Genetic Evolution and Self-Organization of Cellular Robotic System*

Yoshio KAWAUCHI**, Makoto INABA**
and Toshio FUKUDA***

A cellular robotic system (CEBOT) is a system composed of many kinds of units called "cells". A cell has a simple function and limited intelligence. In task executions, many cells are required to carry out a same task cooperatively to supplement their functions each other. If some cells have malfunctions, the total performance of the system can be maintained by exchanging the malfunctioning cells. Therefore, CEBOT is expected to be adaptable to any kinds of tasks and environments. It is important to study self-organization and self-evolution of CEBOT, because both the hardware and software of CEBOT consist of many kinds of cells which are autonomous agents as mentioned above. This paper addresses self-organization of the hardware and self-evolution of the software based on the Genetic Algorithm. An outline of cells developed by the authors is reported. A self-evolutional knowledge base addressed in this paper is based on the Genetic Algorithm. The self-evolutional knowledge base is applied to a simple task planning system installed into a manipulator system and is verified. The effectiveness of the knowledge base is demonstrated by showing a learning capability of the manipulator in experiments.

Key Words: Genetic Algorithm, Self-Organization, Evolution, Multi-Agent System, Distributed Autonomous System, Task Planning, Mechatronics and Robotics

1. Introduction

As one of the way to use a system to execute many kinds of tasks under different circumstances, a system has been proposed which is divided into simple elements with functions and knowledge hereinafter called cells and which dynamically regroups these cells. This system has been proposed and reported under the name of Cellular Robotic System (CEBOT), and is similar to structures of living organisms in that it builds a complicated system by grouping simple elements and that this build-up takes place in a self-organizing fashion (Fig. 1)⁽¹⁾⁻⁽⁷⁾. In order for CEBOT to execute unknown tasks under unknown circumstances without human assistance, it is desirable that

Fig. 1 Concept of CEBOT

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** Applied Technology Dept., Toyo Engineering Corporation, 2-8-1 Akanehama, Narashino-shi, Chiba 275, Japan

*** Dept. of Mechano-Informatics and Systems, Nagoya University, Furo-cho, Chikusa-ku, Nagoya 464-01, Japan

CEBOT. Figure 3 shows the appearance of a mobile cell of CEBOT Mark II. The mobile cell has two wheels controlled by stepping motors. Each cell has sensors for cell recognition (infrared sensor), position and attitude detection (infrared sensor) and obstacle avoidance (ultrasonic sensor). For close distance position and attitude finding (0 - 0.5 m), eight infrared LEDs on a cell and three infrared photo-diodes in the mobile cell are used. The eight LEDs face eight different directions at 45 degrees intervals (Fig. 4 (a)). One ultrasonic transmitter and two receivers are used for obstacle detection (Fig. 4(b)). This sensor arrangement can recognize obstacles at distance as far as 0.7 (m) and inclination angles up to 30 degrees.

Each cell has two communication devices. One is used for communication with separated cells, the other is a communication system based on a busline laid in cells for communication with connected cells.

Fig. 3 Appearance of a mobile cell (Mark II)

Fig. 4 (a) Eight LEDs for position and orientation recognition

Fig. 4 (b) Photo diodes and ultrasonic sensors

3.2 Automatic approach and docking method

Automatic docking has been realized by two cells without telecommunication based on the proposed communication protocol^{(2),(7)}. If more than two cells exist in a system, it is necessary for them to communicate with each other for cell identification and position and orientation recognition. The communication realizes more efficiently autonomous docking than the docking without communication among cells. Communication is achieved by an infrared LED/photo diode pair mounted in a rotating sensor module on an elevated level (Fig. 3). Signal transfer to the LED/photo diode is done by four brush and slip-ring sets. The mobile cell calls for a docking partner with the desired cell function, eventually selects it out of several cells of the same type, and locates its position. Based on the information a master cell obtains, the cells can identify a target cell and dock it and separate autonomously from the cell⁽⁷⁾. Figure 5 shows the appearance of a module which is composed of autonomously docked cells. CEBOT has the ability of hardware self-organization by using mobile cells, connection mechanisms, and communication systems⁽⁷⁾.

4. Self-Organizing Software

4.1 Model of self-organizing system

As an example of a self-organizing system, a task planning system having the self-evolving and self-organizing capabilities is proposed in this paper. As shown in Fig. 6, this system is composed primarily of two parts, namely a group of elements called knowledge-cells and a data base. Knowledge-cell group is composed of a set of basic units called knowledge-cells to be defined later, and stratified as shown in Fig. 7.

Fig. 5 Appearance of a module composed of five cells (Mark II)

Fig. 6 Task planning system having cell structure

Fig. 7 Hierarchical structure of knowledge cell

Knowledge-cell: basic unit of the system. It connects with other knowledge-cells and has its own knowledge and capability of learning. Positive numbers called connection weights are assigned to connections between knowledge cells. The normalized connection weight is called connection intensity. The normalization means that the sum of all the connection weights on the connection line of the knowledge cell is 1. A vector which has connection intensity as its element is defined as the knowledge possessed by that knowledge-cell (Fig. 8).

Data base: knowledge possessed by a knowledge-cell is used for search and estimation of which cells among a number of stratified knowledge-cells should be used, and each knowledge-cell stores knowledge for procedural actions and various data which cannot be described by its connection intensity, and accesses to the database whenever the cell is activated by a certain task. This database is renewed or modified along with the knowledge of knowledge-cells.

4.2 Basic actions

Figure 9 describes the basic action of the system. The boxes shown in Fig. 9 represent various processes to be explained below.

Connection weight: A positive number assigned to a connection between knowledge-cells

$w(i,j), w(i,k), w(i,l), w(i,m)$

Connection intensity: A normalized connection weight

$w(i,j)/W, w(i,k)/W, w(i,l)/W, w(i,m)/W$
 $W = w(i,j) + w(i,k) + w(i,l) + w(i,m)$

Knowledge: A vector composed of connection intensity

Cell-i[$w(i,j)/W, w(i,k)/W, w(i,l)/W, w(i,m)/W$]

Fig. 8 Knowledge cells and their knowledge

Fig. 9 Basic Motion of task planning system composed of knowledge-cells

Process 1: Calculation of correctness

Correctness is defined by Eq. (1).

$$C_p(i) = \sum_{k=1}^m \{ \sigma(i, k) C_p(k) \} \quad (1)$$

where $C_p(i)$ and $C_q(k)$ are correctness of cell (i) of layer p and that of cell (k) of layer q , respectively, $\sigma(i, k)$ is the connection intensity between cell (i) and cell (k), and m represents the number of cells in the lower layers which are connected with cell (i). Correctness ranges in value from 0 to 1, and represents the degree of compatibility between input data and cells. As based on Eq. (1), if the correctness of all the cells connected with cell (i) is 1, then the correctness of cell (i) is also 1, and the probability that cell (i) is employed is high. After the correctness of a number of knowledge-cells is set equal to 1 as input data, the correctness of all the cells is computed based on their

initial values and Eq.(1)

Process 2: Selection of cells

After the correctness of all the cells is computed, cell selection is carried out considering the values of correctness. As an example of selection, cells with higher correctness may be chosen⁹. If the system has a subsystem which is capable of executing a given task, then process 4 is carried out ; otherwise, process 3 is executed.

Process 3: Production of new cells

When there are no cells or groups of cells (modules) which satisfy given conditions, then new knowledge cells are generated. The production of new cells is based on a genetic cell production algorithm which uses natural selection by living organisms as a model (refer to the next section).

Process 4: Changing connection weights between cells

If a cell is selected, the connection intensities between cells increase and the cell is selected more easily when the same demand is imposed on the system. Otherwise, connections of unemployed cells weaken.

Process 5: Reconfiguration of cell number and module number

In order to efficiently search for and produce cells and modules which satisfy the next demand, connections between cells may be changed. Grouping of cells having similar abilities is necessary to search for or produce in a few steps cells which satisfy the demand.

5. Genetic Cell Production Algorithm

In the models shown in Fig.7, connections between cells are changed or the numbers of cells and layers are reconfigured. When the system does not contain a subsystem which satisfies the environment or a given task, then it is necessary to produce a new subsystem. In this section, a genetic cell production algorithm (to be abbreviated below as GCPA) will be proposed which incorporates a genetic algorithm (GA) method that uses genetics and evolution of living organisms as models in the process of new cell production.

GA is one of the search methods applied in recent years towards the optimization problem in combinations and others, and its basic actions are shown below^{(8),(9)} :

- 1: Coding of objects according to genes. (Coding)
- 2: Fitness functions computed from various code rows are established and calculated.
- 3: Genes (code rows) with higher fitness functions are selected. (Reproduction)
- 4: Crossover between selected genes is initiated. (Crossover)
- 5: Codes are changed with a certain probability.

(Mutation) (Fig. 10)

The basic concept of GA is that among these steps, steps 3, 4 and 5 are grouped as a generation and are carried out over many generations to obtain genes with higher fitness functions. Thus, GA can be said to model the survival of the fittest in a system of living organisms. In a similar way, CEBOT must adapt itself to differently changing unknown tasks and environments. For this reason, the concept of GA is applied to the new cell generation in the systems as shown in Fig.11 and a new genetic cell production algorithm is proposed. The GCPA proposed here consists of the procedures as follow :

1. Features possessed by cells (such as functions and knowledge) as genes are matched. (Coding)
2. The evaluation function possessed by each knowledge cell is calculated. (Fitness function)
3. A new knowledge cell candidate 1 is selected according to the state amount owned by cells. (Reproduction-1)
4. A candidate 2 is selected according to state amounts. (Reproduction-2)
5. A cross-over position is randomly determined, the features of cells are crossed over, and candidate 1 is expected to have the new features after cross-over is operated. (Crossover)

As an example, GCPA was applied to the model defined in the previous section (Fig.6 and 7). In GCPA, a gene and its fitness function must be

Fig. 10 Concept of genetic algorithms

Fig. 11 Genetic cell production algorithms

determined. In this example, the knowledge of the cell defined by Fig. 8 is used as a gene and the correctness defined by Eq. (1) is used as the fitness function. Moreover, Table 1 shows relationship among GA, GCPA and a living system.

6. Experiments

The distributed system under discussion in this paper has structures as shown in Fig. 6. Here, each cell can be considered as a subsystem for processing a certain sub-task, and more sophisticated tasks are processed by combining such cells efficiently. In order to verify efficient combinations of cells and generating actions, therefore, experiments were conducted, as an example to show a system behavior, by using the experimental equipment as described follow.

6.1 System composition of experimental equipment

The equipment for experiments is composed of a "robot manipulator" which handles tasks and a "task board" in which tasks are set by a computer (Fig. 12). The robot manipulator has a 6-axle force torque sensor mounted on its end effector. The task-board consists of 9 numbered joysticks, and each joystick can move in four directions, namely up, down, left, or right. Both the manipulator and the task-board are connected to a computer, and the computer imbeds certain tasks in the task-board (Fig. 13). In these experiments, the task is defined as follows.

Task : to move certain numbered joy-sticks in certain directions in a certain determined order.

An example of the task given here is "to move #2 joystick right at step 1 and move #5 upward at step 2". Moreover, although the manipulator is controlled by the same computer, what type of task is given is not communicated at all. Also, the manipulator recognizes the end of the task by receiving a task termination signal from the computer.

Table 1 Comparison among GA, GCPA and natural world

Natural	GA	GCPA
gene	character	connection weight
chromosome	string	knowledge
phenotype	parameter set (quantity of systems)	ability of a system (quality of systems)
	fitness function	correctness

Fig. 12 Appearance of the experimental system

Fig. 13 Relationships among experimental equipment, operator and knowledge system (GCPA)

6.2 Correspondent relations between distributed knowledge system and experimental equipment

In the present experiments, new knowledge cells were produced and connection intensities are varied according to the algorithm shown in section 5 while the task given to the task-board was carried out. Here, the task is expressed as a combination of a ID of joystick and the direction of the joystick operation. These task descriptive methods and data structures have already been published⁶⁾. It is assumed here that the addresses and operational directions of joysticks are selected as subsystems and correspond to the cells shown in Fig. 7, and combinations of joysticks and their operational directions are described by sets of those cells. In the present experiments, a four-layered

Table 2 Correspondence between respective layers of knowledge-cell and experimental equipment

Knowledge Cells	Experimental Equipment
Layer-4	Complicated Tasks
Layer-3	Given Tasks
Layer-2	Address of Joy-sticks
Layer-1	OperationalDirection

Table 3 Values of G_{ij} and H_i set at task board

H1	H2	H3	H4				
7	84	29	31				
G11	G12	G13	G14	G31	G32	G33	G34
0.871	0.043	0.043	0.043	0.043	0.043	0.871	0.043
G21	G22	G23	G24	G41	G42	G43	G44
0.043	0.871	0.043	0.043	0.043	0.043	0.043	0.871

structure is considered as a special case of a system defined and modeled in Fig. 7. The layers are called the first to the fourth layer from the lowest upward. The tasks are described by the operational directions and numbers of the joysticks, the first layer (layer-1) of known knowledge cells is used as the layer for describing moving directions, and a second layer (layer-2) is formed above the first layer and used as the layer for expressing the numbers of the joysticks. Tasks formed by combinations of these are assigned to cells in the third layer (layer-3) and sets of tasks to cells in the fourth layer (layer-4). Table 2 shows the relationships between the distributed knowledge system and the experimental equipment. Moreover, relationships among the manipulator, the task-board, and GCPA are shown in Fig. 13. The operator gives the address of the joystick to be operated to the computer and GCPA. The computer possesses a certain model described by G_{ij} and H_i defined in Table 3 and the next section, and generates a task by using this model and establishes it on the task-board. In the self-organizing system, the correctness of the cell corresponding to a given joystick is set equal to 1, and an action row is generated according to the algorithm as shown in Figs. 9 and 11, and this action is carried out on the task-board by the use of the manipulator.

Signals are transmitted to the self-organizing system only in cases where the operation carried out by the manipulator is identical to the task established beforehand. The self-organizing system creates models within itself through a number of trials. At the initial stages of the experiments, the knowledge cells inside the self-organizing system are connected on an equal basis, and since the number of cells in the third and fourth layers is small, the task-board is

operated randomly combining permutations for the purpose of generating operational rows, and the processing of the tasks takes time. However, it is possible to learn characteristics of the task-board by operating the task-board a number of times; for example, a correct solution is more easily obtained if joystick-1 is pushed down in the direction of 1. Thus, the time taken for obtaining correct solutions (number of operations) can be expected to be gradually reduced. These points will be verified by the experiments indicated in the following sections.

6.3 Experimental procedures

The experiments were conducted by the following procedures.

STEP 1. The relative frequency (G_{ij}), which indicate probability that operational direction (j) of joystick (i) is correct, is given.

STEP 2. A positive constant(H_i) is assigned to each joystick (i).

STEP 3. Correct tasks are set on the task-board.

A correct task is expressed in terms of which joystick should be moved in which direction and at which step. The correct direction of each joystick is G_{ij} , and the order of priority of joystick operations is then determined stochastically by using H_i . For example, in case $G_{ij}=0.8$, for joystick (i) there is 80% probability that direction j is chosen as a correct one. However, this does not always mean that it should be pushed down in direction j ; there is 20% probability that other directions are correct. These correct directions are changed at each trial.

STEP 4. The robot manipulator is informed of the number of the joysticks to be moved for the execution of the task in question. This corresponds to Process 1 of Fig. 9.

STEP 5. Until the task is completed (until task terminating signals arrive from the computer), the manipulator keeps moving joy-sticks in various directions.

STEP 6. At the completion of the task, the manipulator carries out self-organization of knowledge for more efficient processing of tasks on the task-board by changing the knowledge structure and producing new knowledge cells. The procedures from Process 2 to Process 5 of Fig. 9 are carried out.

STEP 7. Return to STEP 3.

All these procedures are carried out, and the total number of joystick operations (to be called operation time) is recorded.

6.4 Experimental results

Experiments were carried out according to the method described in the previous section, and the time for task execution was recorded and plotted in Fig. 14. The time for task execution is corresponded to a

Fig. 14 Results of experiments

Fig. 15 Change in number of cells contained in each layer at initial and final conditions of experiment

number of actions of the manipulator between a time when the manipulator received task from a computer in Fig. 13 and a time when the manipulator received the task termination signals from the computer. Figure 14 shows the number of trials on the horizontal axis and operation times on the vertical axis. When the number of trials is small, the characteristics of the task board have not been learned and joysticks are operated randomly so that the operation times are high. As the number of trials increases, that of knowledge-cells increases, and both tight and weak relationships are formed among knowledge-cells. This is equivalent to the fact that each joystick on the task-board is closely related to the operational directions that are apt to be correct. As the number of trials increase, the operation times are reduced because the task-board is operated by using the empirical knowledge.

The jumps on the number of trials in Fig. 14 represent cases where low probabilities of G_{ij} in Table 3 were chosen as correct tasks and indicate times when new cells are being generated. The operation times at the time of new cell generation tend to decrease, which implies that this system has learned the characteristics of the task-board through empirical learning and produces knowledge-cells more efficiently. Moreover, the number of cells in each layer is different as shown in Fig. 15, which shows an example of software self-organization of CEBOT based on the GCPA. The system creates knowledge-cells to make the total system adapt to the given tasks and environment.

7. Conclusions

This paper reported the self-organization and self-evolution of a dynamically reconfigurable system from the viewpoint that a system must possess self-organization and self-evolution if it is to adapt itself to unknown environments and tasks. In order for a system composed of sets of subsystems to adapt itself efficiently to unknown environments and tasks, the generation and deletion of new subsystems are necessary, and a genetic cell production algorithm was proposed which is an application of a genetic algorithm having as its basic principle the modeling of natural selection in the world of living organisms. This algorithm was then applied to a task planning system of a cellular robot, a form of a dynamically reconfigurable robotic system, and its effectiveness was verified by experiments in which during the operation of unknown objects, models of those objects are self-organized internally. Thus, this system is considered to be self-evolving, because the system generates subsystems by using an algorithm modeled after a gene of a living organism and also because the system as a whole improves efficiency by changing the connections among subsystems.

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