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Papers

Dynamically Reconfigurable Robotic Systems
- Optimal Knowledge Allocation for Cellular Robotic System (CEBOT) -

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Cellular robotics (CEBOT) has been previously reported by the authors as one realization of a dynamically reconfigurable robotic system (DRRS). CEBOT is considered a very flexible system and will be applicable to a robotic system which works in various environments. When CEBOT is required to perform tasks, many cells, which can be knowledge sources, communicate with each other and then carry out the tasks automatically. So CEBOT is also a decentralized coordinated reasoning system and a distributed intelligent system. In designing a distributed intelligence system, the distribution of the communication volume among the cells becomes a central issue. For the case of CEBOT, it is best that reasoning can be carried out among each knowledge source with as little communication as possible. Therefore, each cell must have the ability to reallocate their knowledge automatically in order to reduce the amount of communication; this is called intelligent communication in this paper. In this paper, we propose a communication evaluation method based on the amount of communication information, and also describe an optimal knowledge allocation method on CEBOT (as one realization of a distributed coordinated reasoning system) by introducing a sensitivity function for knowledge allocation.

Key-words: Robotics, Communication, Artificial Intelligence, Cellular Robotic System, Distributed Cooperative System

1. Introduction

The authors have worked on the research and development of Cellular Robotics (CEBOT), one of the distributed intelligent systems, and reported the basic concept, automatic approach, docking, separation, and a method for determining the optimal structure.[1,2,3,4] CEBOT is considered to be a dynamically reconfigurable robot in terms of both hardware and software since it consists of cells which have independent functions and intelligence (Please refer to Fig.1). When CEBOT is required to perform tasks, many cells communicate with each other and then carry out the tasks automatically. In this case, decentralized coordinated reasonings are carried out among the cells. The relationship between the communication information among the cells and the knowledge amounts of each cell becomes a central issue.

The difficulty in designing a decentralized coordinated reasoning system as well as advantages such as persistency, flexibility and expansibility are commonly mentioned by some researchers; however, the relationship between the communication information and knowledge amounts have not been adequately studied yet..[5]

As mentioned above, CEBOT is one of the distributed intelligent systems. Main interests in this system are methods of connecting and coordinating cells in addition to the change in the knowledge amounts and communication information. In other words, we need to find what change will happen to the relationship between the knowledge amount and communication information, as well as whether they are carried out optimally and automatically after many tasks were performed.

Each cell must have the ability to reallocate their knowledge automatically in order to reduce the amount of communication. This is called the intelligent communication in this paper. It is important to study the intelligent communication and optimal knowledge allocation because of the difficulty in designing a distributed intelligent system, such as problems concerning size of intelligence sources and coordinating methods, which tends to increase as the entire system becomes more complicated and gigantic.

In this paper, we propose one of the communication evaluation methods based on the amount of communication, and also describe an optimal knowledge allocation method on CEBOT, which is one realization of distributed coordinated reasoning systems, by quantifying the volume of communication information and the knowledge amounts.

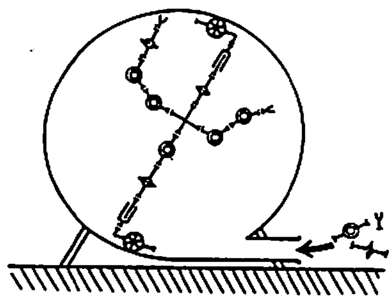

Fig. 1. Conceptual figure of CEBOT (when it works in the tank)

2. Communication Information among Cells

2-1. Definition of the Communication Information

The cells transmit information when they join and separate with each other. It is necessary to quantify the amount of information in order to equalize the transmission load. In general, in information engineering, when we let E be the event which takes place with the probability of P(E), the information volume required to notify that the event E takes place, or I(E), is defined as follows[6]

$$I(E) = \log_2\{1/P(E)\} \text{ [bit]} \quad \ldots\ldots\ldots\ldots (1)$$

We use this definition for the communication information among cells. Based on the definition of the communication information, the amount of information transmitted among the cells, or T(E), is calculated as follows:

$$T(E) = \log_2\{1/P(E)\} \times \Delta t \text{ [s]} \quad \ldots\ldots\ldots\ldots (2)$$

Δt is the time which is required to transmit 1 bit of information by using the communication system of CEBOT.

2-2. Example of Communication Information

CEBOT has the communication protocols which are used when cells join and separate.[4] Those protocols define the kinds of communication language and their meanings. To find out the amount of information which each communication language possesses. We first need to determine the probability with which each event takes place. Shown in Table 1 are communication languages used for sell separation. In the communication for separation, the communication master cells need to recognize the functions and addresses of the communication slave cells, and make the sensors face each other to prepare for the transmission. In this case, whatever communication language from 07 to E(07-E) we try to send, all of languages from 01 to 06(01-06) need to be sent. The probability that each event from 01 to 06 takes place should be same as the sum of the probabilities that the events from 07 to E take place. Therefore, each probability of 01-06 should be one seventh of all the events, and the remaining one seventh has to be divided by the events of 07-E. On the hypothesis mentioned above, we calculated the probabilities and amount of information for each communication language on their separation (Please refer to Table 2). In the same way, based on the communication protocols for separation, we show the probability and amount of information for each language in Tables 3, 4, and 5. In Table 3, the amount of information for transmitting the functions among cells is calculated by using the number of cells. The amount of information for each function language in the joining communication is shown in Table 4, and the amount of information for each control language is shown in Table 5.

Table 1. Protocols of separation communication

H-Digit	M-Digit	L-Digit	Description
0			
1	Sender Cell's Address	Cell-Function	Cells with desired FUNCTION
2		Receiver Cell Address	Desired FUNCTION cell answers
3			Calls cell_address
4			Waiting for end of adjustment
5			Waiting for end of adjustment
6	Data θ_2		Transfers data θ_2
7	Sender Cell Ad.	Receiver Cell Ad.	Auto docking
8			
9			
A	Speed	Distance (6 bit)	Forward(speed,distance)
B			Backward(speed,distance)
C	Radius	Degree (5bit)	Turn right(radius,degree)
D			Turn left(radius,degree)
E	Distance		Keep the distance
F			

Table 2. Amount of information for separation communication

H	P(E)	Bit
01	1/7	2.81
02	1/7	2.81
03	1/7	2.81
04	1/7	2.81
05	1/7	2.81
06	1/7	2.81
07	1/14	3.81
A	1/28	4.81
B	1/112	6.81
C	1/112	6.81
D	1/112	6.81
E	1/112	6.81

Table 3. Amount of information of cell function

Cell Type	P(E)	Bit
Mobile Cell	5/16	1.68
Bending Cell	3/16	2.42
Rotating Cell	3/16	2.42
Sliding Cell	2/16	3.00
End Effector Cell	3/16	2.42

Table 4. Amount of information of function language (joining communication)

Func.	P(E)	Bit
00	4/37	3.21
01	4/37	3.21
02	4/37	3.21
03	4/37	3.21
04	10/37	1.89
05	10/37	1.89
06	0/37	0
07	1/37	5.21

Table 5. Amount of information of control language (joining communication)

Ctrl	P(E)	Bit
0x	2/5	
10	1/5	2.32
11	1/5	2.32
20	1/55	5.78
21	1/55	5.78
22	1/55	5.78
23	1/55	5.78
24	1/55	5.78
25	1/55	5.78
30	1/110	6.78
31	1/110	6.78
32	1/110	6.78
33	1/110	6.78
34	1/110	6.78
40	1/110	6.78
41	1/110	6.78
42	1/110	6.78
43	1/110	6.78
44	1/110	6.78

Ctrl	Bit
00-05 (M. C.)	3.00
06-08 (B. J. C.)	3.74
09-A (R. J. C.)	3.74
B-C (S.J.C.)	4.34
D-F (E. E. C.)	3.74

3. Evaluation of Communication Information

3-1. Evaluation Function of Communication Information

Let us define the communication information by using the following functions. If the communication information which is transmitted from cell a to cell b is ${}^aE_b$,

$$ {}^aE_b = \Delta t_1 \times \sum_i \log_2\{1/P(E_i)\} + \Delta t_2 \times \sum_j \log_2\{1/P(E_j)\} \ [\mathrm{s}] \quad \dots\dots\dots (3) $$

where,

Δt_1: time required to transmit one bit for separation
Δt_2: time required to transmit one bit for joining
$P(E_i)$: probability for the signal for separation being used
$P(E_j)$: probability for the signal for joining being used

We assume that a single cell is able to transmit information with plural cells. When a certain cell x receives the information from n cells (from a_1 $-a_n$) and gives information to the cells from b_1 to b_m, the communication information E(x), if we consider both ways of communication, is calculated as follows (Please refer to Fig.2).

$$ E(x) = \sum_{i=1}^{n} ({}^{a_i}E_x) + \sum_{j=1}^{m} ({}^{x}E_{b_j}) \ [\mathrm{s}] \quad \dots\dots\dots (4) $$

where,

n: total number of cells which send information to cell x
m: total number of cells which receive information from cell x

3-2. Results of Simulation

Using the definitions above, we calculate the communication information in each cell is required when a certain task is carried out. We set a condition in which two movable cells (MC1, MC2) and a bending cell are located between the movable cells shown in **Fig.3**. Communication from the automatic approach to the completion of separation are shown in **Fig.4**. In this figure, a broken line indicates the communication when cells are separated; a solid line designates the communication when cells are joined. The communication information in each stage, which was calculated in section 2-2, is used here. Also, 1/150[s/bit] is used for separation communication in CEBOT and 1/800[s/bit] is used for joining communication for COMBUS, which is communication bus of CEBOT. Thus, we can quantify the transmission load by using equations (3) and (4).

Table 6. Communication information of each cell

E(x)	Communication Amount %
E(user)	1.75
E(mc1)	50.0
E(mc2)	5.15
E(bjc1)	43.1

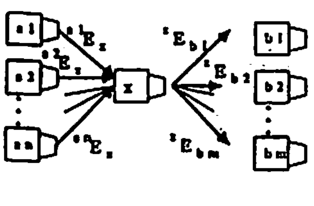

Fig. 2. Evaluation function of the communication information

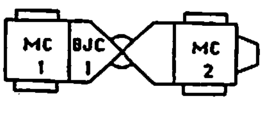

Fig. 3. State of cell's joining

4. Definition of Knowledge Amounts

4-1. Knowledge Amounts

If a cell is seen as a intelligent source, CEBOT is considered to be one of the decentralized coordinated reasoning systems. The knowledge amount is defined as follows. When event E (which has the probability of P(E)) is recognized, we define this situation as the possession of the knowledge amount K(E). K(E) is also defined as follows,[7]

$$ K(E) = \log_2\{1/P(E)\} \ [\mathrm{bit}] \quad \dots\dots\dots\dots (5) $$

When Cell x knows n events (E_1, E_2, ...E_n), the knowledge amount of cell x is defined as K(x),

$$ K(x) = \sum_{i=1}^{n} K(E_i) \ [\mathrm{bit}] \quad \dots\dots\dots\dots\dots (6) $$

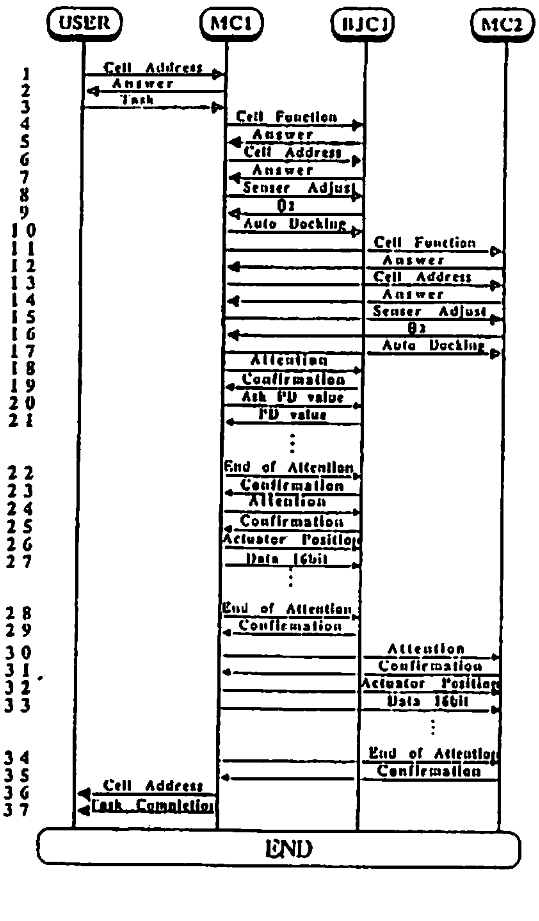

Fig. 4. Process of communication

Next, how to calculate the probability that event E takes place becomes a central issue. To do this calculation, we use a following method (a weighted function).

4-2. Weighted Function

The probabilities of possessing knowledge vary with the area of knowledge we take into consideration. Now, we think of a closed set of elements (knowledge) and the probability that each element takes place in the set. When we give each element in the set of knowledge an original value (a weighted function) and let the weighted function of knowledge K_E be W_E, the probability that the element takes place in the set can be calculated by equation (7).

$$P(E) = W_E / \sum_i W_{Ei} \quad \ldots\ldots\ldots\ldots\ldots (7)$$

$\sum_i W_{Ei}$ is the sum total of weighted functions which the system possesses (Ω).

We can consider a weighted function as a number of stages which are required to transmit the knowledge. In this case, we are able to know the frequency with which the knowledge is utilized. When the knowledge is utilized, the amount of communication that a cell receives while a task is carried out is assumed to be the frequency with which the knowledge is utilized. In this paper, we assume that the frequency with which a cell needs to receive information can be calculated by a weighted function. In addition, we define the cell which requires less communication in carrying out tasks than other cells as more sophisticated knowledge. Accordingly, the more sophisticated the knowledge is, the smaller the value of both W_{Ei} and $P(E_i)$. This will increase the value of $K(E_i)$. It should sound reasonable that the more sophisticated the knowledge, the larger the value for $K(E_i)$ is given.

Using a weighted function, the knowledge amount can be calculated in equation (8).

$$\begin{aligned} K(E) &= \log_2\{1/(W_E/\Omega)\} \\ &= \log_2(\Omega) - \log_2 W_E \ [\text{bit}] \quad \ldots\ldots\ldots (8) \end{aligned}$$

W_E is a weighted function of event E.

The variation of the weighted function due to the composition of the knowledge is as follows. Consider the case in which n pieces of knowledge are compounded into one sophisticated knowledge. Now K_i denotes the knowledge of Event i, and its knowledge amount $K(K_i)$ is abbreviated to K(i). If we suppose that the knowledge amount of K* or [K(*)] is the sum total of a pieces of knowledge,

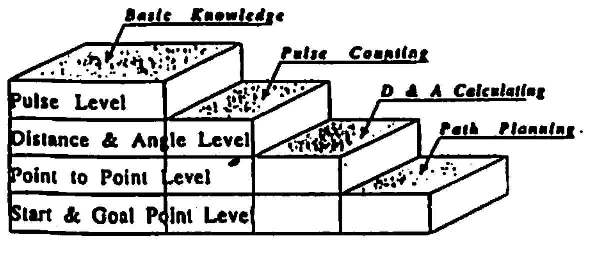

Fig. 5. Kinds of knowledge

$$K(*) = K(1) + K(2) + \cdots + K(n) \ [\text{bit}] \quad \ldots (9)$$

The weighted function of Knowledge K_i is denoted by W_i when Equation (8) and (9) are utilized:

$$\begin{aligned} K(*) &= \log_2(\Omega) - \log_2(W*) \\ &= \log_2\{(\Omega)/(W*)\} \ [\text{bit}] \quad \ldots\ldots\ldots\ldots (10) \end{aligned}$$

$$\begin{aligned} \sum K(i) &= \{\log_2(\Omega) - \log_2(W_1)\} \\ &+ \{\log_2(\Omega) - \log_2(W_2)\} \\ &+ \cdots + \{\log_2(\Omega) - \log_2(W_n)\} \\ &= n\log_2(\Omega) - \log_2(W_1 \cdot W_2 \cdots W_n) \ [\text{bit}]. \ldots (11) \end{aligned}$$

Since the right side of Equation (10) is equal to the right side of Equation (11), the following conclusion is drawn.

$$\begin{aligned} \Omega/W* &= \Omega^n/(W_1 \cdots W_n) \\ &= \Omega/\{(W_1 \ldots W_n)/\Omega^{n-1}\} \\ W* &= (W_1 \cdots W_n)/\Omega^{n-1} \quad \ldots\ldots\ldots\ldots (12) \end{aligned}$$

As shown above, the weighted function in compounding knowledge can be calculated.

4-3. Example of Knowledge Amounts

We consider the control of a pulse motor of the movable cells in CEBOT. There are four kinds of knowledge shown in Fig.5.

(1) Basic Knowledge(K1): The most basic knowledge for the communication and address of cells. When only this knowledge is possessed, the cells are required to have the motor controlled by other cells through communication for every pulse when it moves.

(2) Pulse Counting Knowledge (K2): Since this knowledge can transform the target value into a number of pulses, it only has to be given the target value.

(3) Distance & Angle Calculating Knowledge (K3): the knowledge by which the distance and angle between two points can be calculated if the coordinates of the starting point, target point and passing points are given.

(4) Path Planning Knowledge (K4): The knowledge by which the cell can reach the target if the coordinates of the starting point and target point are given.

In order to calculate the knowledge amount, we need to find out the frequency and volume of communication. There are two stages for the communication. First, the following actions have to be made: functioning of cells, addressing, attaching faces of censers, and sending the command to measure the relative positions (STEP 1). Next, communication need to be transmitted depending on the purpose.

We focus on the frequency and volume of communication when the movable cell moves from point P_1, through $P_2, \ldots, P_{n-1}$, to P_n.

(1) In case of possessing K1 (Pulse Level) The communication frequency in parallel forward movement (N_s) is calculated by using {distance/amount of parallel forward movement} as shown in Equation (13).

$$N_s = \sum_{i=1}^{n-1} [\sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2} / \delta] \quad \ldots (13)$$

δ is the amount of parallel forward movement by one pulse.
[ ] is the Gause sign (and so forth).
The communication frequency in revolution (N_r) is calculated by using {revolution angle/amount of rotation by one pulse} as shown in Equation (14).

$$N_r = \sum_{i=1}^{n-2}\left[\cos^{-1}\{A/B\}/\theta\right] \quad \ldots\ldots\ldots\ldots (14)$$

θ is a revolution amount by one pulse.

$$A = (x_{i+1} - x_i)(x_{i+2} - x_{i+1}) + (y_{i+1} - y_i)(y_{i+2} - y_{i+1})$$

$$B = \sqrt{(x_{i+1} - x_i)^2(y_{i+1} - y_i)^2} + \sqrt{(x_{i+2} - x_{i+1})^2 + (y_{i+2} - y_{i+1})^2}$$

When we denote the communication amount required to transmit one pulse as E_{u1} (for separation) and E_{d1} (for joining), the communication amount E_{s1} is calculated by Equation (15):

$$E_{s1} = (N_s + N_r)\times E_{u1}\ (\mathrm{or} E_{d1}) \quad \ldots\ldots\ldots (15)$$

(2) In cases of possessing K1 and K2 (Distance & Angle Level)

The value of Pulse Level at which the cell can move varies with each communication. Let Δ and Θ be a possible amount of parallel forward movement for each communication and a possible amount for revolution, respectively. In addition, we designate the communication amount required to send a target value as E_{u2} (separation) and E_{d2} (joining). In the same manner as Pulse Level, the communication amount E_{s2} can be calculated in Equation (16).

$$E_{s2} = (N_s + N_r)\times E_{u2}\ (\mathrm{or} E_{d2}) \quad \ldots\ldots\ldots (16)$$

However,

$$N_s = \sum\{[\sqrt{(x_{i+1} - x_i)^2(y_{i+1} - y_i)^2}/\Delta] + 1\}$$

$$N_r = \sum\{\left[\cos^{-1}\{A/B\}/\Theta\right] + 1\}$$

A and B are defined as above.

(3) In the case of possessing K1, K2 and K3 (Point to Point Level)

The communication frequency N is designated as n, the number of points from which information is sent. One point is transmitted in the form of a coordinate (x_i, y_i). Since both x_i and y_i are transformed into the bit unit, they become the amounts of information, $\log_2 x_i$ and $\log_2 y_i$. When the information amount required to notify the coordinates in one transmission is denoted as E_{u3} (for separation) and E_{d3} (for joining), the communication information E_{s3} can be calculated by equation (17).

$$E_{s3} = \sum_{i=1}^{n}(\log_2 x_i + \log_2 y_i) + n\times E_{u3}\ (\mathrm{or} E_{d3}) \quad \ldots\ldots\ldots\ldots (17)$$

(4) In case of possessing K1 ...K4 (Start & Goal Point Level)

When n=2 in equation (17), the communication amount E is applicable. One of the examples is the case in which the movable cell in the CEBOT designed by the authors moves along the route shown in Fig.6. In the existing system, given δ=7.9cm, θ=4.4°, Δ=63cm, Θ=31°, the communication frequency (weight W_i), while the cell moves from points a to c, is calculated by the above equation. The results are shown in **Table 7**. If we think of this communication frequency as the weighted function in Section 4-2, the knowledge amount for each frequency is also shown in Table 7. The amount of information, when the required knowledge is possessed, is shown in **Table 8**. In Table 8, a, b, c, and d denote Start & Goal Point Level, Point to Point Level, Distance & Angle Level, and Pulse Level, respectively. In step 2, we calculated, by figuring out the entropy {p(x)log[1/p(x)]} by Table 2, that E would be 3.1 bits when E_u is considered to be the average communication information for separation of cells. On the other hand, the number of bits for a communication comes to 63 bits after the communication languages 01-06 and the addresses (8 bits per communication) were sent.

One example of quantifying the knowledge amount is described above. In this case, the knowledge amount in the fixed conditions to a certain hardware is calculated; however, it is possible in any cases to quantify the knowledge amount by suitably determining the weighted function.

5. Optimal Knowledge Allocation

5-1. An Optimal Knowledge Allocation Method

Each cell possesses its E(x), which denotes the amount of communication transmitted among cells. We consider the situation in which n units of cells (x_1, x_2,....,x_n) and the communication information ($E(x_1)$, $E(x_2)$,....$E(x_n)$) exist. In this case, from the general theory of distributed coordinated reasoning systems, we can define the optimal knowledge allocation as a situation in which the communication was

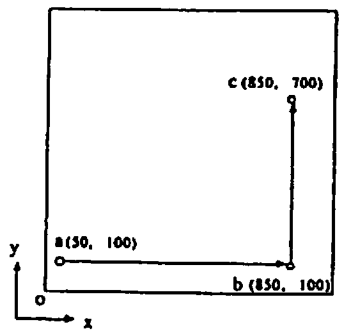

Fig. 6. Route of cell's movement

Table 7. Communication frequency and knowledge amount when cells possess each knowledge

Communication times		Knowledge(bit)	
w1	200	K1	0.08
w2	6	K2	5.14
w3	3	K3	6.14
w4	2	K4	6.72

Table 8. Amount of information required when cell possess each knowledge

Amount of information(bit)	
a	87
b	100
c	146
d	683

transmitted with the equal value of $E(x_1)$, $E(x_2)$,...,$E(x_n)$. In other words, the optimal knowledge allocation means carrying out the tasks with the most evenly distributed amount of information among cells.

In addition, we define the allocation by which the value of σ^2 is minimized as the optimal knowledge allocation of cells to a certain task. The arithmetic mean E of transmission load of x_1, x_2,...,x_n can be calculated in equation (18), and the value of allocation (σ^2 can be calculated in equation (19).

$$E = (1/n) \times \sum_{i=1}^{n} E(x_i) \ [\mathrm{s}] \quad \cdots\cdots\cdots\cdots (18)$$

$$\sigma^2 = (1/n) \times \sum_{i}^{n} \{E(x_i) - E\}^2 \quad \cdots\cdots\cdots\cdots (19)$$

The communication amount which single cell is able to possess has a upper limit because of other restrictions such as the capacity of memories. Thus, each cell has the following limitation:

$$K(x) \leq \alpha \ [\mathrm{bit}] \quad \cdots\cdots\cdots\cdots\cdots\cdots (20)$$

α is a upper limit of a cell.
The total sum of the knowledge amounts has also the following limitation:

$$\sum K(x) \leq \beta \ [\mathrm{bit}] \quad \cdots\cdots\cdots\cdots\cdots\cdots (21)$$

β is a upper limit of the system.
By taking this condition into consideration, this problem becomes one of the problems of optimizing. This allows us to solve the various problems.

5-2. Result of Simulation

We will the examples of the optimal knowledge allocation by using the definition above. To do so, we assume the following hypotheses:

(1) The moves mentioned in Section 4-3 have already been made, in which the three cells are supposed to move from a to b to c in Fig.6.

(2) Cells are able to possess only the four kinds of knowledge mentioned in Section 4-3.

(3) Cells are not able to possess all kinds of knowledge because memory capacity is limited.

(4) The system in which a user and three cells communicate is stratified as shown in Fig.7.

(5) The cell, which is located in the upper part of the system, or the user can supply the highest level of information. We limit the amount of information each cell can possess, but we assume that the system can compensate for this as the four kinds of knowledge which the cell can possess are regarded as follows. When the information (the coordinates of start and goal points in this case) is externally supplied to the highest level of the system (Path Planning Knowledge) the highest level of knowledge breaks down the information into that which can be recognized by the lower level of knowledge (the coordinates of start, goal, and every turning point). In the same manner, the information is transmitted to the lower stage of the system and finally reaches the lowest level, or Control Actuator (Please refer to Fig.8). If the single cell possesses all of the knowledge, the information can be broken down to the hardware level (Control Actuator) only by being given the coordinates of start and goal points from the outside.

Nevertheless, a cell needs to utilize the knowledge which is possessed by other cells when it does not have all the knowledge required (Please refer to Fig.9). In Fig.9, because cell x does not possess the knowledge of K2, cell x needs to compensate for this by asking cell y for this knowledge (c bits) and receiving the knowledge which was resolved by cell y (d bits). In total, cell x needs to make (a+b+c) bits of external communication.

In this simulation, the values of K1,....,K4 and a,....,d are quantified after they are assigned to each other as shown in Table 7 and 8. It is obvious that the maximum pieces of knowledge each cell can possess is three. Also, we assume that each cell can possess any two of three pieces (K2, K3, K4) since all the cells must have K1 (Basic Knowledge), which is required for any kind of communication. If all the cells possess three kinds of knowledge, we have 27 ways of knowledge allocation since there are three units of cells and three ways of knowledge allocation for each cell (${}_3C_2$). We calculated the amount of information communicated by

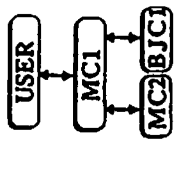

Fig. 7. Stratified communication system

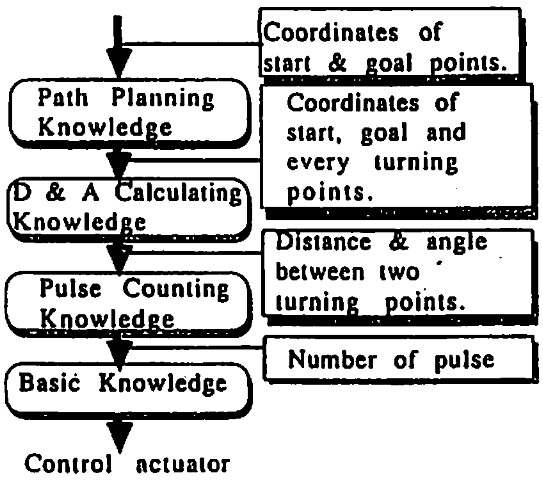

Fig. 8. Relationship of knowledge

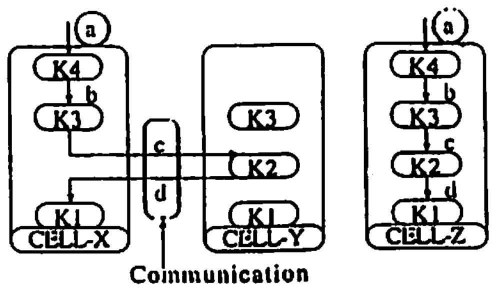

Fig. 9. Compensation of knowledge by communication

each cell and user to find the optimal knowledge allocation using the assumptions and methods mentioned above.

Some of the results and communication systems are shown in **Fig.10** and **Table 9**. Simulation No.1 had the lowest value (σ^2) of the 27 systems and simulation No.3 had the biggest. Therefore, we can conclude that simulation No.1 had optimal knowledge allocation. In this system, the master cell (MC1) has the highest level of knowledge (K4), the slave cells (MC2 and BJC1) have other knowledge. Information is transmitted from top to bottom, a concept which agrees with the general theory. In simulation No.3, none of the cells possess K2, so users have to use remote communication, which is very inefficient and control the cells by using a large number of bits. As a result, this required a great amount of communication and the distribution value turned out to be the largest of all the simulations. To make a comparism, simulation No. S was carried out in which all cells possess all four kinds of knowledge. Shown in **Fig.11** and **Table 10** are the results of simulations in which we changed the kind of knowledge (K1, K2, K3, and K 4) in each cell. From these results, we can conclude that the more knowledge the cell possesses, the less communication is required and the lower distribution value the system has.

6. Sensitivity to the Variation of the Knowledge Amount

6-1. Sensitivity of Cell

As mentioned before, we need to allocate the knowledge and equalize E(x) so that σ^2 can be minimized. In this case, it is important to decide from which cell to which cell the knowledge should be moved. To decide this, we define the extent to which a change in a certain cell's knowledge amount influences the fluctuation of the transmission load as sensibility S(x, y):

$$S(x,y) = -\frac{E(x)_{k2} - E(x)_{k1}}{K_2(y) - K_1(y)} \quad \cdots\cdots\cdots\cdots (22)$$

The knowledge amount, which cell y possesses in the situation of i, is denoted as $K_i(y)$.

S(x, y) indicates the extent to which the variation in the knowledge amount in cell y influences the communication information of Cell x. Using the value of S, we consider how the variation in the knowledge amount of Cell y influences the communication information of the whole system. The communication information of the whole system is calculated in equation (23):

$$\Phi = \sum_j \sum_i {}^iE_j \ [\mathrm{s}] \quad \cdots\cdots\cdots\cdots\cdots (23)$$

Using equation (4), the total sum of the communication amount of cell j is calculated in equation (24):

$$E(j) = \sum_i ({}^iE_j + {}^jE_i) \ [\mathrm{s}] \quad \cdots\cdots\cdots\cdots (24)$$

Therefore, the influence of the variation in the knowledge amount of cell y on the communication information of cell j is expressed in the following equation, substituting equation (24) for equation (22):

Table 9. Results of simulations (1)

No.	ΔE(USER) E1	ΔE(MC1) E2	ΔE(BJC1) E3	ΔE(MC2) E4	E=(1/4)Σ ΔE(i)	σ^2=(1/4)•Σ(E-ΔE(i))^2
1	0.58	1.11	0.42	0.11	0.56	0.13
2	0.58	1.49	0.13	0.78	0.75	0.24
3	17.6	19.9	1.15	1.15	9.95	78.1
S	0.58	0.80	0.11	0.11	0.40	0.09

Table 10. Results of simulations (2)

No.	ΔE(USER) E1	ΔE(MC1) E2	ΔE(BJC1) E3	ΔE(MC2) E4	E=(1/4)Σ ΔE(i)	σ^2=(1/4)•Σ(E-ΔE(i))^2
S1	4.55	6.25	0.85	0.85	3.13	5.54
S2	0.97	1.33	0.18	0.18	0.67	0.25
S3	0.67	0.93	0.13	0.13	0.47	0.12
S4	0.58	0.80	0.11	0.11	0.40	0.09

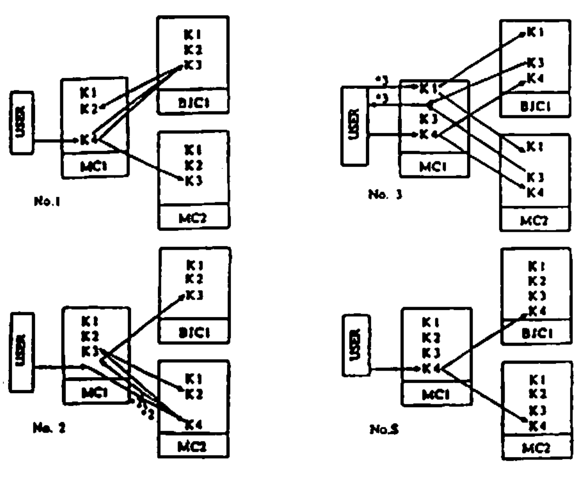

Fig. 10. Knowledge allocation and communication (1)

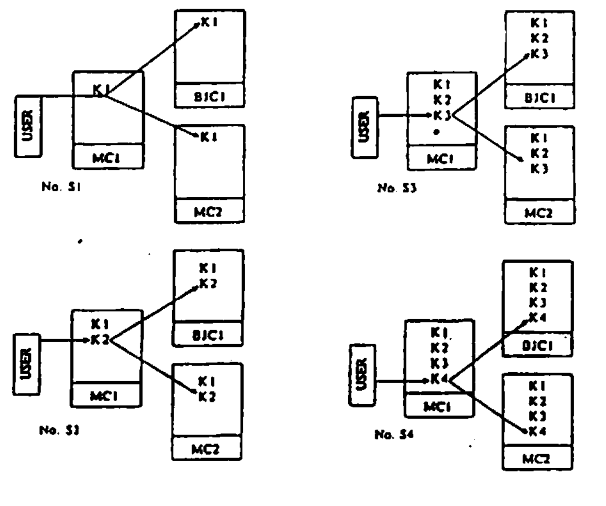

Fig. 11. Knowledge allocation and communication (2)

Table 11. Results of simulations (3)

No.	ΔE(USER) E1	ΔE(MC1) E2	ΔE(BJC1) E3	ΔE(MC2) E4	$E=(1/4)\Sigma\Delta E(i)$	$\sigma^2=(1/4)\cdot\Sigma(E-\Delta E(i))^2$
A	17.6	19.9	1.15	1.15	9.95	78.1
B	0.58	2.88	1.15	1.15	1.44	0.75
C	0.58	3.91	2.18	1.15	1.96	1.60
D	0.58	3.91	1.15	2.18	1.96	1.60

$$S(j,y) = -\frac{\sum_{i}(\Delta^i E_j + \Delta^j E_i)}{\Delta K(y)} \text{ [s/bit]} \quad \ldots\ldots (25)$$

The sensitivity of the whole system is,

$$S_y = -\frac{\Delta\Phi}{\Delta K(y)} = -\frac{\sum_j \sum_i \Delta^i E_j}{\Delta K(y)} \quad \ldots\ldots\ldots (26)$$

Using

$$\sum_j \sum_i \Delta^i E_j = \sum_j \sum_i \Delta^j E_i$$

$$(1/2) \times \sum_j \sum_i (\Delta^i E_j + \Delta^j E_i)$$

$$= \sum_j \sum_i \Delta^i E_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (27)$$

After substituting equation (27) for equation (26), the relationship between the sensitivity of the whole system (Sensitivity S_y) and the sensitivity of each cell (Sensitivity S(j, y) is expressed in equation (28).

$$S_y = -\frac{(1/2) \times \sum_j \sum_i (\Delta^i E_j + \Delta^j E_i)}{\Delta K(y)}$$

$$= (1/2) \times \sum_j \frac{-\sum_i (\Delta^i E_j + \Delta^j E_i)}{\Delta K(y)}$$

$$= (1/2) \times \sum_j S(j,y) \text{ [s/bit]} \quad \ldots\ldots\ldots (28)$$

The values in this equation indicate the extent to which the communication information of the whole system diminishes when certain knowledge is given to a certain cell. In other words, the larger the value of S is (when we apply the cell which can greatly reduce the communication information by acquiring a small amount of knowledge), the more communication the whole system can reduce. This fact indicates that we should allocate the knowledge to the more sensitive cell, and this finding can be a guideline for optimal knowledge allocation.

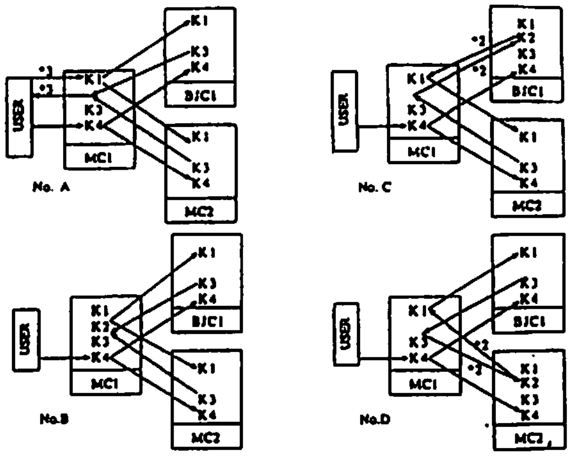

Fig. 12. Knowledge allocation and communication (3)

Table 12. Sensitivity of each cell and system

No.	S(user,y)	S(mc1,y)	S(bjc1,y)	S(mc2,y)	Sy
B	3.31	3.31	0.0	0.0	3.31
C	3.31	3.11	-0.20	0.0	3.11
D	3.31	3.11	0.0	-0.20	3.11

6-2 .Result of Simulation

In Section 5-2, we examined knowledge allocation and communication information using 27 kinds of simulations. The distribution value in the knowledge allocation is the largest in simulation No.3 because it does not have Knowledge K2 in the system. Using the sensitivity theory mentioned above, we will figure out in which cell knowledge K2 should be allocated in order to make the system function efficiently. The knowledge amount and communication information in the early stage is shown in **Fig.12(No.A)** and **Table 11(No.A).** In addition, the knowledge amount and communication information of each cell when K2 (5.14 bits; please refer to Table 7) is allocated to MC1, MC2, and BJC1 is shown in Fig.12 and Table 11. Using the communication information in Table 11, we calculated the sensitivity of cells and the whole system. The results are shown in **Table 12.** The cell with greater sensitivity can reduce the communication information more per bit of K2. Therefore, we conclude that the system can be the most efficient in the case of No.B in which K2 is allocated to MC1. The results when K2 is allocated to each cell are brought together in Table 11. Even if we compare the distribution values of the systems, No.B has the smallest value. This verifies that K2 needs to be allocated to MC1 to maximize the efficiency of the whole system.

7. Conclusions

(1) We proposed to quantify the communication information and knowledge amounts among cells and presented the examples.
(2) We quantified the amount of information transmitted among cells, proposed the optimal knowledge alloca-

tion by using its evaluation function, and showed the examples.

(3) We introduced the concept of sensitivity as an indicator of knowledge allocation and showed examples.

In this paper, we presented a method to equalize communication information to attain optimal knowledge allocation in an automatic, decentralized coordinated reasoning system and applied the idea to our Cellular Robotic System (CEBOT). This method can be applied to general decentralized coordinated systems and offers guidelines for achieving a solution to the optimal knowledge allocation problem.

References:

1) T. Fukuda, . and S. Nakagawa, : A Dynamically Reconfigurable Robotic System (Concept of a System and Optimal Configurations)", Proc. of IECON'87, pp.588-595, (1987).

2) T. Fukuda and S. Nakagawa.: "Approach to the Dynamically Reconfigurable Robotic System", Journal of Intelligent and Robotic Systems 1, pp.55-72 (1988).

3) T. Fukuda/and Y. Kawauchi: "Cellular Robotic System (CEBOT) as manipulator", Proc. of IEEE International Conference on Robotics and Automation'90, pp.662-667 (1990).

4) T. Fukuda, Y. Kawauchi, M. Buss and H. Asama: "A Study on Dynamically Reconfigurable Robotic Systems (3rd Report, Recognition and Communication System of Cell-structured Robot "CEBOT")", Trans. of Japan Society of Mechanical Engineers, 56-523, pp.709-716, (1990).

5) Kobayashi: "Information Engineering, pp.104-112, published by Shoukousha (1986).

6) Abramson (Translated by Miyagawa), The introduction of information theory, (1949), pp.12-52, published by Kougakusha (1949).

7) .G. N. Saridis, Proc. of IEEE International Workshop on Intelligent Robots and Systems'89. pp..24-30.(1989)