PAPER *IEICE/IEEE Joint Special Issue on Autonomous Decentralized Systems*

Performance Analysis of Local Communication by Cooperating Mobile Robots

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SUMMARY This paper presents a novel technique for analyzing and designing local communication systems for distributed mobile robotic systems (DMRS). Our goal is to provide an analysis-base guideline for designing local communication systems to efficiently transmit task information to the appropriate robots. In this paper, we propose a layered methodology, i.e., design from spatial and temporal aspects based on analysis of information diffusion by local communication between robots. The task environment is classified so that each analysis and design is applied in a systematic way. The spatial design gives the optimal communication area for minimizing transmission time for various cooperative tasks. In the temporal design, we derive the information announcing time to avoid excessive information diffusion. The designed local communication is evaluated in comparison with global communication. Finally, we performed simulations and experiments to demonstrate that the analysis and design technique is effective for constructing an efficient local communication system.
key words: *distributed mobile robotic system, local communication, cooperative task, communication system analysis and design*

1. Introduction

Distributed mobile robotic systems (DMRS) are currently expected to accomplish complicated tasks through intelligent cooperation. A major and essential issue for cooperation in such distributed systems is communication between robots. There are roughly two types of communication as shown in Fig. 1:

(1) Communication announcing a task to the number of robots required for the task.
Information content: Attributes of multiple tasks (e.g., the place and type of task).

(2) Communication for task execution.
Information content: Common data (such as a map being constructed) describing the status of task execution and which is partly updated by robots.

The above procedure can generally be applied to most of many-robot cooperative tasks.

Global communication has been often utilized in previous studies for systems composed of a few (less than ten) robots [1]–[5]. However, many more robots (tens or even hundreds) are required to realize flexible and concurrent cooperative task execution.

Global communication has the following problems when applied to DMRS where tens or even hundreds of robots execute different cooperative tasks in parallel.

- Different tasks performed in parallel generally require only local communication among cooperating robots. If a global communication medium is used, the efficiency of information transmission decreases due to unnecessary information processing.
- If one or a few central station(s) manage(s) the communication, increasing the load causes communication bottlenecks and may necessitate coordination between stations, making the overall system control complicated.

For these reasons, local communication has been frequently applied in recent research [6]–[8]. The authors have been working on the simple local communication model shown in Fig. 2 where a robot sends a packet of information within a limited area. This model has the advantages below.

- The communication can be easily implemented us-

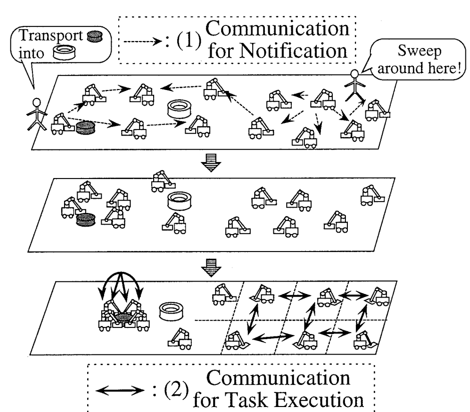

Fig. 1 Two types of communication for cooperation.

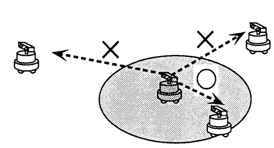

Fig. 2 Local communication between mobile robots.

Manuscript received October 8, 1999.
Manuscript revised January 4, 2000.
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ing infrared devices [9] or camera images [10].

- Information transmission takes place in distributed and concurrent manner, which reduces excessive information processing.
- The overall system becomes robust against addition, removal, or breakdown of robots.

The information contained in a packet is diffused between robots by repeated local transmission along robots' movement. In both communication types (1) and (2) in Fig. 1, the information must be transmitted to the number of robots necessary for *efficient* cooperation, in minimum time without excessive information diffusion. It is therefore important to know how information is diffused to design an efficient local communication system.

Recent studies on applying communication to DMRS [6]–[8] have rarely discussed design on a mathematical basis. Related studies in the field of communication theory [11] do not directly apply as they do not take account of various cooperative tasks or transmission to a limited number of robots.

This paper seeks to provide analytical guidelines for designing local communication in DMRS. The analysis and design will be conducted in two steps:

Spatial analysis and design Maximizing the efficiency of spatial information transmission between robots to minimize transmission time.
Design Parameter: Local communication area

Temporal analysis and design Improving the communication efficiency by transmitting the information to appropriate robots without excessive diffusion.
Design Parameter: Information announcing time

Although the basic framework of the analysis and design has been reported [12], the evaluation of a designed local communication system and its systematic application to a given environment were not addressed. In this paper, the class of task environments covered by these analyses are specified by introducing an environment-dependent parameter in Sect. 2. The spatial and temporal analysis and design are described in Sects. 3 and 4 respectively based on the "equation of information diffusion." The analysis and design can be applied to a large environment including tens or hundreds of robots cooperating in a distributed manner. The designed local communication system is evaluated in comparison with global communication in Sect. 5. We will also show simulations with numerical examples and experiments in Sect. 6 to verify the performance of the local communication system.

2. Formulating Information Diffusion

We will formulate information diffusion by local communication as a fundamental analysis that the following sections will be based on. The "equation of information diffusion" will be derived after we explain our local communication model.

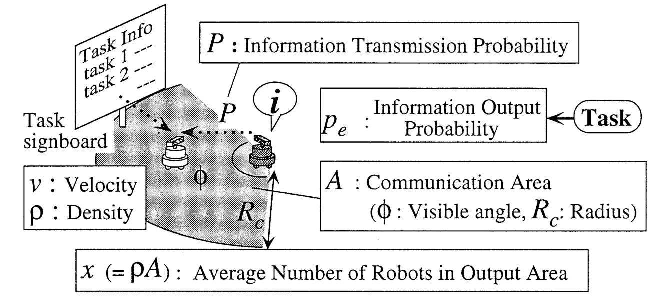

Fig. 3 Local communication model.

2.1 Local Communication Model

We will employ the simplified model of local communication shown in Fig. 3. This model has the advantages of load distribution and easy implementation. Principal parameters of the model are listed below.

ρ:	Density of robot population
R_c, ϕ, A:	Radius, visible angle and area of output range of information ($A = 0.5R_c^2\phi$)
x ($=\rho A$):	Average number of robots in output range
p_e:	Probability of information output from a robot
c:	Information acquisition capacity
$r(t)$:	Ratio of informed robots at time t
m:	Total number of robots in the system
n_e:	Desired number of robots the information is to be transmitted to
$\mathcal{M}$:	Set of parameters that decide movement of robots
T_{ann}	Information announcing time from task signboards

We assume "task signboards" as a means of notification. These signboards show information about tasks during a period T_{ann} within the communication area. The contents depend on the cooperative tasks; e.g. the initial and final positions of the object of the transfer task, or the area to be explored for the map generation task. Generally, all the information is first shown on task signboards. In this model, communication takes place in the following manner:

(i) Each robot sends information in the form of a "packet" within a limited area A, with certain probability p_e usually determined by the task.

(ii) There is an upper limit c in the number of robots from which each robot can obtain information.

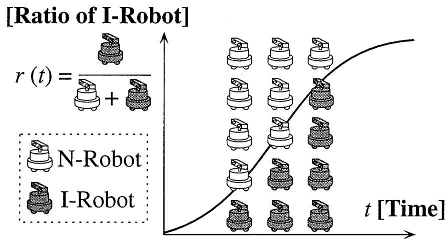

Fig. 4 Information diffusion among robots.

(iii) Each robot executes the information reception process in every time unit that is long enough for acquisition. If any information is available, the robot receives it.

The time and the length are regularized as time unit (tu) and length unit (lu) so that the analysis can be generally applied to various cases. Parameter p_e in (i) represents the frequency of transmission of an information packet (Fig. 3). The interval T_{com} between information transmission can be determined according to the cooperative task. If T_{com} is longer than a time unit, p_e equals the inverse of T_{com}; otherwise, p_e is the same as T_{com}.

We define the upper limit in (ii) as the "information acquisition capacity" c. If a robot finds more than c robots outputting information, two cases are possible.

(a) The robot cannot receive information from any robots. [*interfering communication*]

(b) The robot can receive information from c robots. [*non-interfering communication*]

2.2 Equation of Information Diffusion

Information used in cooperative tasks is diffused among robots by repetition of local communication as shown in Fig. 4. By allowing a packet to include multiple slots for different data, the diffusion of different information can be regarded as independent. We define "I-Robots" as those robots that received the specified content of information $\mathcal{I}$ in a packet, and N-Robots as those not receiving the information. The ratio of I-Robots at time t is represented by $r(t)$.

The transmission time can be defined as the number of time units described in (iii) before the information is received by the required n_e robots.

Let us briefly describe the differential equation of $r(t)$ that describes the diffusion process [13]. The increase of $r(t)$ per time Δt, $\Delta r(t)$, corresponds to the percentage of newly generated I-Robots at time t. We define the "*information transmission probability*" P as the probability that a robot can successfully obtain information from others at time t, which is a function of c, p_e, x and t. The increment $\Delta r(t)$ is proportional to the ratio of N-robots $1 - r(t)$ and $P(c, p_e, x, t)$. The diffusion process is then modeled as the following "*equation of information diffusion*."

$$\frac{dr(t)}{dt} = \beta(\mathcal{M}, x)\ P(c, p_e, x, t)\ \{1 - r(t)\} \qquad (1)$$

where $\beta(\mathcal{M}, x)$ stands for the effect of robot motion.

Table 1 Task environment classified by MTI (N_{max}).

N_{max}		Small ($< N_b(c)$)	Large ($\geq N_b(c)$)
Analysis/ Design	Spatial	× (Not needed)	○ (Needed)
	Temporal	○	○
Evaluation function	Spatial	×	Info. trans. time W
	Temporal	Diffusion rate (Ratio of I-Robots $r(t)$)	
Design parameter	Spatial	×	Commun. area A (R_c)
	Temporal	Task announcement time T_{ann}	
Input parameter	Spatial	×	ρ, A, c
	Temporal	x_{max}	Designed x_{opt}
		n_e, $\mathcal{M}$	

2.3 Classification of Task Environment

The types of local communication in DMRS will be classified by introducing an environment-dependent parameter "maximum transmission index (MTI)." We will then explain the kind of analysis and design required for the given task environment.

Let N be the "average transmission index (ATI)" as:

$$N = p_e \times x = p_e \times \rho A \qquad (2)$$

The "maximum transmission index (MTI)" N_{max} is defined for the maximum communication area A_{max} as

$$N_{max} = p_e \times x_{max} = p_e \times \rho A_{max} \qquad (3)$$

where x_{max} is the average number of robots with output information for A_{max}. The MTI is a combined parameter taking account of the given task (p_e), the environment (ρ) and the robot capacity (A_{max}).

Since interference becomes significant for large N_{max} in a rather dense environment, *spatial* analysis and design of communication area are necessary to maximize the transmission efficiency. By contrast, if p_e or ρ is small, the communication area can be constantly set to A_{max}. However, *temporal* analysis and design are required in both cases so that the information can be transmitted to n_e robots without excessive diffusion.

The environment-dependent parameter MTI, therefore, can be utilized to decide what kind of analysis and design is needed for the given cooperative task (Table 1). Here $N_b(c)$ denotes N where the probability of interference $b\%$ (two or more robots are sending information in the communication area) for the information acquisition capacity c; for instance, $N_{5\%}(1) = 0.35$, $N_{10\%}(1) = 0.5$ for random search task.

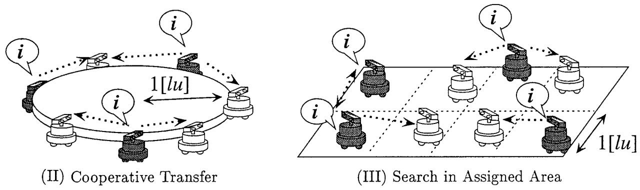

Fig. 5 Model of cooperative tasks.

Table 1 also summarizes evaluation functions and related parameters. The spatial analysis and design of communication area A (R_c) contributes to minimum-time transmission by maximizing P in Eq. (1), which increases the "diffusion velocity" $dr(t)/dt$. In the temporal analysis and design, T_{ann} is derived to transmit information to n_e robots without excessive diffusion.

3. Spatial Analysis and Design

The analysis and design are performed first for transmission to an arbitrary robot, and then to multiple robots. The evaluation function and related parameters in the spatial design are described in Table 1. Here, the design parameter is the communication area A (R_c) since other parameters (ρ, p_e and c) are dependent on the environment, task or robot capacity. The evaluation function, information transmission time W, should be minimized for efficient local communication. We define the *optimal communication area* A_{opt} (R_{copt}) as the value of A (R_c) that gives the minimum value of W.

Before this optimization, some typical cooperative tasks are modeled. The optimal communication area will be derived first for transmission to an arbitrary robot and next to multiple robots. To make the analysis more understandable, we will use the average number x ($=\rho A$) of robots in the communication area as the parameter to be optimized. Once the optimal value x_{opt} is obtained, A_{opt} or R_{copt} can be derived in a straightforward manner.

3.1 Models of the Cooperative Tasks

We will model the following three typical cooperative tasks (Fig. 5):

- **(I) Random search of the area** [14]–[16]: Robots move randomly to search the environment.
- **(II) Cooperative transfer** [17], [18]: Robots transport a circular object by gripping the edge (Fig. 5(II)).
- **(III) Search in assigned area** [19], [20]: Each robot searches an assigned area (Fig. 5 (III)).

The radius of the object in (II) and the length of an edge in (III) are normalized to 1[lu].

3.2 Information Transmission Probability

We will derive the information transmission probability P after modeling the spatial distribution of robots. The spatial distribution of robots for each task in 3.1 is modeled by the following probability:

$$\Pr[i \mid i \subset \mathcal{S}(x)] \equiv \Pr[i \text{ robots exist in area } x] \qquad (4)$$

(I) Random search of the area When robots are situated randomly on a plane, the number of robots in a certain area is Poisson distributed as follows:

$$\Pr[i \mid i \subset \mathcal{S}(x)] \;=\; \frac{\{\rho A\}^i}{i!}e^{-\rho A} \;=\; \frac{x^i}{i!}e^{-x} \qquad (5)$$

(II) Cooperative transfer When the total number of robots is m, the average number of robots x in an area is expressed as the product of the density $(m-1)/(2\pi)$ and the length of an arc of the circular object that is included in the area. Therefore, $\Pr[i|i \subset \mathcal{S}(x)]$ is expressed using a binomial distribution as follows:

$$\Pr[i|i \subset \mathcal{S}(x)] \;=\; {}_{m-1}C_i\left(\frac{x}{m-1}\right)^i\left(1-\frac{x}{m-1}\right)^{m-1-i}$$
$$\text{where} \quad x = \frac{2(m-1)}{\pi}\sin^{-1}\frac{R_c}{2} \qquad (6)$$

(III) Search in assigned area For this task, we approximate the distribution in Eq. (4) using normal distribution $N(\mu, V)$ based on computer simulations since it is difficult to obtain an analytical model. While the average μ is $x-1$ excluding the sending robot for large x, it has different characteristics when x is $0 \cdots 1$. The model $\sqrt[3]{x^3+1}-1$ in Eq. (7) is an example of μ that approaches $x-1$ for large x and also has a good approximation near $x = 0 \cdots 1$. The variance $V = 0.6\,\mu$ is derived as an approximation of simulations as well.

$$\mu \;=\; \sqrt[3]{x^3+1}-1, \quad V \;=\; 0.6\sqrt{\mu} \qquad (7)$$

The information transmission probability P will first be computed in the most basic case of transmission between two arbitrary robots. Next, the technique is extended to transmission between multiple robots. We use P_I and P_N to represent interfering and non-interfering communication respectively.

To an Arbitrary Robot: We define the probability Q_{ij} that j robots out of i robots in a communication area are sending information. The product of $\Pr[i|i \subset \mathcal{S}(x)]$ and binomial distribution Q_{ij} is expressed as follows [21]:

$$Q_{ij}(p_e, x) = \Pr[i|i \subset \mathcal{S}(x)]\ {}_iC_j p_e^j (1-p_e)^{i-j} \qquad (8)$$

Thus P is derived as the probability that a robot successfully receives information sent by another robot:

$$P_I(c, p_e, x) \;=\; \sum_{i=1}^{c}\sum_{j=1}^{i} Q_{ij} + \sum_{i=c+1}^{\infty}\sum_{j=1}^{c} Q_{ij} \qquad (9)$$

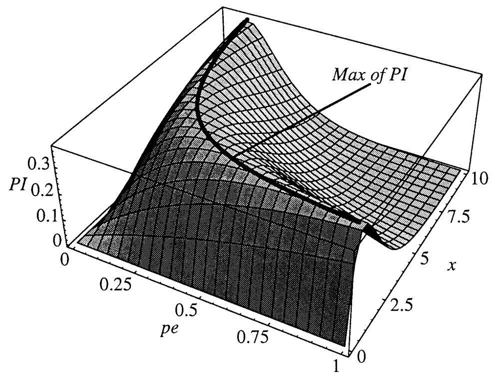

Fig. 6 P plotted versus (p_e, x) (random search, c=1).

$$P_N(c, p_e, x) = P_I(c, p_e, x) + \sum_{i=c+1}^{\infty} \sum_{j=c+1}^{i} \frac{c}{j} Q_{ij} \tag{10}$$

To Multiple Robots: The probability $\bar{r}_j(t)$ that there is at least one I-Robot for information $\mathcal{I}$ among j robots is expressed as $1-(1-r(t))^j$. $P(c, p_e, x, t)$ is derived from Eqs. (9) and (9) as follows:

$$P_I(c, p_e, x, t) = \sum_{i=1}^{c} \sum_{j=1}^{i} Q_{ij} \bar{r}_j(t) + \sum_{i=c+1}^{\infty} \sum_{j=1}^{c} Q_{ij} \bar{r}_j(t) \tag{11}$$

$$P_N(c, p_e, x, t) = P_I(c, p_e, x, t) + \sum_{i=c+1}^{\infty} \sum_{j=c+1}^{i} Q_{ij} \bar{r}_c(t) \tag{12}$$

3.3 Optimal Communication Area

We are now ready to derive the optimal value x_{opt} that will minimize the information transmission time.

3.3.1 To an Arbitrary Robot

The information transmission time W, the average time required for successful transmission, is derived as $1/P$ based on geometric distribution [22]. Therefore, the optimal value x_{opt} maximizing P minimizes W.

In order to derive x_{opt}, we first express P as a function of (p_e, x) when c is given as the three-dimensional graph shown in Fig. 6 (an example of random search in interfering communication, c=1). Next, according to the task-dependent parameter p_e, the optimal value x_{opt} is obtained as indicated by "Max of P_I" in Fig. 6. The graph in Fig. 7 is the projection onto the (p_e, x)-plane of the curve represented by "Max of P_I" in Fig. 6. x_{opt} is obtained for various p_e from this graph.

For a random search with interfering communication, $P_I(c, p_e, x)$ is derived from Eqs. (5) and (9):

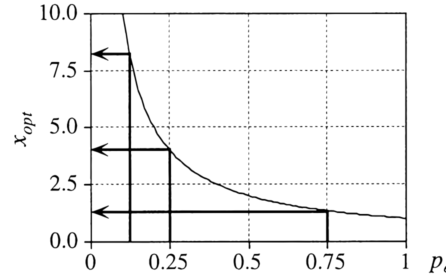

Fig. 7 x_{opt} plotted versus p_e (random search, c=1).

$$P_I(c, p_e, x) = e^{-p_e x} \left(\sum_{k=0}^{c} \frac{(p_e x)^k}{k!} - 1 \right) \tag{13}$$

By solving $\frac{d}{dx} P(c, p_e, x) = 0$, we can derive x_{opt} that maximizes P in a simple formula:

$$x_{opt} = \sqrt[c]{\frac{c!}{p_e^c}} = \frac{\sqrt[c]{c!}}{p_e} \tag{14}$$

In Eq. (14), x_{opt} is inversely proportional to p_e (probability of information output). This means that the communication area should be small (large) when information transmission is frequent (sparse). It can also be observed that x_{opt} becomes larger as c (information acquisition capacity) increases. These characteristics agree with our senses. However, we must note that x_{opt} is not simply proportional to c.

For non-interfering communication or in other tasks, x_{opt} is computed in the same way.

3.3.2 To Multiple Robots

In this case, x_{opt} is the value that minimizes information diffusion time to multiple robots. In the equation of information diffusion, $\beta(\mathcal{M}, x)$ is a coefficient accounting for the effect of robot motion [12]. The value x_{opt} is obtained as x maximizing the term $\beta(\mathcal{M}, x) P(c, p_e, x, t)$ on the right-hand side of Eq. (1). Since this is obtained similarly as for an arbitrary robot, we are not going into details.

The analysis so far clarifies the relationship between the optimal communication area and parameters of DMRS. This is of great help for the spatial design of a local communication system in DMRS.

4. Temporal Analysis and Design

Temporal analysis and design determine how long to let the information diffuse so it can be transmitted to the desired n_e robots. This applies to both cases in Table 1.

4.1 Calculating Diffusion Time

In *temporal* analysis and design for local communica-

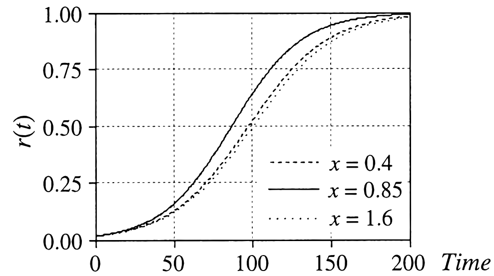

Fig. 8 Information diffusion $r(t)$ (c=1, p_e=1.0).

tion, the information announcing time T_{ann} is determined so that a particular content of information $\mathcal{I}$ is transmitted to n_e robots without excessive diffusion. T_{ann} can be controlled as an expiration time assigned to the information generated. Other input parameters are x_{opt} (x_{max} for small MTI N_{max}) and $\mathcal{M}$ describing robot motion. Robot motion is modeled as a straight movement of velocity v $[lu/tu]$with a random direction change within the range $\theta°$ at every τ $[tu]$. Thus $\mathcal{M}$ is expressed as $\mathcal{M} = \{v, \theta, \tau\}$ [12].

We assume information for each task in communication (1), or its status update made by each robot in communication (2), is diffused independently as stated in 2.2.

To see the fundamental property of the diffusion process $r(t)$ in Eq. (1), let us first analyze the simplest case of information diffusion, namely a random search in interfering communication with information acquisition capacity $c = 1$. Calculating Eq. (11) with $c = 1$, Eq. (1) can be arranged as:

$$\frac{dr(t)}{dt} = ar(t)\ \{1 - r(t)\} \quad \text{where} \quad a = \beta(\mathcal{M}, x)e^{-p_e x}p_e x \tag{15}$$

This is known as a logistic equation, so $r(t)$ is derived as the following logistic function.

$$r(t) = \frac{r(0)e^{at}}{r(0)\{e^{at} - 1\} + 1} \tag{16}$$

Figure 8 shows the calculated $r(t)$ for $x = 0.4$, 0.85, 1.6. Other parameters are $\rho = 0.125$, $\phi = 360°$, and parameter sets of robot motion (v, θ, τ) are (0.2, 60°, 3). The initial value of $r(0)$ is given as $0.02 = 1/50$, assuming that initially one robot of a total of 50 has the information. Here, the optimal value x_{opt} is computed as 0.85 using the optimization methodology in 3.3. As seen in Fig. 8, the information is diffused the most rapidly with derived $x_{opt} = 0.85$.

The diffusion time $T(n_e)$ required for the information to diffuse to n_e out of m robots can be calculated easily from Eq. (16) as:

$$T(n_e) = -\frac{1}{a}\log\left\{\frac{m - n_e}{(m-1)n_e}\right\} \quad \text{where} \quad a = \beta\ e^{-p_e x}p_e x = \beta\ P_I(1, x, p_e) \tag{17}$$

Equation (17) describes the characteristics of diffusion time for given parameters. The diffusion time $T(n_e)$ is inversely proportional to β and P_I (to an arbitrary robot).

Information announcing time T_{ann} can be determined by assigning some margin such as 3σ of diffusion time $T(n_e)$ [13].

4.2 Approximation Using Logistic Equation

Next, a linear approximation will be introduced to clarify the relationship between diffusion time and other parameters. Although $r(t)$ can be obtained by solving Eq. (1) numerically, it is difficult to understand its characteristics since the information transmission probability $P(c, p_e, x, t)$ derived as Eq. (11) or (11) is generally nonlinear.

The analysis of information diffusion has great significance when tasks are announced in an environment where the robot density is low. In this case, there is little possibility that two or more robots are in its possible communication area. P is, therefore, approximated by $\Pr[i \geq 1 | i \subset \mathcal{S}(x)]$, the probability that there is at least one robot in its communication area, regardless of interference and information acquisition capacity. If robots are randomly distributed with low robot density, $\Pr[i \geq 1 | i \subset \mathcal{S}(x)]$ is approximated as:

$$\Pr[i \geq 1 | i \subset \mathcal{S}(x)] \ = \ 1 - e^{-p_e x} \ \simeq \ p_e x \tag{18}$$

The error of the resultant logistic function is about 10% even if $p_e x$ is as much as 0.5. The approximation simplifies Eq. (17) to the following form:

$$T(n_e) = -\frac{1}{\beta(\mathcal{M}, x)p_e x}\log\left\{\frac{m - n_e}{(m-1)n_e}\right\} \tag{19}$$

Equation (19) estimates the diffusion time in a simple manner, and clearly explains the diffusion time $T(n_e)$ and parameters as x and n_e.

The analytical results obtained here are very helpful in the temporal design of local communication.

5. Local versus Global Communication

This section will evaluate the local communication designed on an analytical basis so far in comparison with global communication. The evaluation index here is the time T it takes for n_f robots out of all m robots to transmit information to n_e robots.

5.1 Analysis of Global Communication

As a counterpart, we consider global communication based on time-division multiple access (TDMA) to a single medium like radio, which most of the global-communication based studies utilize [3]–[5]. In this model, time slots for communication are assigned to

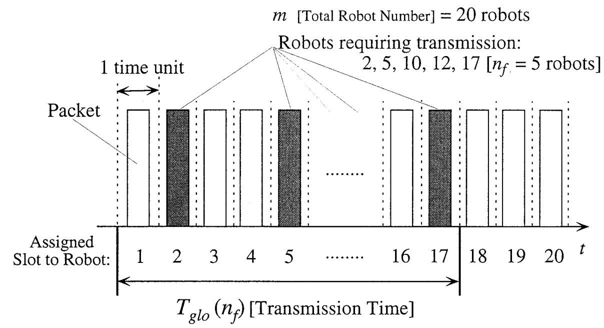

Fig. 9 Model of global communication.

robots in turn by a centralized manager or a token-passing method. The communication terminates when n_f robots send the information since the output information is broadcast globally.

In Fig. 9, $(m,\ n_f) = (20,\ 5)$ and robots #2, #5, #10, #12, #17 have the information to send. If time slots are assigned from robot #1 by turns, the transmission time T_{glo} is 17.

We will calculate the average time $T_{glo}(n_f)$ needed so that n_f out of m robots are assigned time slots. $T_{glo}(n_f)$ is the expectation of the number of time units required until n_f robots finish outputting information when a slot is assigned to an arbitrary robot at time 1,2,. . .,m [tu]. This can be computed using hypergeometric distribution as follows:

$$T_{glo}(n_f) \quad = \quad \sum_{i=n_f}^{m} \frac{{}_{i-1}C_{n_f-1}}{{}_{m}C_{n_f}} \times i \tag{20}$$

$T_{glo}(n_f)$ is an increasing function of n_f and is independent of n_e.

5.2 Evaluation Using Transmission Time

Here, $T_{loc}(n_e)$ denotes the derived $T(n_e)$ in Eq. (19) and will be compared to $T_{glo}(n_f)$. The diffusion time $T_{loc}(n_e)$ is independent of n_f as information from multiple robots can be contained in a packet.

We consider a basic random search task in which a total of $m = 50$ robots search a square environment of size $20\times20[lu]$ ($\rho = 0.125$). The evaluation is performed for n_f = 1, 10, 20 and n_e = 10, 20. We use the derived optimal communication area x_{opt} of the lowest capacity, interfering communication with $c = 1$. Other parameters are p_e=1.0 and robot motion (v, θ, τ) = (0.5, 90°, 3).

As illustrated in Fig. 10, $T_{loc}(n_e)$ for local communication is plotted versus n_e as a dotted line (indicated by "Local"). The transmission time $T_{glo}(n_f)$ for global communication is indicated by the thin solid line ("Global"). $T_{glo}(n_f)$ is plotted parallel to the n_e axis since it is not dependent on n_e, but only on n_f.

Figure 10 indicates that if n_e is smaller than the intersection of $T_{loc}(n_e)$ and $T_{glo}(n_f)$, local communica-

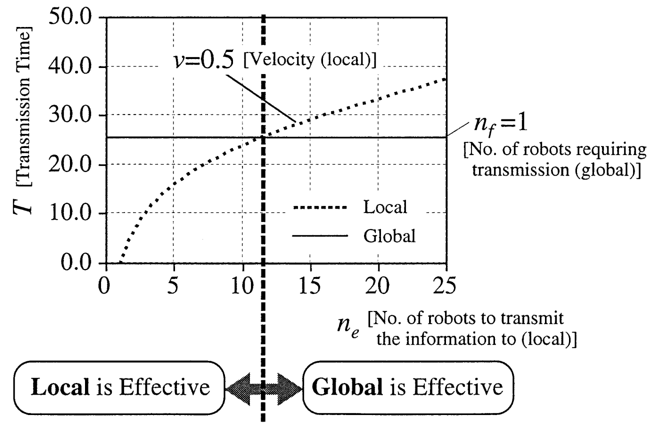

Fig. 10 Evaluation of local and global communication.

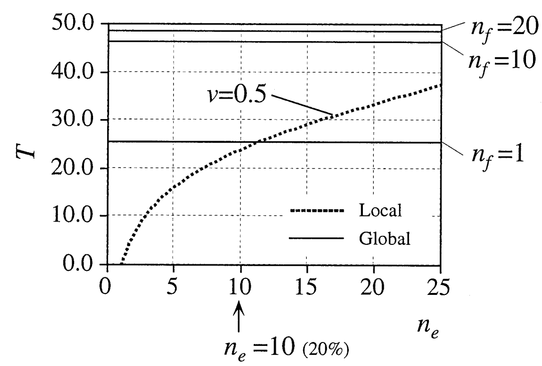

Fig. 11 Comparison of transmission time.

tion is more effective. By contrast, for n_e greater than this intersection, global communication is effective.

Figure 11 shows the result calculated using the above parameters. Even if only one robot requires transmission, namely n_f =1, $T_{glo}(n_f)$ is 25 ($\sim m/2$) [tu] and is nearly equal to m [tu] when n_f = 20%, 40% of m (= 50). $T_{loc}(n_e)$ increases monotonically as n_e increases.

By investigating the result in Fig. 11, we can conclude that:

(1) Local communication is effective when many robots transmit the information to a relatively small number of robots (in the above example, to less than 20% of total m).
(2) Global communication is effective when a few robots transmit to many robots (in the above example, to more than 20% of total m).

Statement (1) means that local communication, of even the lowest capacity, is advantageous in environments where many robots form several groups according to given tasks and execute them cooperatively in a distributed manner. In contrast, from (2) above, global communication is considered to be effective if it is utilized in centralized environments where a few managing robots issue commands to many robots.

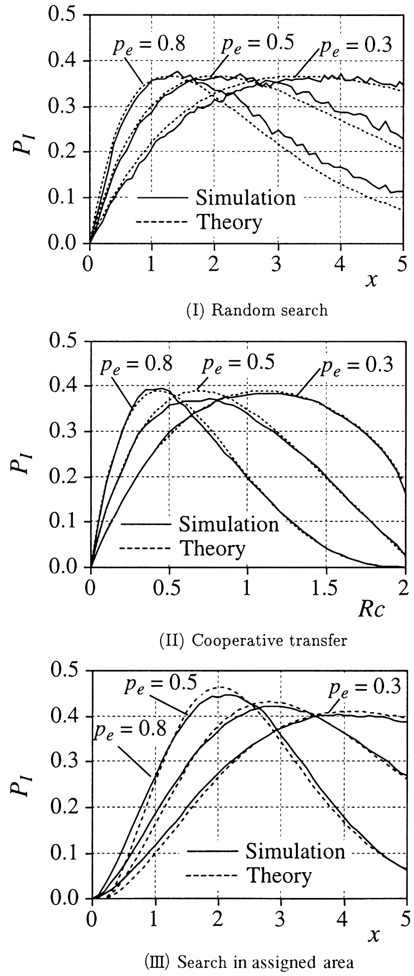

Fig. 12 Information transmission probability P_I versus p_e.

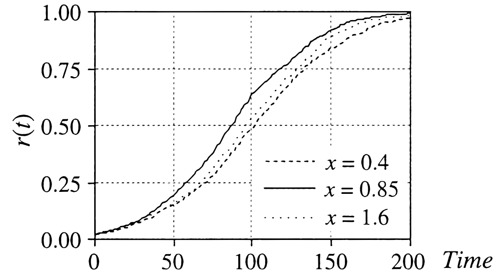

Fig. 13 Simulation of diffusion $r(t)$ (c=1, p_e=1.0).

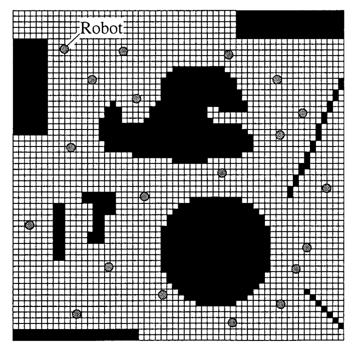

Fig. 14 A task environment for cooperative map generation.

6. Simulations and Experiments

Computer simulations and experiments were performed to demonstrate the validity of the spatial and temporal design of local communication addressed so far.

6.1 Simulated Verification of Analysis and Design

Multiple mobile robots performing the tasks modeled in 3.1 are implemented on a computer to simulate the information transmission to an arbitrary robot and to multiple robots. The simulation results will be compared to analytically predicted values. Although we deal with only interfering communication here, non-interfering cases can also be verified likewise.

6.1.1 Verification of Spatial Design

To an Arbitrary Robot: Figure 12 shows the results of the simulations. Here the information acquisition capacity $c = 1$, probability of information output $p_e = 0.3, 0.5, 0.8$, and simulation time is 500 [tu] for each task. There are 25 robots for (I) and (III), and 10 for (II).

The values of analysis turned out to be a good model of the simulations, and P takes the maximum value at x_{opt} (R_{copt} for cooperative transfer tasks) that gives the maximum of P in the analysis; the accuracy of the analysis is thus confirmed.

To Multiple Robots: We simulated the information diffusion process in an environment where 50 robots search randomly in a 20 × 20 [lu] square workspace. Figure 13 shows the simulation result obtained using the same parameters as in the calculation of Eq. (16) in Fig. 8.

The calculated diffusion process in Fig. 8 models the simulation results well, verifying the effectiveness of the information diffusion model.

Furthermore, as predicted in the analysis in Fig. 8, information diffusion is the most rapid with calculated $x_{opt} = 0.85$ in Fig. 13. This demonstrates the effectiveness of the optimal communication area in transmission to multiple robots.

Simulations demonstrated that the optimal communication area derived by the analysis is valid.

Numerical Example: Let us now show a numerical example of spatial design for a cooperative search and map generation task [15]. An unknown square environment of 60 × 60 grids (denoted by [gr], 1 [gr] = 1 [lu]) in Fig. 14 is searched by 20 robots moving 1[gr] at 1[tu] randomly. Each robot sends out its position and a local map (size 10 × 10 [gr]) of the surrounding square area, representing each grid by one Empty, Filled, or

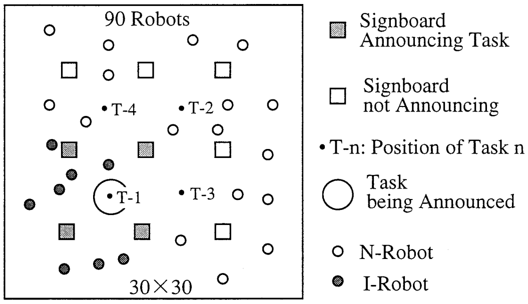

Fig. 15 Environment of cooperative task simulation.

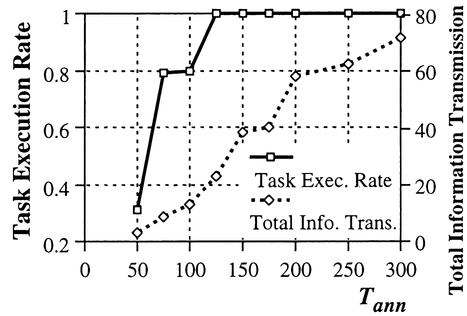

Fig. 16 Evaluation indices of temporal analysis and design.

Unknown. The map generation task terminates if the whole environment is represented by Filled or Empty.

If a packet has a header of 15 [byte], ten slots of information including a 10×10 [*gr*] local map (200 [bit]) and the robot's position 2 [byte], the packet size is 2192 [bit] = 274 [byte]. Since one time unit [*tu*] is a sufficient time for transmitting one packet (see Sect. 2), we define 1 [*tu*] as two one-packet transmissions, so $1t_u = 2 \times 2192/2400 = 1.82$ [sec] for a transmission rate of 2400 [bps]. If the other parameters are c=1 and p_e=0.5, the optimal communication area R_{copt}=7.57[*lu*] using Eq. (14) for random search (interfering) in the given environment of ρ=20/60^2=5.56× 10^{-3}. By using this R_{copt}, the maximum value of P is computed as:

$$\begin{aligned} P_{max} &= e^{p_e x_{opt}}\ p_e x_{opt}\ r(t) \\ &= e^{p_e \rho \pi R_{copt}^2}\ p_e \rho \pi R_{copt}^2\ r(t) \end{aligned} \quad (21)$$

As the minimum value of information transmission time $W_{min} = 1/P_{max}$ as explained in 3.3.1, $W_{min} = 2.71[tu]$ for $r(t) = 1$. This is estimated as 5.05 [sec] at a transmission rate of 2400 [bps].

6.1.2 Verification of Temporal Design

Evaluation of Designed Task Announcing Time: The temporal design of the information announcing time was verified using the cooperative task shown in Fig. 15. There are four tasks to be executed cooperatively at the "task execution positions" (T-1 ··· T-4). The information about the task (the task execution position, remaining announcing time and the ID of task) is announced during T_{ann} simultaneously from the four nearest task signboards out of a total of nine. After diffusing information by random walk until announcing duration expires, robots go straight to the nearest task execution position. Tasks are started as soon as n_e=10 robots out of a total of 90 robots reach the execution position.

In the square environment of size 30×30 [*lu*] in Fig. 15, the density of robots is $\rho = 0.1$, and that of signboards is $\rho_{sign} = 0.044$. To verify the temporal design, we assume a small MTI N_{max} and a constant communication radius $R_{cmax} = 1.0$. The parameters of random motion (v, θ, τ) are (0.1, 60°, 3).

We will investigate two indices, the *task execution rate* and the *total information transmission*, in this simulation to verify the temporal analysis and design. The former is the ratio of executed tasks, and the latter stands for how many times information is passed among robots per task. The relationships between these two indices and T_{ann} are shown in Fig. 16.

Using formula (19), we can derive diffusion time $T(n_e)$ as 74.5. To ensure the information transmission T_{ann} is calculated as 142.6 by adding a margin of three times the standard deviation σ of $T(n_e)$.

Figure 16 shows that all the tasks are executed if T_{ann} exceeds 142.6, which shows the derived T_{ann} is effective for transmitting the information to the appropriate robots. This implies that the task execution is reliable if T_{ann} is long enough. However, this leads to higher communication cost and delay of task execution because of excessive diffusion as total information transmission increases (Fig. 16). In this respect, task announcement time T_{ann} obtained using our temporal design can provide an effective guideline.

Numerical Example: In the above cooperative task example, let an information slot contain the information of the task execution position (8 [byte]), the task ID (1 [byte]) and time before T_{ann} expires (2 [byte]). Assuming that a packet includes five slots and a header 15 [byte], it has 75 [byte] (600 [bit]) of data. One time unit [*tu*] is calculated as $2 \times 600/2400 = 0.5$ [sec] in the same way as the map generation task in 6.1.1. The designed $T_{ann} = 142.6[tu]$ equals 71.3 [sec].

The average time required for $n_e = 10$ robots to gather can be obtained as $56.4[tu] = 28.2$ [sec] by estimating the average distance ($78.3[tu] = 39.2$ [sec] considering 3σ margin) from the task position to 10th nearest robot in a Poisson distribution. As a result, a task will be started within $130.9[tu] = 65.5$ [sec] (at latest $220.9[tu] = 110.5$ [sec] including 3σ margin) after the announcement.

Please note that this is a case where the communication area is limited to a very small value. Without communication, a robot should sweep the area of $100[lu^2]$ to encounter ten other robots ($10/\rho = 100$) on average. Since the sweeping width is $2R_c = 2.0$, a robot

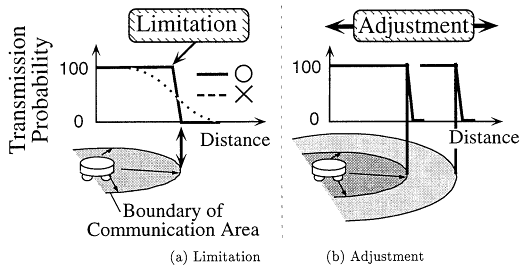

Fig. 17 Control of communication area.

should travel an average distance of $100/2.0 = 50.0[lu]$, which takes $500[tu]$ at a velocity of $v = 0.1[lu/tu]$. This demonstrates that information transmission based on local communication can be a powerful tool for covering a large area by a relatively small number of robots.

6.1.3 Discussion on Robustness

Task execution based on the designed local communication system is sufficiently reliable because the analysis and design allows a 3σ margin. However, in a dynamic environment where many robots are working on different tasks, a task may fail to be executed due to insufficient information diffusion or unexpected breakdown or removal of robots. One solution to these problems is to improve the robustness of the system by adaptive parameter tuning. By enabling robots (and task signboards) to measure such changing parameters as ρ or p_e and to redesign the communication area or announcing time accordingly, the failed tasks can be reported and executed again. Although this extension is beyond the scope of this paper, we believe this robustness improvement can be realized based on the fundamental analysis and design established so far.

6.2 Experiment of Local Communication

We conducted experiments on information transmission to verify the derived principles of spatial design. Local communication is realized using an infrared device so that the communication area can be limited and adjusted to the desired distance as shown in Fig. 17.

The modulation scheme is Frequency Shift Keying (FSK), and the transmission rate is 2400 [bps]. The communication distance can be adjusted by changing the current to LED from 1 to 4 [m]. The limitation is realized by reading the data only if the error rate of the header of the received packet is below a specified threshold. Infrared LEDs are arranged circularly together with four sensors in the center to produce a 360° communication range (Fig. 18).

We have chosen the random search as a basic task. The probability P is measured for transmission to a *receiver* robot from *transmitter* robots randomly distributed within 2.5 [m] as shown in Fig. 19. This is interfering communication, with the density of robots $\rho = 0.092$, the information output probability $p_e = 1.0$.

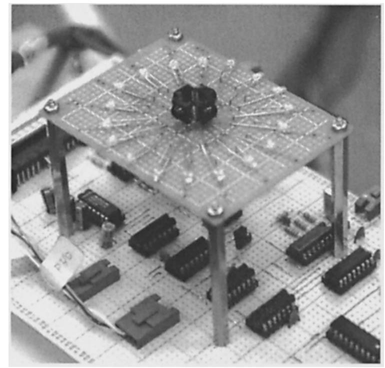

Fig. 18 Photo of infrared communication device.

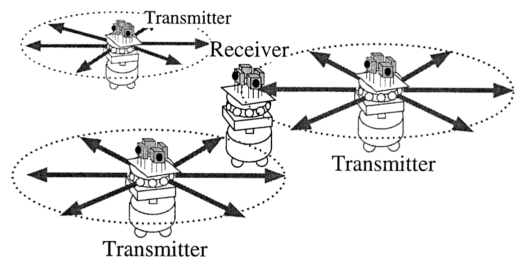

Fig. 19 Verification of optimal communication area.

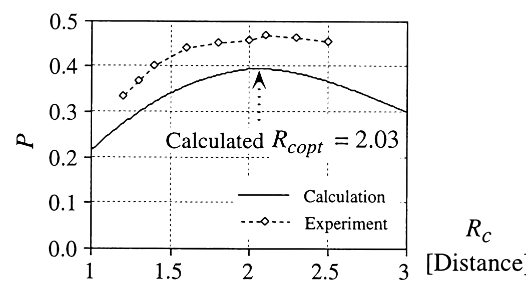

Fig. 20 Experimental results of P.

The transmitter robots transmit 200 [bytes] of data within different communication distances from 1.0 to 2.5 [m]. Figure 20 shows the experimental result of information transmission probability P compared to the theoretical value calculated using the methodology shown in 3.3.1. It is first observed in Fig. 20 that P takes the maximum in the experiment at the analytically derived optimal communication area R_{copt}. This demonstrates the effectiveness of the spatial design for local communication. The offset between experimental and analytical values is considered to be due to occlusion, that is, if a transmitter robot is shaded by another, there may be no interference of transmission to a receiver.

The effectiveness of designs for other tasks can be verified in the same way.

7. Conclusion

This paper presented a technique for analyzing and designing local communication for cooperation in DMRS. Efficient cooperation requires a communication system in which the task information is transmitted to the appropriate robots in minimum time, without excessive diffusion. We proposed dividing the design into two phases, spatial and temporal designs based on the analysis of information diffusion. This technique allows us to construct an efficient local communication system in a plain and systematic fashion as the evaluation function and design parameters were clearly specified.

We examined the properties of the equation of information diffusion and showed how to apply the analysis and design to given task environments using the parameter MTI.

Spatial design optimizes the communication area that leads to minimum transmission time. In temporal design, given the optimal communication area, the information announcing time is derived to transmit the information to the appropriate robots without superfluous diffusion. Through comparison with global communication, we showed that local communication is effective in distributed environments where robots are performing cooperation concurrently.

Simulations and experiments have shown that the proposed design method is helpful for building efficient cooperative systems.

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