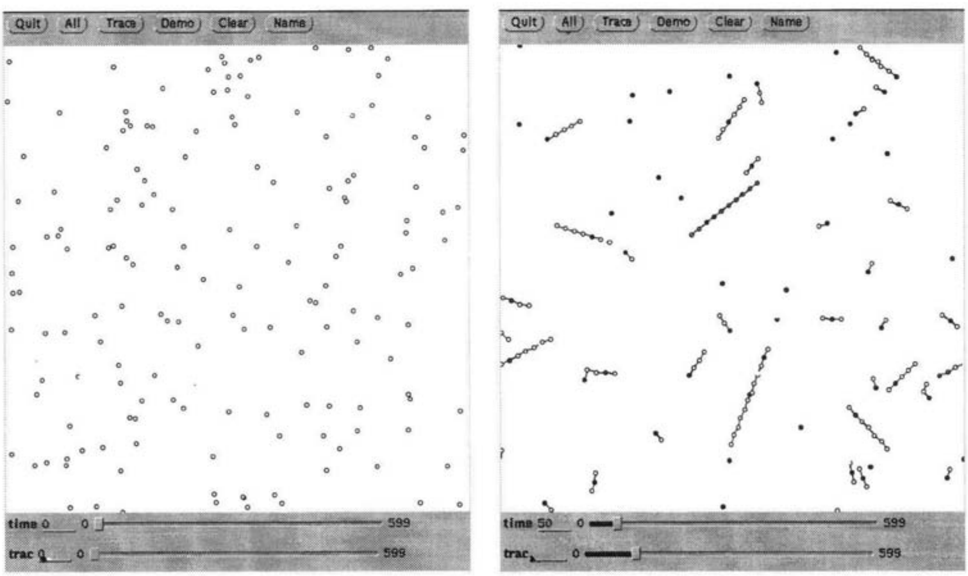


Figure 18. The three cases of changing the group.

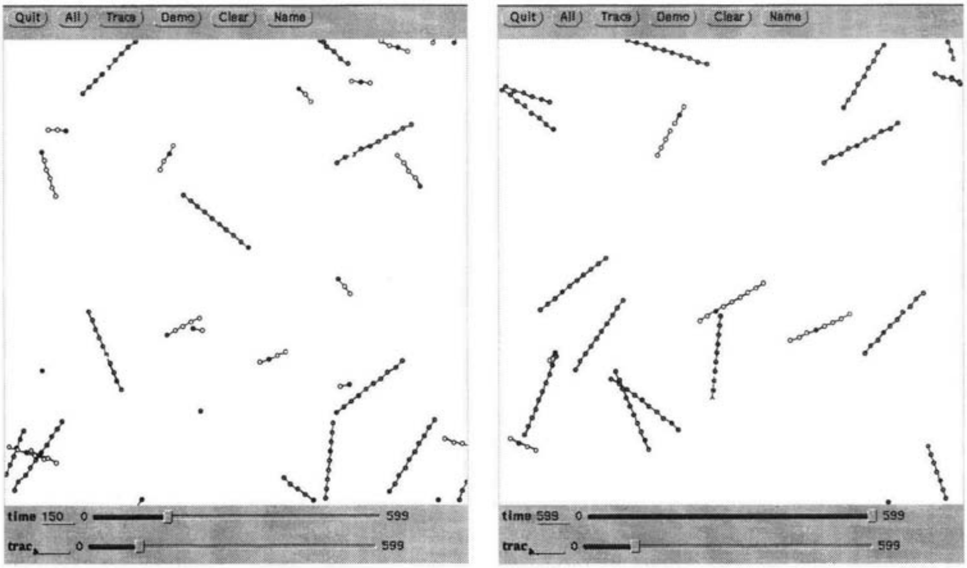


(a) $t = 0$ (b) $t = 50$

Figure 19. Simulation of group formation.

listed in Table 1, and total robot number N is 160 in the environment (40×40) to see the group formation better. When robots reach edges of the environment, they are assumed to appear on the opposite edge for simplicity.

Figure 19a–d shows the group formation process with desired group size $k_d = 10$. These simulation results show that groups of desired size are formed using our algorithm. Starting from initial state at time 0 in Fig. 19a, almost all groups are completed



(c) $t = 150$ (d) $t = 600$

Figure 19. (Continued).

at time 600 in Fig. 19c. These simulation results show that robot groups utilized in previous sections can be organized using only local communication.

7. CONCLUSIONS

We have carried out a series of mathematical analyses to clarify the improvement of the efficiency in local communication of multiple mobile robots. The analytical results have made it clear that:

- Group behavior improves the efficiency of local communication: the information is transmitted to necessary robots in a shorter time than individual random motion.
- There exists an optimal group size with which the information transmission time is minimized: this optimal group size can be derived from the analysis, even if the number of robots to transmit the information is stochastically distributed.

The improving effects of group behavior stated above were verified by computer simulations that were implemented a many-robot environment. The analytical results help the design of robot behavior according to given tasks and save us from time-consuming simulations of many robots. We developed an algorithm for group formation as well and showed its effectiveness by computer simulations.

As future work, we intend to develop a learning scheme of grouping that can adapt to unknown environments where the desired number of robots varies, using dynamic reconfiguration of robot groups.

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APPENDIX: ANALYSIS ON OPTIMALITY OF k_{opt}

As shown in Fig. 7, an increase of group size k moves the graph of $r(t)$ upwards and heightens the diffusion velocity. However, the transmission time $T(n_e, k)$ does not decrease monotonously as k increases, but in fact takes the minimum value at $k = n_e$. This property of optimal group size is explained based on two different analyses for (a) $k < n_e$ and (b) $k > n_e$ as shown in Fig. A1.

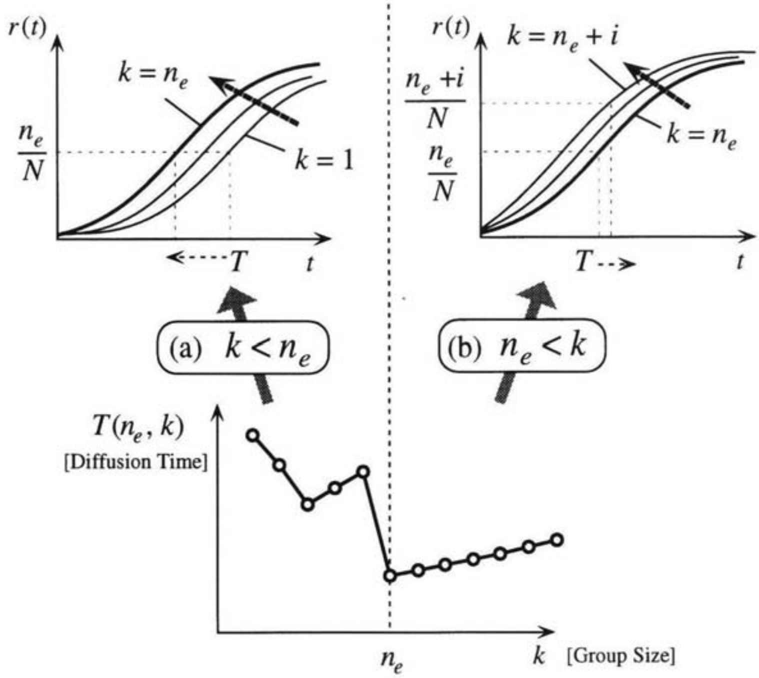

Figure A1. Consideration on the optimal group size k_{opt}.

(a) $k < n_e$

When k is smaller than n_e, the information should be transmitted to the ratio $r(t) = n_e/N$. $T(n_e, k)$ has a general tendency to decrease as k increases as shown in Fig. A1a. However, there is an exception that $T(n_e, k)$ increases during some range of k. This corresponds to the situations that n_e is not divisible by k. For instance, if $n_e = 6$ and $k = 4$, the information is not transmitted to $n_e(= 6)$ robots unless two groups (total eight robots) obtain the information. Then it takes more time than the case where $k = 3$, where the transmission is completed when just six robots (but the same two groups) acquire the information.

(b) $k > n_e$

Let $k(> n_e)$ be $n_e + i$. $T(n_e, k)$ is the time elapsed before the information is transmitted to the ratio $r(t) = (n_e + i)/N$. Although the diffusion velocity becomes higher when k is raised from n_e to $n_e + i$, this is overridden by the effect that it takes a longer time for an increased number of robots to obtain the information as shown in Fig. A1b.

To summerize the analyses for (a) and (b), $T(n_e, k)$ is minimized at $k = n_e$. Thus in general, the optimal group size k_{opt} is equal to n_e as (10).

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