Paper:

Adaptive Division-of-Labor Control Algorithm for Multi-Robot Systems

Yusuke Ikemoto*, Toru Miura, and Hajime Asama*****

*Graduate School of Science and Engineering for Research, University of Toyama
3190 Gofuku, Toyama 930-8555, Japan
E-mail: yikemoto@eng.u-toyama.ac.jp
**Graduate School of Environmental Science, Hokkaido University
CN10 W5, Kita-ku, Sapporo 060-0810, Japan
E-mail: miu@ees.hokudai.ac.jp
***Department of Precision Engineering, School of Engineering, The University of Tokyo
7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan
E-mail: asama@robot.t.u-tokyo.ac.jp
[Received December 25, 2009; accepted April 20, 2010]

An advanced function for multi-robot systems is the division of labor. There are some studies proposing a multi-agent reinforcement learning method for a division of labor. However, it often requires much time to converge. Many studies focusing on division-of-labor control inspired biological phenomenon have been reported. In those methods, whether heterogeneous or homogeneous state is determined by self-organization, however, group performance improvement is not guaranteed because decentralized control is typically complicated. In this study, we propose adaptive division-of-labor control, enabling adaptive selection of homogeneous or heterogeneous group state. We demonstrate the adaptability of proposal method versus working conditions and address the performance improvement by mathematical analysis. To evaluate the effectiveness of the proposed method, we treat foraging by multi-robot systems and confirm that the robot group inevitably organizes the division of labor with group performance improvement in computer simulations.

Keywords: multi-robot system, collective behavior, division of labor, adaptability

1. Introduction

Division of labor in multi-robot systems is an advanced collective behavior that needs swarm intelligence. Multi-robot systems conduct given labor collectively: it is expected to yield group performance improvement with the division-of-labor control. Division of labor is generally possible in which plural tasks with multi robot systems. When division of labor is carried out, tasks are assigned to each robot and a behavior strategy of a robot is specialized for assigned tasks. Then, the robot behaviors in the group become heterogeneous. All robots execute given tasks without division of labor, the robot behaviors may become homogeneous since each robot behave to optimize task performances in similar fashion. The former state, where robots behave with division of labor, is called a heterogeneous state. The latter state, where robots behave without division of labor, is called a homogeneous state. In this study, adaptive division-of-labor control means the ability to enable a robot group to automatically select whether homogeneous or heterogeneous state according to working conditions by decentralized control. In addition, it is desired that the division of labor bring in the performance improvement for adaptability [1].

To realize a division of labor in a multi-robot system, many studies using learning involve division-of-labor algorithms. Multi-robot reinforcement learning algorithms for cooperative behavior has been reported [2–5]. The division of labor by learning or other computational optimization algorithm is expected the collective performance improvement and optimality is discussed. However, the use of a learning algorithm is often accompanied by a time cost for learn it, along with complicated interaction protocols.

The insects world presents many examples of the division of labor. Eusocial insects organize the division of labor through caste differentiation, adaptively behave according to environmental changes. Division of labor is one of the advanced social activities that is seen in many livings include human. Eusocial insects, including termite, evolutionarily acquire such a division-of-labor manner [6]. Recently, there are many studies of the approaches that modeling the division-of-labor mechanism of eusocial insects [7].

Such studies have proposed three major kinds of models: response threshold model is proposed by [8, 9]. These models achieve the regulation of hierarchy ratio with an individual internal threshold to determine the labor specialization. The threshold reinforcement model [10] is the model that the positive feedback is introduced to response threshold. The positive feedback signal, i.e., a learning

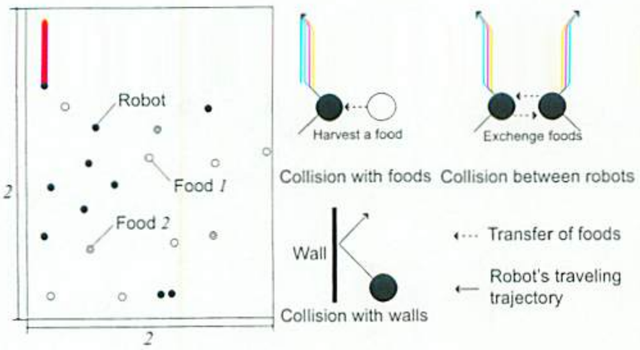

Fig. 1. Working space and collision rules of robots.

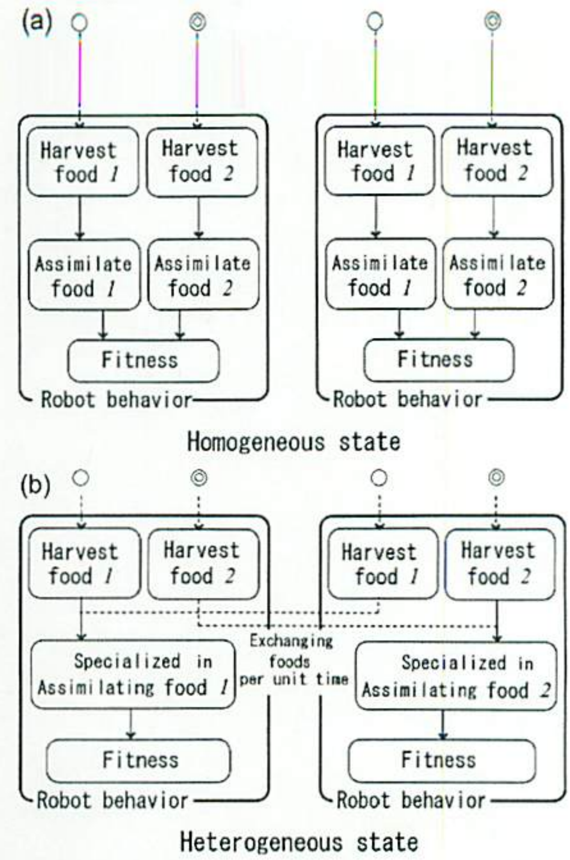

Fig. 2. Division of labor for robot group system. (a) Homogeneous state. (b) Heterogeneous state.

component, works to increase labor frequency. The reinforcement of the labor frequency in an individual is reported to generate a labor specialization. The social inhibition model is proposed to explain the polymorphism in social insects [11, 12].

Common dynamics of the division of labor involve a heterogeneous state generated by self-organization thorough interaction among individuals. The individual's internal non-learned property is exposed to the group state. The division of labor of the biologically-inspired model without trial-and-error process is brought out by phase transition. It is however that its performance improvement is not guaranteed in their models.

To address more effective division-of-labor control, we propose a method of adaptive division-of-labor control; however, the discussions about phase transition mechanism is insufficiency and the cases of high dimensional task have not been evaluated [13]. Our objective here is to propose division-of-labor control method for a robot group and to show its adaptability of proposed method versus working conditions and to address performance improvement by mathematical analysis. In particular, the proposed method is evaluated using a situation of food forage labor by robot group. Then, it is proved theoretically that the group performance is certainly improved using proposed method. We clarified the dynamical structure to show how group performance is improved in two tasks cases. In addition, we evaluate the proposed method in the case of four kinds of tasks. Finally, the proposed algorithm and its dynamical behaviors are evaluated using computer simulations.

2. Robot Tasks

2.1. Task and Working Space

2.1.1. Task Overview

In this study, we used the following simple foraging problem, which includes a division of labor, through interaction by a robot group in the working space as shown in **Fig. 1**. The working space is defined as a 2×2 square. The number of robots is n in the working space. A robot moves in a working space, harvesting the food when a robot contacts with food. It is defined that a robot can carries out those action; moving, harvesting, and assimilating, in parallel.

There are m kinds of food; the labor of robots is to assimilate the food that is harvested. There is a possibility that a robot may physically contacts with foods, walls, and other robot. Robots may exchange food when contacting with each other. An interaction between robots consists of contacting and mutual exchanging foods. When a robot harvests food, the food disappears and new food is spatially replaced randomly, so the amount of foods is defined as constant.

Let $N = \{1, 2, \ldots, n\}$, $M = \{1, 2, \ldots, m\}$, where n and m respectively signify the number of robots and the number of robot strategies; $j \in N$ and $i \in M$ respectively denote the agent number and strategy number. Let E_i be the agent strategy that is the necessary set of the behavior primitive for the i-th labor execution. The labor of robots is described as the following.

$$E_i = \{\text{Assimilating } i\text{-th food}\} \quad \ldots\ldots\ldots \quad (1)$$

Robots harvest and assimilate m kinds of food in solitude if the group state is homogeneous. Robots harvest or exchange the food with other robots and assimilate food using a specialized behavior if the group state is heterogeneous as shown in **Fig. 2**. States of a robot are determined by behavior strategy frequency and the amount of food the robot harvests. Let ${}^jx_i$ and ${}^jy_i$ be the frequency of assimilation and amounts of the i-th food that the j-th robot harvests per unit time, respectively. For example, the j-th robot can assimilate the i-th food with frequency ${}^jx_i$ as the following.

$$ {}^jx_i = \{j\text{-th frequency of } E_i\} \quad \cdots\cdots (2)$$
$$\sum_i^m {}^jx_i = 1,\ {}^jx_i \geqq 0$$

Fitness, that is working performance, is defined by the amount of assimilated foods per unit time. The problem is that each robot needs to determine the strategy frequency ${}^jx_i$ by the amount of food the robot harvests ${}^jy_i$ and interactions between robots to maximize fitness. ${}^jx_i$ and ${}^jy_i$ are continuous values and ${}^jx_i$ is determined by a continuous differential equation detailed below.

2.1.2. Robot Behavior

A robot has no directionality and can move omnidirectionally. The initial states of both robots and food are random locations. Robots have behaviors of three kinds for foraging: moving in a working space, harvesting food, and exchanging food with other robots. The labor of robot E_i is assimilating the food as defined in the above subsections. For foraging, a robot generally moves with linear uniform motion with velocity $30_{[1/s]}$. The robot harvests the food on the working space if it contacts food. Interactions occur when the distance between a robot and another robot, food, or wall equals 0.

2.1.3. Food-Related Behavior

Initially state, food appears randomly in the working space. The food disappears from the working space if a robot harvests food. After that, new food is spatially replaced randomly. Therefore, the food amount is defined as constant. The working space has m kinds of food with the number corresponds to the number of robot's strategies m. The quantities of i-th food are defined as C_i. For example, when $m = 2$, and the numbers of 1st food and 2nd food are 7 and 3, respectively, we have $(C_1, C_2) = (7,3)$. C_i does not correspond to ${}^jy_i$. Here, C_i is the amount of food in the working space and ${}^jy_i$ is the amount of food that the j-th robot has for assimilation.

2.2. Labor Performance Definitions

The optimal ratio of strategy frequency is defined as the same ratio existing in a food C_i. Therefore, the optimal strategy frequency is defined as $({}^jx_1 : {}^jx_2 : \ldots : {}^jx_m) = (C_1 : C_2 : \ldots : C_m)$.

Let ${}^jG$ be the fitness matrix of the j-th robot, which determines the amounts of food assimilated per unit time and dynamics of strategy frequency ${}^jx$. The fitness matrix is represented as the matrix in which the i-th diagonal element is equal to ${}^jy_i$ and all of non-diagonal elements equal to $\sum_i^m {}^jy_i$ as follows:

$$ {}^jG = \begin{bmatrix} {}^jy_1 & & \sum_i^m {}^jy_i \\ & \ddots & \\ \sum_i^m {}^jy_i & & {}^jy_m \end{bmatrix} \quad \cdots\cdots (3)$$

This fitness matrix is not explicitly given to a robot. A robot takes that through collecting foods. The ${}^jG$ consists of ${}^jy_i$ because the amounts of food that a robot can assimilate are dependent on the amounts of food that a robot harvests. ${}^jG$ is determined according to the frequency with which a robot contacts with the food per unit time, e.g., ${}^jg_{12}$, that is the element of ${}^jG$, is the fitness when ${}^jx_1 = 1$ and ${}^jx_2 = 1$. The term ${}^jg_{12}{}^jx_1{}^jx_2$ is one for given fitness and corresponds to the amount of food that the robot can assimilate per unit time. The robot fitness ${}^j\phi$ is obtained by summing of these terms.

Fitness given by j robot's assimilation of food i is described as ${}^jf_i({}^jx)$. Without interactions among robots, i.e., no exchanges of food to be assimilated, the fitness simply corresponds to $({}^jG{}^jx)_i$, where $(\cdot)_i$ denotes the i-th row element, which is regarded as the expected value or degree of demand for each labor. In the case of robots' interaction with other robots, we define ${}^jf_i({}^jx)$ with interaction terms between other robots as follows:

$$ {}^jf_i({}^jx) = ({}^jG{}^jx)_i + {}^jh_i \quad \cdots\cdots (4)$$

${}^jh_i$ is fitness generated from interactions. In interactions, the sum of food to be assimilated by both robots must have a law of conservation, so $\sum_j^n {}^jh_i = 0$ must be satisfied at any time. With this fitness, robots conduct activities with strategy frequency ${}^jx$, so j-th robot fitness is obtained as ${}^j\phi = \sum_i^m {}^jx_i{}^jf_i({}^jx)$, so we can determine the group mean fitness as follows:

$$\langle {}^j\phi \rangle = \frac{1}{n}\sum_j^n {}^j\phi, \quad \cdots\cdots (5)$$

$\langle\cdot\rangle$ is the mean related to j.

3. Division-of-Labor Control Algorithm

The simple gradient method cannot be used, for example $\frac{d{}^jx_i}{dt} = \frac{\partial\langle{}^j\phi\rangle}{\partial{}^jx_i}$, because there is the constraint $\sum_i^m {}^jx_i = 1$. The optimization problem is transformed by gradient projection [14–16] in which optimization on $\sum_i^m {}^jx_i = 1$ is described by a replicator equation [17]. Time evolution of the strategy frequency ${}^jx$ is defined using the replicator equation in the case of the diploidic genome model [18], which has been studied in the area of population genetics. Replicator dynamics here represent the dynamics of ${}^jx_i$ in a robot as following:

$$\frac{d{}^jx_i}{dt} = {}^jx_i\left({}^jf_i({}^jx) - {}^j\phi\right). \quad \cdots\cdots (6)$$

The dynamics of Eq. (6) is limited to a simplex manifold S_m:

$$S_m = \{{}^jx \in R^n | {}^jx_i \geq 0, \sum_i^m {}^jx_i = 1\}. \quad \cdots\cdots (7)$$

The dynamics of ${}^jx_i$ defined by Eq. (6) gives the local optimality of individual mean fitness on S_m [19].

Interaction term ${}^jh_i$ is determined based on hypothesis in the previous section. Although termites communicate

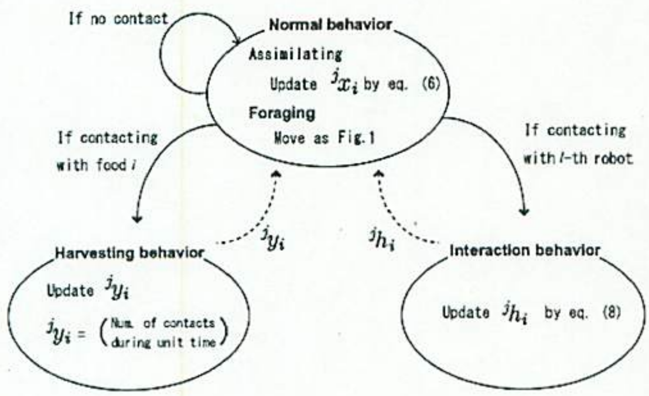

Fig. 3. Transition rules of robot's behavior.

by using pheromone diffusion, in proposed algorithm, the pheromone is food to be assimilated. Let ^jp_i be food to be assimilated that a robot transport to another robot. To satisfy this condition, ^jh_i simply is described with mutual diffusion of ^jp_i as follows:

$$^jh_i = D\left(^lp_i - {}^jp_i\right), \quad \ldots \ldots \ldots \ldots (8)$$

where

$$D = \begin{cases} \alpha: & \text{when interacting with another robot} \\ 0: & \text{when not interacting with others} \end{cases} \quad . \quad (9)$$

Therein, $l \in N, \neq j$ denotes the number of robots that interact with the i-th robot; α determines the value at which robots can exchange their fitness. If the ^jp_i is the labors the robot must execute, it is expected that labors, actually food to be assimilated, can be exchanged between robots, so the ^jp_i is determined as follows:

$$^jp_i = \left(^jG^jx\right)_i. \quad \ldots \ldots \ldots \ldots (10)$$

To clarify the proposed algorithm, **Fig. 3** explains transition rules of robot's behavior.

^jp_i means not only the amount of food that a robot collects at per unit time but also expected fitness with ^jx_i. The interaction defined by Eq. (8) generates the flow of expected fitness in a robot group. ^jh_i works as the global feedback to individual's ^jx_i with differences of ^jp_i between robots. When the differences of ^jp_i are amplified, phase transition is caused in a group and it is expected that the heterogeneous state is generated. In the case of homogeneous state, the differences of ^jp_i are close zero and regarded as that there is no interaction between robots. For heterogeneous, because of asymmetry property of ^jh_i in a group, the food to be assimilated move through robots. These dynamics of both differentiation and group mean fitness are explained as below section in detail.

4. Analysis of Adaptability and Performance Improvement

4.1. Analysis Setup

Two mathematical analyses are conducted on a two-dimensional labor situation. First is the division and regulation property of the division rate in heterogeneous state is provided. Second is the proof that the organizational condition of the homogeneous or heterogeneous state provided with the first analysis include an adaptive division of labor. Concretely, the proposed algorithm constantly organizes a homogeneous or heterogeneous state with increasing group mean fitness $\langle ^j\phi \rangle$.

Let the numbers of robots be set to $n = 2$. For these analyses, the time of the evolution of the strategy frequency is assumed to be continuous and Eq. (6) is represented as follows:

$$\frac{d^jx_i}{dt} = {}^jx_i\left(^jf_i(^jx) - {}^j\phi\right). \quad \ldots \ldots \ldots (11)$$

The dynamics of Eq. (11) are also limited to simplex manifold S_2 described by Eq. (7). Additionally, it is assumed that the interactions among robots are carried out uniformly and continuously, so the time evolution of D is assumed to be continuous and a robot interacts in mean field approximation as follows:

$$^jh_i = D\left(\langle ^jp_i \rangle - {}^jp_i\right), \quad \ldots \ldots \ldots \ldots (12)$$

The mathematical meaning of D is the degree to which strength fitness distribution feed back to phenotype dynamics of a robot, i.e., the coefficient determines the strength of fluctuation from a group to an individual state. Based on the above Eqs. (11) and (12), D obtains the condition for the division-of-labor decision. ^jp_i is described by the function of ^jx_i on simplex S_2 because of $\sum_i^m {}^jx_i = 1$:

$$^jp_1 = g_{12} - (g_{12} - g_{11})\,^jx_1 \quad \ldots \ldots \ldots (13)$$

$$^jp_2 = g_{21} - (g_{21} - g_{22})\,^jx_2. \quad \ldots \ldots (14)$$

$^jf_i(^jx_1, {}^jx_2)$ are also described by ^jx_i, simply described as ^jf_i.

$$^jf_1 = (1-D)\,^jp_1 + D\langle ^jp_1 \rangle \quad \ldots \ldots \ldots (15)$$

$$^jf_2 = (1-D)\,^jp_2 + D\langle ^jp_2 \rangle. \quad \ldots \ldots \ldots (16)$$

Eq. (11) is transformed as follows using Eq. (7):

$$\frac{d^jx_1}{dt} = {}^jx_1(1 - {}^jx_1)\left(^jf_1 - {}^jf_2\right) \quad \ldots \ldots \ldots (17)$$

$$\frac{d^jx_2}{dt} = {}^jx_2(1 - {}^jx_2)\left(^jf_2 - {}^jf_1\right), \quad \ldots \ldots \ldots (18)$$

The dynamical system represented by Eqs. (15), (16), (17), and (18) has three fixed points on S_2: $(^jx_1, {}^jx_2) = (1,0)$, $(0,1)$, and $(^jx_1^*, {}^jx_2^*)$, that satisfy $^jf_1^* = {}^jf_2^*$ and

$$x_1^* = \frac{g_{12} - g_{22} - Dk\langle x_1 \rangle}{(1-D)k} \quad \ldots \ldots \ldots (19)$$

$$x_2^* = \frac{g_{21} - g_{11} - Dk\langle x_2 \rangle}{(1-D)k}, \quad \ldots \ldots \ldots (20)$$

where

$$k = g_{12} - g_{11} + g_{21} - g_{22}. \quad (21)$$

From analysis, the case of no interaction, i.e., $D = 0$, is analyzed at the beginning. When $D = 0$, Eqs. (15) and (16) are transformed to ${}^j f_i = {}^j p_i$. In this case, the fixed point $({}^j x_1^*, {}^j x_2^*)$ is specifically explained as (x_1', x_2'). With Eqs. (19) and (20):

$$x_1' = \frac{g_{12} - g_{22}}{k} \quad (22)$$

$$x_2' = \frac{g_{21} - g_{11}}{k}. \quad (23)$$

Strategy frequency converges to one of $({}^j x_1, {}^j x_2) = (1, 0)$, $(0, 1)$, and $({}^j x_1', {}^j x_2')$. According to [20], Eq. (11) is known to have a unique stable fixed point on S_2 if ${}^j f_i$ is a monotonically decreasing function related to ${}^j x_i$, i.e., when the following conditions is satisfied, the fixed point $({}^j x_1', {}^j x_2')$ is stable at $D = 0$.

$$g_{12} - g_{22} > 0 \quad (24)$$

$$g_{21} - g_{11} > 0 \quad (25)$$

Conditions, that the fixed point $({}^j x_1', {}^j x_2')$ is not included on boarders of S_2 and outside of the S_2 are as follows:

$$g_{12} - g_{11} > 0 \quad (26)$$

$$g_{21} - g_{22} > 0 \quad (27)$$

If ${}^j G$ does not satisfy those conditions, robots need not organize a heterogeneous state because replicator dynamics in a robot have maximization principle of ${}^j\phi$ and the optimal state is that all j-th strategy frequencies converge at $({}^j x_1, {}^j x_2) = (1, 0)$ or $(0, 1)$, and a homogeneous state always becomes optimal, so these situations are deselected from cases in this paper. The individual mean fitness is described as ${}^j f_1 = {}^j f_2 = {}^j\phi' = -\frac{|{}^j G|}{k}$ at any j. The group mean fitness is obtained as follows, using Eq. (5),

$$\langle \phi' \rangle = -\frac{|{}^j G|}{k}. \quad (28)$$

4.2. Differentiation Conditions

For $D > 0$, ${}^j f_i({}^j x)$ is not a monotonically decreasing function at any time because Eq. (11) includes a Eq. (12) term depending on group state feedback, so ${}^j f_i = {}^j p_i$ is not always satisfied. Let ζ, ξ, and η be ratios of the number of robots located at $(1, 0)$, $(0, 1)$, and $({}^j x_1^*, {}^j x_2^*)$, and satisfy $0 \leq \zeta, \xi, \eta$, $\zeta + \xi + \eta = 1$. $\langle {}^j x_i \rangle$ is determined using a self-consistent method as follows:

$$\langle {}^j x_1 \rangle = \zeta \cdot 1 + \xi \cdot 0 + \eta \cdot {}^j x_1^* \quad (29)$$

$$\langle {}^j x_2 \rangle = \zeta \cdot 0 + \xi \cdot 1 + \eta \cdot {}^j x_2^*. \quad (30)$$

With Eqs. (29), (30), (22), and (23),

$$\langle x_1 \rangle = \frac{Q_1 + Q_4}{kQ_3} \quad (31)$$

$$\langle x_2 \rangle = \frac{Q_2 - Q_4}{kQ_3} \quad (32)$$

Table 1. Cluster existing conditions.

	case	ζ	ξ	η	J_1	J_2	J_3
one-cluster	case 1	1	0	0	−	+	+
	case 2	0	1	0	+	−	+
	case 3	0	0	1	+	+	−
two-cluster	case 4	ζ	0	η	−	+	−
	case 5	0	ξ	η	+	−	−
	case 6	ζ	ξ	0	−	−	+
three-cluster	case 7	ζ	ξ	η	−	−	−

$$x_1^* = \frac{Q_1}{kQ_3} \quad (33)$$

$$x_2^* = \frac{Q_2}{kQ_3}, \quad (34)$$

where

$$Q_1(\zeta, D) = g_{12} - g_{22} - \zeta k D \quad (35)$$

$$Q_2(\xi, D) = g_{21} - g_{11} - \xi k D \quad (36)$$

$$Q_3(\zeta, \xi, D) = 1 - \zeta D - \xi D \quad (37)$$

$$Q_4(\zeta, \xi) = \zeta(g_{21} - g_{11}) - \xi(g_{12} - g_{22}), \quad (38)$$

where the following condition is satisfied for the above equations.

$$Q_1 + Q_2 = kQ_3 \quad (39)$$

$$\zeta Q_2 - \xi Q_1 = kQ_4 \quad (40)$$

With $0 \leq {}^j x_i \leq 1$ and $0 \leq \langle {}^j x_i \rangle \leq 1$,

$$0 \leq \frac{Q_1 + Q_4}{kQ_3}, \frac{Q_2 - Q_4}{kQ_3} \leq 1 \quad (41)$$

$$0 \leq \frac{Q_1}{kQ_3}, \frac{Q_2}{kQ_3} \leq 1 \quad (42)$$

We conduct stability analysis with particular emphasis on the time evolution of ${}^j x_1$ with Test Unit Analysis [21] because ${}^j x_1 + {}^j x_2 = 1$. Let J_1, J_2, and J_3 be a Jacobian in the neighborhood of fixed points $(1, 0)$, $(0, 1)$, and $({}^j x_1^*, {}^j x_2^*)$.

$$J_1 = \frac{(1 - D)Q_2}{Q_3} \quad (43)$$

$$J_2 = \frac{(1 - D)Q_1}{Q_3} \quad (44)$$

$$J_3 = -\frac{(1 - D)Q_1 Q_2}{kQ_3^2}. \quad (45)$$

where $\langle \cdot \rangle$ is ${}^j x_i^*$-independent because n is assumed to be large. It is assumed that all strategy frequency is on one of the fixed points, as described above.

Hereinafter, the region guarantees linear stability of D, ζ, ξ, and η with Eqs. (29), (30), (43), (44), and (45) in one-cluster states, two-cluster states, and three-cluster states. Cluster conditions are summarized in **Table 1.** Linear stability conditions of each case from 1 to 7 are obtained with a Jacobian. Let Reg.$_1$, Reg.$_2$, and Reg.$_3$ be regions of D, ζ, ξ, and η that satisfy stability conditions of one-cluster states, two-cluster states, and three-cluster states, respectively.

For a one-cluster state, all ${}^jx_i$ converges at one fixed point. With Eqs. (15) and (16), we have ${}^jf_i = {}^jp_i$. In case 1, $(\zeta,\xi,\eta) = (1,0,0)$ and $({}^jx_1, {}^jx_2) = (1,0)$ must be satisfied. $J_1 = g_{21} - g_{11}$ are derived by substituting Eqs. (36) and (37) into Eq. (43). With condition Eq. (25), $J_1 > 0$, so a one-cluster state satisfying case 1 does not exist. In case 2, $(\zeta,\xi,\eta) = (0,1,0)$ and $({}^jx_1, {}^jx_2) = (0,1)$ must be satisfied. $J_2 = g_{12} - g_{22}$ are derived by substituting Eqs. (35) and (37) into Eq. (44). With condition Eq. (24), $J_2 > 0$, so the one-cluster state satisfies case 2 does not exist. In case 3, $(\zeta,\xi,\eta) = (0,0,1)$ and $({}^jx_1, {}^jx_2) = ({}^jx_1^*, {}^jx_2^*) = ({}^jx_1', {}^jx_2')$ must be satisfied. $J_1 = g_{21} - g_{11}$ are derived by substituting Eqs. (36) and (37) into Eq. (43) and $J_2 = g_{12} - g_{22}$ are derived by substituting Eqs. (35) and (37) into Eq. (44). With condition Eq. (25), $J_1 > 0$ and with condition Eq. (24), $J_2 > 0$ at any D. $Q_1 = g_{12} - g_{22}$ and $Q_2 = g_{21} - g_{11}$ when $(\zeta,\xi,\eta) = (0,0,1)$. With conditions Eqs. (24) and (25), $J_3 < 0$ is satisfied at only $D < 1$, so the one-cluster state satisfies case 3 exist with those conditions. Reg.$_1$ satisfying conditions of case 1, 2, and 3 above is summarized as follows:

$$\text{Reg.}_1 = \{(\zeta,\xi,\eta) = (0,0,1), D < 1\}. \quad \quad (46)$$

For a two-cluster state, all ${}^jx_i$ converges to one of two kinds of fixed points. In cases 4 and 5, J_1 and J_2 must mutually satisfy opposite signs. However, $J_1J_2 = (1-D)^2\frac{Q_1}{Q_3}\frac{Q_2}{Q_3} > 0$ because of condition Eq. (42) and $k > 0$, so the two-cluster state satisfies case 4 and 5 does not exist. In case 6, $(\zeta,\xi,\eta) = (\zeta,\xi,0)$ and $\zeta + \xi = 1$ must be satisfied. Then, $Q_1 = 1 - D$ because of $\zeta + \xi = 1$ and $J_1 = Q_2, J_2 = Q_1$, and $J_3 = -\frac{Q_1Q_2}{1-D}$, so the two-cluster state satisfying case 6 exists when $Q_1, Q_2 < 0$ and $1 - D < 0$. Reg.$_2$ satisfying the above conditions of case 4, 5, and 6 is summarized as follows:

$$\text{Reg.}_2 = \{\zeta + \xi = 1, \eta = 0, \\ Q_1 < 0, Q_2 < 0, D > 1,\}. \quad \quad (47)$$

For a three-cluster state, all ${}^jx_i$ converge to one of three fixed points. In case 7, $J_1 < 0$, $J_2 < 0$ and $J_3 < 0$ must be satisfied. However, no region satisfying the above conditions exist. Reg.$_3$ satisfying the above conditions for case 7 is empty set:

$$\text{Reg.}_3 = \{\emptyset\}. \quad \quad (48)$$

To summarize, at $1 - D < 0$ $(1 - D > 0)$, the system organizes a heterogeneous (homogeneous) state.

4.3. Fitness Analysis

Focusing an increasing and decreasing of group mean fitness $\langle {}^j\phi \rangle$, we proof below that conditions for increasing $\langle {}^j\phi \rangle$ correspond to stable regions of the homogeneous or heterogeneous state provided in the previous section. Our proposed algorithm realizes adaptive division of labor.

Group mean fitness is determined as following with ζ, ξ, η, D using self-consistent analysis:

$$\begin{aligned}\langle {}^j\phi \rangle = {} & \zeta\,(1\cdot f_1(1) + 0\cdot f_2(0)) \\ & +\xi\,(0\cdot f_1(0) + 1\cdot f_2(1)) \\ & +\eta\,(x_1^*\cdot f_1(x_1^*) + x_2^*\cdot f_2(x_2^*)). \quad \quad (49)\end{aligned}$$

Here,

$$\begin{aligned}(1-D)x_1^* + D\langle x_1 \rangle &= \frac{Q_1 + DQ_4}{PQ_3} \\ &= \frac{g_{12} - g_{22}}{k} \\ &= x_1' \quad \quad (50)\end{aligned}$$

$$\begin{aligned}(1-D)x_2^* + D\langle x_2 \rangle &= \frac{Q_2 - DQ_4}{PQ_3} \\ &= \frac{g_{21} - g_{11}}{k} \\ &= x_2', \quad \quad (51)\end{aligned}$$

we have

$$\begin{aligned}x_1^*f_1^* + x_2^*f_2^* &= \frac{g_{12}g_{21} - g_{11}g_{22}}{k}, \\ &= \phi' \quad \quad (52)\end{aligned}$$

and

$$\begin{aligned}f_1(1) - \frac{g_{12}g_{21} - g_{11}g_{22}}{k} &= -(g_{12} - g_{11})\left(1 - D - x_1' + D\langle x_1 \rangle\right) \\ &= -(g_{12} - g_{11})\left(x_2' - D\langle x_2 \rangle\right) \\ &= -(g_{12} - g_{11})\left(\frac{g_{21} - g_{11}}{k} - D\frac{Q_3 - Q_4}{kQ_1}\right) \\ &= -(g_{12} - g_{11})\frac{Q_3(Q_1 - D(1 - \zeta - \xi))}{kQ_1} \\ &= -(g_{12} - g_{11})\frac{(1-D)Q_3}{kQ_1} \\ &= -x_1'J_1 \quad \quad (53)\end{aligned}$$

$$\begin{aligned}f_2(1) - \frac{g_{12}g_{21} - g_{11}g_{22}}{k} &= -(g_{21} - g_{22})\left(1 - D - x_2' + D\langle x_2 \rangle\right) \\ &= -(g_{21} - g_{22})\left(x_1' - D\langle x_1 \rangle\right) \\ &= -(g_{21} - g_{22})\left(\frac{g_{12} - g_{22}}{k} - D\frac{Q_2 + Q_4}{kQ_1}\right) \\ &= -(g_{21} - g_{22})\frac{Q_2(Q_1 - D(1 - \zeta - \xi))}{kQ_1} \\ &= -(g_{21} - g_{22})\frac{(1-D)Q_2}{kQ_1} \\ &= -x_2'J_2 \quad \quad (54)\end{aligned}$$

Substituting Eqs. (52), (53), (54) in Eq. (49), we have the following simple relationship:

$$\langle {}^j\phi \rangle = \phi' - \zeta x_1' J_1 - \xi x_2' J_2. \quad \ldots \ldots \ldots (55)$$

The first term on the right side in Eq. (55) is a value depending on ${}^jG$, not ζ, ξ, η, and D. When $J_1 > 0$ and $J_2 > 0$, in this case $D < 1$ is satisfied, $\langle {}^j\phi \rangle$ decreases with ζ or ξ increases, so $\langle {}^j\phi \rangle$ become maximum with $\zeta = 0$ and $\xi = 0$. These conditions correspond to Reg.$_1$. When $J_1 < 0$ and $J_2 < 0$, in this case $D > 1$ and $Q_1 < 0$, $Q_2 < 0$ are satisfied, $\langle {}^j\phi \rangle$ increases with ζ or ξ increases because the second and third terms on the right side in Eq. (55) become positive. These conditions correspond to Reg.$_2$, indicating that the group state organized through the division dynamics provided by previous analysis with adaptively division of labor in two-dimensional labor.

5. Simulation Results

5.1. Simulation Setup

This section demonstrates the effectiveness of our proposed algorithm through computer simulation. A robot must make a determination based on the ratio of the amount of foods. When a robot interacts with other robots, during Δt, their fitness is exchanged with rules of Eq. (8). Concretely, robots exchange the amount in unit time of food. Variable values are calculated using the Euler method with $\Delta t = 0.001$ iteration.

5.2. Evaluation of Differentiation

5.2.1. Simulation Description

The basic property of differentiation organization is evaluated in fixed condition $m = 2$ and $n = 10$. The amounts of food in working space is defined as $(C_1 : C_2) = (7:3)$. To examine the relationship between the differentiation property and contact frequency, α, i.e., the amount of that a robot exchange foods to be assimilated per interaction, is changed dynamically based on equation Eq. (56) with initial value $\alpha = 0$ (cf., **Fig. 4(d)**).

$$\frac{d\alpha}{dt} = \begin{cases} 0.002, & 0 \le t < 50 \\ -0.002, & 50 \le t \le 100 \end{cases} \quad \ldots\ldots (56)$$

Through this simulation, the time evolutions of strategy frequency, and group mean fitness are evaluated during $0 \le t \le 100$.

5.2.2. Results

In simulation results, **Figs. 4(a)**, **(b)**, and **(c)** show the time evolution of ${}^jx_1$, ${}^jx_2$, and $\langle {}^j\phi \rangle$, respectively. **Figs. 5(a)**, **(b)**, **(c)**, and **(d)** described the time evolutions of ${}^jf_1$, ${}^jf_2$, ${}^jh_1$, and ${}^jh_2$, respectively. On those figure, dot means the values for each j. At $t = 50$, a robot group organizes a heterogeneous state and is separated into two groups. One group with ${}^jx_1 > 0.9$ where averages are described by solid lines and another group by ${}^jx_2 > 0.9$ where averages are described by dotted lines.

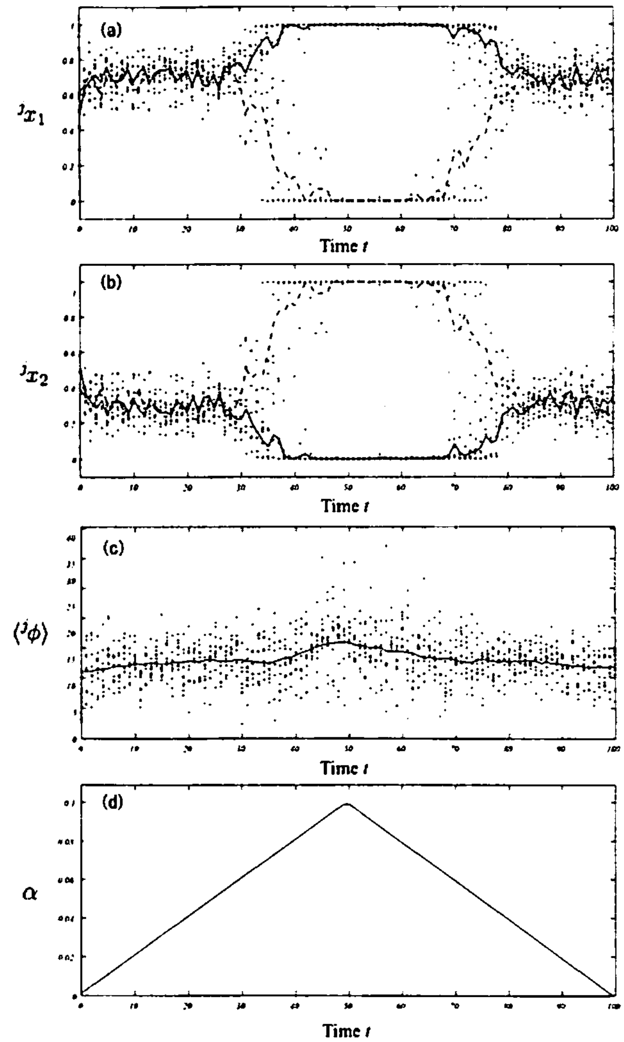

Fig. 4. Simulation result: evaluation of differentiation. Time evolution of ${}^jx_1$, ${}^jx_2$, and $\langle {}^j\phi \rangle$.

The system organized a homogeneous state at $\alpha < 0.05$ and heterogeneous around $\alpha > 0.05$. With the continuous changes of α, the strategies frequency is discontinuously selected. In the homogeneous state, strategy frequency converges at $({}^jx_1, {}^jx_2) = (0.7, 0, 3)$. In the heterogeneous state, the strategies frequency converges at $({}^jx_1, {}^jx_2) = (1, 0)$ or $({}^jx_1, {}^jx_2) = (0, 1)$ and the ratio of the number of robots is 7 : 3. Group mean fitness increases in the case of heterogeneous state as show in **Fig. 4(c)**. The adaptability is evaluated in the next subsection in detail. With **Figs. 5(a)** and **(b)**, ${}^jf_1$, ${}^jf_2$, that is foods to be assimilated, transit to the specialized labor. It is understood that the labors are efficiently carried out by specialized strategy frequencies.

In the homogeneous state, ${}^jh_i$ is almost 0, meaning that no interactions occur between robots as show in **Fig. 5(c)** and **(d)**. Although robots organize the homogeneous state, ${}^jh_i$ does not exactly converge at 0 because the robot's states have a small amount of fluctuations since interactions between robots include uncertainties. The strat-

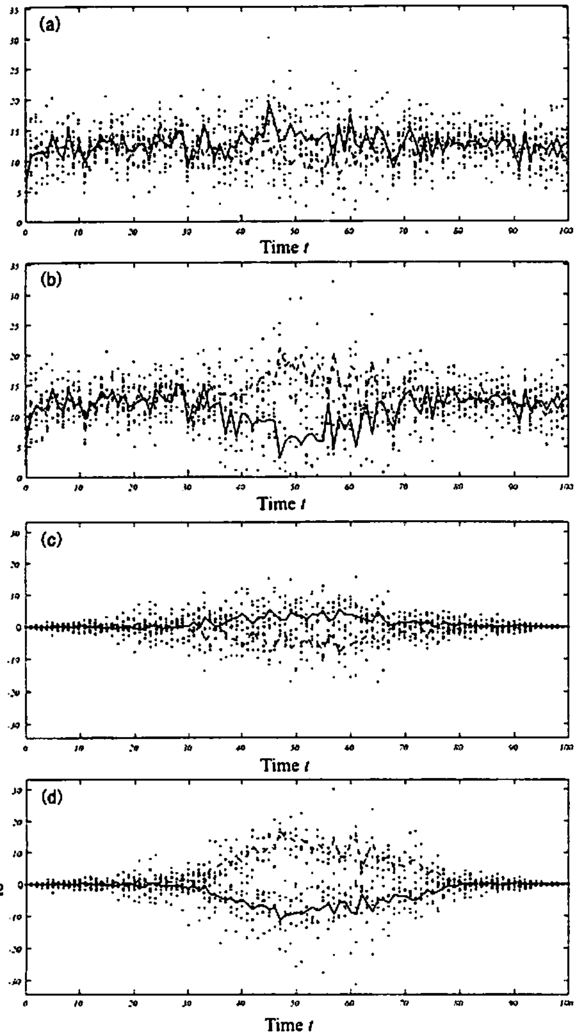

Fig. 5. Simulation result: evaluation of differentiation. Time evolution of $^jf_1$, $^jf_2$, $^jh_1$, and $^jh_2$.

egy frequencies infectiously have fluctuation. The fluctuations is proportional to α according to definition by Eq. (8). If the fluctuations positively amplify through interactions between robots, then the state transits from homogeneous to heterogeneous [22]. Thus adaptive division of labor is driven by the phase transition.

In the heterogeneous state, the flow of foods between robots is contrastingly generated. These result indicates that the specialization strategy frequency and flow of food are generated by efficient desymmetrization.

5.3. Collective Robustness and Performance Improvement

5.3.1. Simulation Description

We confirm that evaluated value, strategy frequency ^jx_i, and group mean fitness $\langle ^j\phi \rangle$ change when division is organized or disorganized. This simulation evaluates performance improvement and homeostasis of the homogeneous or heterogeneous state. To compare $\langle ^j\phi \rangle$ in homogeneous and heterogeneous states, α is fixed at 0 or 0.1 by referencing previous subsection results. In addition, to evaluate the adaptively division of labor, that means $\langle ^j\phi \rangle$ increasing, each ^jx_i are fixed under the **Table 2**. All of another simulation conditions are same as previous simulation conditions. In Term1,2,3,5,7,8, the normal simulation is carried out, and at $\alpha = 0$ or 0.1, the homogeneous or heterogeneous state is selected. In Term4, each ^jx_i is fixed to the values of the end of Term3 with only setting $\alpha = 0$. Strategy frequency is forcibly specialized to heterogeneous state even though without interactions. In Term6, on the contrary, each ^jx_i are fixed to the values of the end of Term5 with only setting $\alpha = 0.1$. In this case, the group state is forcibly homogeneous state even though robots can interact. With the results of Term4 and Term6, the adaptively division of labor is evaluated by group mean fitness increasing and decreasing. In Term9, the strategy frequency is instantaneously fixed at $(^jx_1, ^jx_2) = (0, 1)$ at the beginning of the term $t = 80$. In Term10, on the contrary, strategy frequency is instantaneously fixed at $(^jx_1, ^jx_2) = (1, 0)$ at the beginning of the term $t = 90$. In ordinary circumstances, the group state converge to heterogeneous because of $\alpha = 0.1$. Through these operations, regarded as environmental disturbances, the stability and homeostatic properties of division rate are evaluated.

Table 2. Simulation condition.

Term	t	α	$(^jx_1, ^jx_2)$
Term1	$0 \le t < 10$	0	not fixed
Term2	$10 \le t < 20$	0.1	not fixed
Term3	$20 \le t < 30$	0.1	not fixed
Term4	$30 \le t < 40$	0	fixed to hetero. state
Term5	$40 \le t < 50$	0	not fixed
Term6	$50 \le t < 60$	0.1	fixed to homo. state
Term7	$60 \le t < 70$	0.0	not fixed
Term8	$70 \le t < 80$	0.1	not fixed
Term9	$80 \le t < 90$	0.1	fixed to $(0,1)$ at $t = 80$
Term10	$90 \le t \le 100$	0.1	fixed to $(1,0)$ at $t = 90$

5.3.2. Results

Figures 6(a) and **(b)** show the time evolution of $^jx_1$ and $^jx_2$ simulated based on the condition **Table 2. Fig. 6(c)** shows the average of $\langle ^j\phi \rangle$ during each term. A comparison of the Term4 and Term5 shows that group mean fitness $\langle ^j\phi \rangle$ in the Term4; the division is forcibly organized in this term, and remains low against the evaluated value in Term5, indicating the effectiveness of the roles of ^jh_i. This compression indicates that robots cannot improve group performance with division that is not organized by appropriate interaction. The performance decreasing is also obvious from Eq. (55). Without the forcible heterogeneous state, homogeneous state is ordinary selected. Then, the Jacobian of the second and third terms in the right side of the equation must be positive, the group mean fitness decrease because of $\zeta > 0$ and $\xi > 0$,

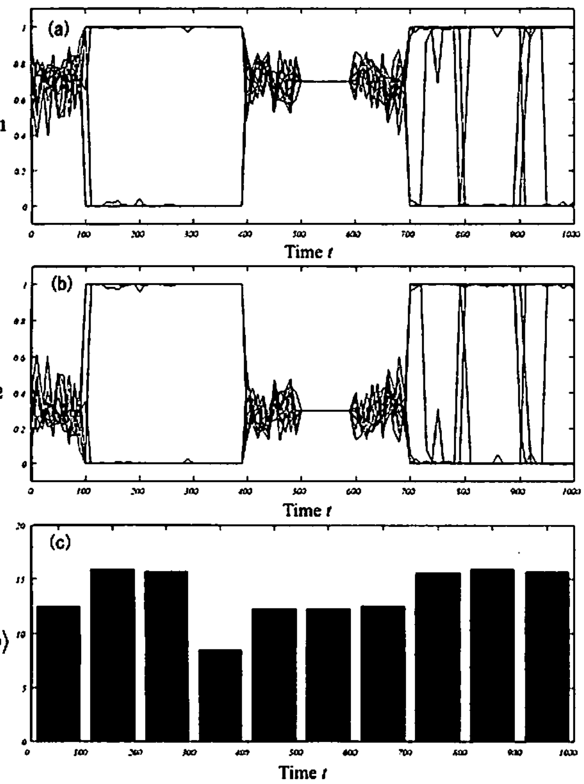

Fig. 6. Simulation result: convergence property for environmental disturbance.

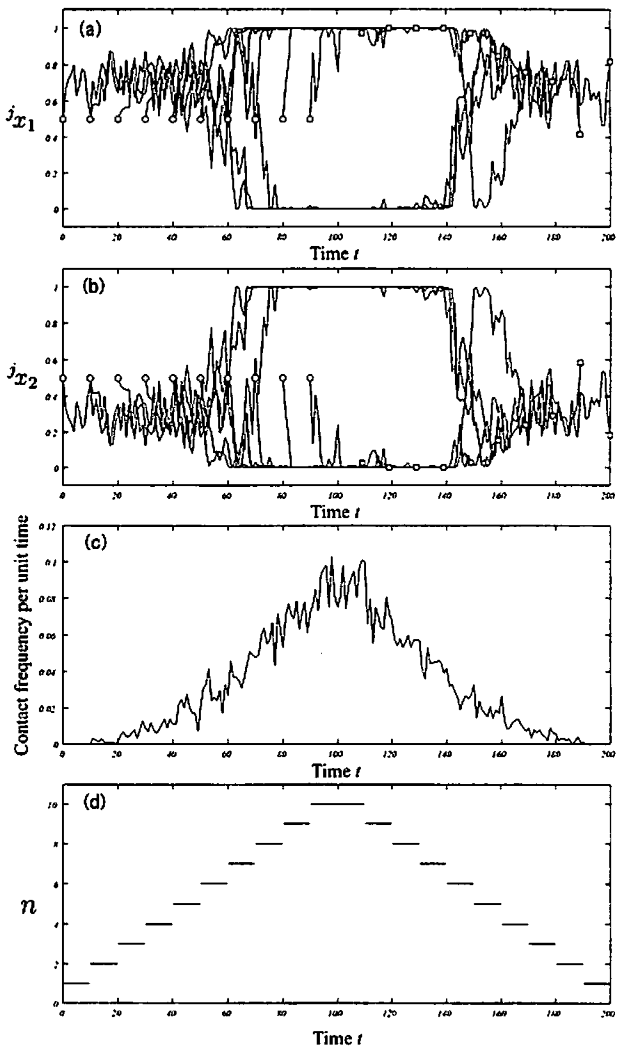

Fig. 7. Simulation result: convergence property for variances of the number of robots.

which means the heterogeneous state.

Comparing Term3 and Term6 shows that, for the evaluated value in Term6, the division is forcibly disorganized in this term, and also remains low against the value evaluated in the Term3. This comparison indicates the improvement of performances with division. To explain using Eq. (55), without the forcible homogeneous state, heterogeneous state is ordinary selected. Then, the Jacobian of the second and third terms in the right side of the equation must be negative, the group mean fitness cannot increase with $\zeta = 0$, $\xi = 0$, which means the homogeneous state. These two comparisons of results suggest that the proposed algorithm has functions that are not only self-organized state but also adaptive division of labor.

In Term8 where the state is heterogeneous, it is observed that strategy frequencies are fluctuated. This is caused by a spatial bias of robots distribution in working space. When the density of robots distribution become high (low), a force for heterogeneous (homogeneous) is generated because interaction frequencies between robots are high (low).

At $t = 80$ and $t = 90$, all $({}^jx_1, {}^jx_2)$ is set to $(0,1)$ and $(1,0)$ is used as an assumption of some accidents in Term8 and Term9 such as breakdown robot. Robots can recover and organize the ratio of division as it was before. This result confirms the adequacy of the stability analysis; the algorithm has a homeostatic property. It is considered that the roles of ${}^jh_i$ is not only exchange the foods to be assimilated but also order formation of heterogeneous state and regulation of division rate.

5.4. Scalability of Robot Number

5.4.1. Simulation Description

We demonstrate the scalability of the number of robots with $m = 2$ and $\alpha = 0.1$. All other conditions are the same as the simulation in above, except for n changes from 1 to 10. The j-th robot carry out the labors during $20(j-1) \leq t \leq 20(11-j)$ in the working space (cf., **Fig. 7(d)**). When the robot is put randomly into the working space, the strategy frequency is initialized as $({}^jx_1, {}^jx_2) = (0.5, 0.5)$. This simulation indicates that the division of labor can be implemented with the scalability of the number of robots, and depends on contact frequency.

5.4.2. Results

Figures 7(a) and **(b)** shows the time evolution of ${}^jx_1$ and ${}^jx_2$, respectively. White circles and white squares indicate values $({}^jx_1, {}^jx_2)$ when the robot is put into and picked up from working space, respectively. **Fig. 7(c)** shows the time evolution of summation of contact frequency per time. The contact frequencies increase (decrease) according to increasing (decreasing) the number for robot on working space. When, $n \geq 7$, the heterogeneous state is organized because it is considered that the spatial density of robots increases satisfying enough interaction for division. At $t = 70$, $t = 80$, $t = 90$, and $t = 100$, the number of robots where strategy frequencies satisfy $({}^jx_1 > 0.9, {}^jx_2 > 0.9)$ are respectively $(5,2)$, $(5,3)$, $(6,3)$, and $(7,3)$. And at $t = 110$, $t = 120$, $t = 130$, and $t = 140$, this is respectively $(7,3)$, $(6,3)$, $(5,3)$, and $(4,3)$. The ratio of division converges at $(7:3)$ around $n = 10$, however, that does not exactly converge at $(7:3)$ because the system has hysteresis with changes of the number of robots.

This result is just straightforward, however, indicates the asset effectiveness because proposed algorithm is operated with contact frequency. This is one of the reason that the adaptive division of labor is achieved with local interaction. When α is determined, the group state is selected autonomously and driven to either a homogeneous or heterogeneous state.

5.5. Application to High-Dimensional Labor

5.5.1. Simulation Description

In previous sections and mathematical analysis in section 4, simulation used $m = 2$. We evaluated the simulation for $m = 4$ and $n = 10$. The amount of foods is defined as $(C_1 : C_2 : C_3 : C_4) = (4:3:2:1)$. As same as the conditions of section 5.2, the transitions of strategy frequency is evaluated with α satisfy Eq. (56) and initializing at $\alpha = 0$ (cf., **Fig. 4(d)**) during $0 \leq t \leq 100$.

5.5.2. Results

Figures 8(a), **(b)**, **(c)**, and **(d)** show the the time evolutions of ${}^jx_1$, ${}^jx_2$, ${}^jx_3$, and ${}^jx_4$. With these results, in even several labors, the homogeneous or heterogeneous state is selected. The strategy frequency of each robot are discontinuously and synchronously organized. In homogeneous state, the strategy frequency converges to around $({}^jx_1 : {}^jx_2 : {}^jx_3 : {}^jx_4) = (0.29 : 0.27 : 0.22 : 0.20)$. This ratio is different from the task ratio, $(4:3:2:1)$, therefore, the optimality is not guaranteed in the event. The one of the reason is that the fitness matrix was not adequate. To solve this problem, the asymmetric components of fitness matrix in Eq. (3) are expected to be adequately designed.

This also indicates the division of labor is organized at $\alpha = 0.05$. In a heterogeneous state, the ratio of numbers of robots converges to $({}^jx_1, {}^jx_2, {}^jx_3, {}^jx_4) = (1,0,0,0)$, $({}^jx_1, {}^jx_2, {}^jx_3, {}^jx_4) = (0,1,0,0)$, $({}^jx_1, {}^jx_2, {}^jx_3, {}^jx_4) = (0,0,1,0)$, and $({}^jx_1, {}^jx_2, {}^jx_3, {}^jx_4) = (0,0,0,1)$ is $(2,2,3,3)$. It is however that, this ratio is different from each simulations. It is considered that the effect of fluctuations caused by robot's behaviors is no longer ignored. When the fluctuations increase, the convergence is reduced.

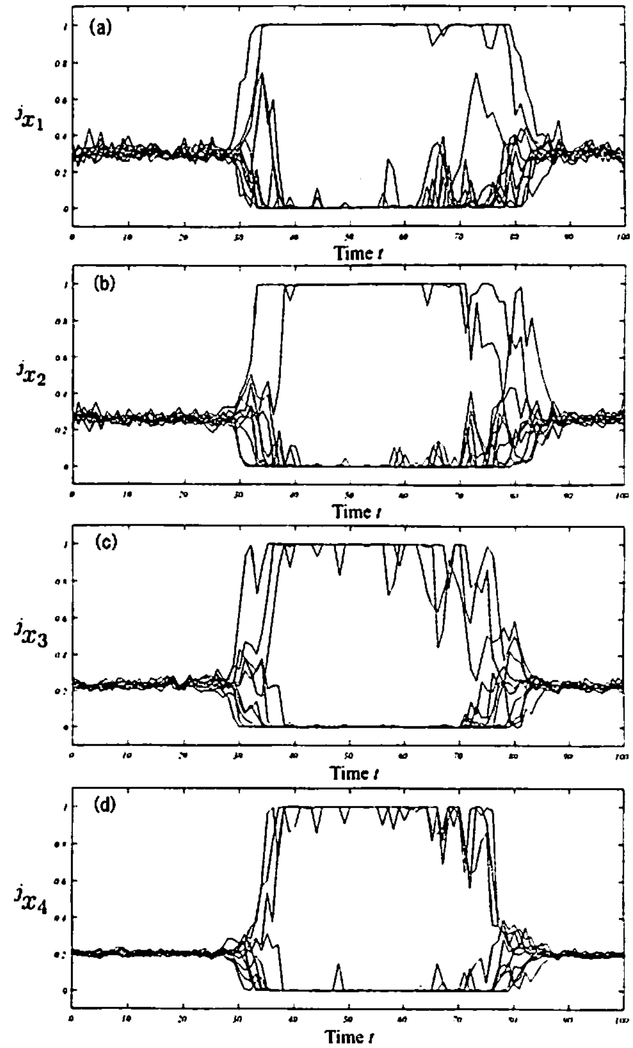

Fig. 8. Simulation result: application to high-dimensional labor.

6. Discussion and Conclusions

The theoretical result presented by Eq. (55) provides information useful to understand the adaptively and the performance improvement in the division of labor. In the proposed algorithm, the division of labor is controlled through the phase transition, which guarantees the group performance improvement. The interactions are simple, but the adaptive division of labor is realized. The determination of whether a state of stabilization or destabilization pertains is described by the Jacobian shown in Eq. (55). Its positive and negative values are directly linked to group fitness improvement. The controlled state, at least the problem of homogeneity or heterogeneity, already satisfies the condition of group performance improvement.

We proposed an adaptive division of labor for robot group, and it was found through theoretical analyses that the group performance is certainly improved in the two-dimensional labor case, and that the dynamical behavior of both robots and group states is observed through computer simulations. We now plan to mathematically analyze of three or more dimensional division-of-labor method, and experiments using real robots.

Acknowledgements

This work was supported by a Grant-in-Aid for Scientific Research on Priority Areas No.454 and a Grant-in-Aid for Young Scientists (B) No.22760289 from the Japanese Ministry of Education, Culture, Sports, Science, and Technology.

References:

[1] S. Garnier, J. Gautrais, and G. Theraulaz, "The biological principles of swarm intelligence," Swarm Intelligence, Vol.1, No.1, pp. 3-31, 2007.

[2] M. Tan, "Multi-agent reinforcement learning: Independent vs. cooperative agents," In Int. Conf. on Machine Learning ICML, Amherst, MA, 1993.

[3] M. V. N. Prasad, V. R. Lesser, and S. E. Lander, "Learning organizational roles in a heterogeneous multi-agent system," Proc. of the Second Int. Conf. on Multiagent Systems, Kyoto, Japan, AAAI Press, 1996.

[4] K. Takadama, S. Nakasuka, and T. Terano, "Multiagent Reinforcement Learning with Organizational-learning Oriented Classifier System," IEEE Int. Conf. on Evolutionary Computation, pp. 63-68, 1998.

[5] T. Yasuda and K. Ohkura, "Autonomous Role Assignment in a Homogeneous Multi-Robot System," J. of Robotics and Mechatronics, Vol.17, No.5, pp. 596-604, 2005.

[6] E. O. Wilson, "Sociobiology: The New Synthesis," Cambridge, MA: Harvard, University Press, 2000.

[7] S. N. Beshers and J. H. Fewell, "Models of division of labor in social insects. Annual Review of Entomology," Vol.46, No.1, pp. 413-440, 2001.

[8] E. Bonabeau, G. Theraulaz, and J. L. Deneubourg, "Fixed response thresholds and the regulation of division of labour in insect societies," Bulletin of Mathematical Biology, Vol.60, pp. 753-807, 1998.

[9] G. Theraulaz, J. Gervet, and S. Semenoff, "Social regulation of foraging activities in Polistes dominulus Christ: a systemic approach to behavioural organization," Behaviour, Vol.116, pp. 292-320, 1991.

[10] G. Theraulaz, E. Bonabeau, and J. L. Deneubourg, "Response threshold reinforcements and division of labour in insect societies," Proc. of the Royal Society of London. Vol.B265, pp. 327-332. 1998.

[11] Z.-Y. Huang, G. E. Robinson, S. S. Tobe, and K. J. Yagi, "Hormonal regulation of behavioural development in the honey bee is based on changes in the rate of juvenile hormone biosynthesis," J. of Insect Physiology. Vol.37, pp. 733-41, 1991.

[12] D. Naug and R. Gadagkar, "Flexible division of labor mediated by social interactions in an insect colony: a simulation model," J. of Theoretical Biology, Vol.97, pp. 123-33, 1999.

[13] Y. Ikemoto, T. Miura, and H. Asama, "Adaptive Division of Labor Control for Robot Group," In The Int. Conf. on Intelligent Robots and Systems 2009(IROS2009), pp. 2409-2414, 2009.

[14] S. Shahshahni, "A new mathematical framework. for the study of linkage and selection," Memoirs of the American Mathematical Society, Vol.17, No.211, Jan. 1979.

[15] K. Sigmund, "The Maximum Principle for Replicator Equations, Lotka-Volterra Approach to Dynamical Systems," M. Peschel, edit., Berlin Akademie Verlag, pp. 63-71, 1985.

[16] E. Akin, "The differential geometry of population genetics and evolutionary games," In Lessard, S., editor, Kluwer, Dordrecht, Mathematical and Statistical Developments of Evolutionary Theory, pp. 1-93, 1990.

[17] P. Schuster and K. Sigmund, "Replicator Dynamics," J. of Theoretical Biology. Vol.100, pp. 533-538, 1983.

[18] J. M. Smith, "Evolution and the Theory of Games," Cambridge University Press, 1982.

[19] R. Horie and E. Aiyoshi, "Variable metric gradient projection method and replicator equation," Proc. of IEEE Int. Conf. on Systems, Man, and Cybernetics, Vol.3, pp. 515-520, 1999.

[20] J. Hofbauer and K. Sigmund, "Evo. Games and Pop. Dynamics," Cambridge University Press, 1998.

[21] T. Mizuguchi and M. Sano, "Proportion Regulation of Biological Cells in Globally Coupled Nonlinear Systems," Physical Review Letters, Vol.75, pp. 966-969, 1995.

[22] S. Camazine, N. R. Franks, J. Sneyd, E. Bonabeau, and J. L. Deneubourg, "Self-Organization in Biological Systems," Princeton Univ. Press, 2003. ISBN 0691116245.

Name:
Yusuke Ikemoto

Affiliation:
Graduate School of Science and Engineering for Research, University of Toyama

Address:
3190 Gofuku, Toyama, 930-8555, Japan

Brief Biographical History:

2006- Post-Doctoral Fellow, RACE (Research into Artifacts, Center for Engineering), The University of Tokyo

2009- Post-Doctoral Fellow, Department of Precision Engineering, School of Engineering, The University of Tokyo

2010- Assistant Professor, Graduate School of Science and Engineering for Research, University of Toyama

Main Works:

- Y. Ikemoto, Y. Ishikawa, T. Miura, and H. Asama, "A mathematical model for caste differentiation in termite colonies (Isoptera) by hormonal and pheromonal regulations," Sociobiology Vol.54, pp. 841-859, 2009.
- Y. Ikemoto, Y. Hasegawa, T. Fukuda, and K. Matsuda, "Gradual Spatial Pattern Formation of Homogeneous Robot Group," The Int. J. of Information Sciences, Vol.171, No.4, pp. 431-445, 2005.

Membership in Academic Societies:

- Society of Evolutionary Studies, Japan (SES)

Name:
Toru Miura

Affiliation:
Graduate School of Environmental Science, Hokkaido University

Address:
N10 W5, Kita-ku, Sapporo, Hokkaido 060-0810, Japan

Brief Biographical History:
1999- JSPS Postdoctoral Fellow
2000- Assistant Professor, Graduate School of Arts and Sciences, University of Tokyo
2004- Associate Professor, Graduate School of Environmental Science, Hokkaido University

Main Works:
- T. Miura, "Developmental regulation of caste-specific characters in social-insect polyphenism," Evolution & Development, Vol.7, pp. 122-129, 2005.
- C. Braendle, T. Miura, R. Bickel, A. W. Shingleton, S. Kambhampati, and D. L. Stern, "Developmental origin and evolution of bacteriocytes in the aphid-Buchnera symbiosis," PLoS Biology, Vol.1, pp. 70-76, 2003.
- T. Miura, A. Kamikouchi, M. Sawata, H. Takeuchi, S. Natori, T. Kubo, and T. Matsumoto, "Soldier caste-specific gene expression in the mandibular glands of Hodotermopsis japonica (Isoptera: Termopsidae)," Proc. of the National Academy of Sciences, USA, Vol.96, pp. 13874-13879, 1999.

Membership in Academic Societies:
- The Society for the Study of Evolution (SSE)
- International Union for the Study of Social Insects (IUSSI)
- Society of Evolutionary Studies, Japan (SES)
- The Zoological Society of Japan (ZSJ)
- Ecological Society of Japan (ESJ)
- The Entomological Society of Japan (ENTSOCJ)
- The Molecular Biology Society of Japan (MBSJ)

Name:
Hajime Asama

Affiliation:
Department of Precision Engineering, School of Engineering, The University of Tokyo

Address:
7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan

Brief Biographical History:
1986- Research Associate of RIKEN (The Institute of Physical and Chemical Research)
1998- Professor, RACE (Research into Artifacts, Center for Engineering), The University of Tokyo
2002- Professor, Department of Precision Engineering, School of Engineering, The University of Tokyo

Main Works:
- D. Chugo, K. Kawabata, H. Kaetsu, H. Asama, and T. Mishima, "Omni-directional Vehicle Control Based on Body Configuration," Industrial Robot, Vol.36, No.5, pp. 461-468, 2009.

Membership in Academic Societies:
- Institute of Electrical and Electronics Engineers, Inc. (IEEE)
- The Japan Society of Mechanical Engineers (JSME)
- The Robotics Society of Japan (RSJ)
- The Japanese Society of Instrumentation and Control Engineers (SICE)

an Article from

Journal of Robotics and Mechatronics

4F Toranomon Sangyo Bldg., 2-29, Toranomon 1-chome, Minatoku, Tokyo 105-0001, Japan
Tel. +813-3508-0051, Fax: +813-3592-0648, E-mail: robot@fujipress.jp
homepage URL: http://www.fujipress.jp/JRM/