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Collective Alteration of Strategic Types

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Abstract

This paper describes a model of the collective alteration of strategic types and reports on the results of two simulations based on the model. In the model, we assume that autonomous robots pursue their own interests, calculate payoffs using recent information on the distribution of the population of choosing strategies, and decide their strategy based on these payoffs. Two simulations were conducted. One assumed global communication. The second assumed local communication. Collective decision making with global communication is affected by communication delays. That with local communication is affected by the way in which strategies are scattered within a group of robots.

1 Introduction

In response to the requirements of the real world, there has been a notable increase in the amount of study emphasizing the importance of adaptability and robustness. Study on emergent behavior is a typical example of such study (e.g. [Brooks 86, Maes 90, Steels 91]). Furthermore, as autonomous robots attract the attention of researchers, a concern over collective behavior or swarm intelligence has also been increasing. Deneubourg and Goss's work on ant-like robots [Deneubourg *et al.* 91], Beni and Hackwood's work on swarm intelligence [Beni and Hackwood 92], and Fukuda's work on cellular robotics [Fukuda *et al.* 90] are typical examples of such collective behavior.

Our current goal is to realize and investigate the dynamics of collective decision making by autonomous robots. In the dynamics, if a small number of robots change and fix their strategic type, then all the robots should change their strategic type. [1] Imagine a flock of birds or a school of fish. We can see that they collectively migrate from place to place. When an enemy, such as an eagle or a barracuda,

[1] Lynne Parker describes *motivational behavior* in the context of Brooks's subsumption architecture [Parker 93]. Motivational behaviors are intentional, and used by robots to control the emergence of their primitive behaviors. Decision making, based on the strategies in this paper is such a motivational behavior. Strategies can be grouped into types. Suppose the case of foraging robots. They can have multiple foraging strategies to search for food, and can also have multiple harvesting strategies to collect the discovered food. With only one strategy, the emergence of primitive behavior would be restricted.

comes toward them, they will scatter in fright. However, once the enemy leaves the area, they will again try to reform their previous group. If we view this example from the aspect of teamwork, we could say that each member is trying to choose the same strategic type as the rest of the group at any instant. In addition, we would like to say that this type of collective behavior is available since they have shared parameters that yield common worth.

This paper describes a model of collective alteration of strategic types and presents the results of two simulations: globally communicating robots and locally communicating robots. The first simulation was inspired by work on computational ecosystems by Huberman and Hogg [Huberman and Hogg 88]. They reported that communication delay and uncertainty of information introduces a variety of trajectories, including chaos, into the transient behavior for choosing a strategy. When a team of robots assumes an equilibrium, it is hard to break the state because of the restoration force. If we create a strong noise in a stable state, however, we could break the state. We, then, speculated about how to make robots create a noise voluntarily in response to stimuli from outside.

The second simulation was inspired by Beckers, Deneubourg, Goss, and Pasteels's work on food recruitment [Beckers *et al.* 90]. In a society of ants, ants can use direct but local, one-to-one communication such as *tandem-running* [2]. They also use an indirect communication device: *pheromone* [3]. These ways of communication are apparently different from the one we used in our simulation of globally communicating robots. Beckers et al., however, reported a phenomenon in food recruitment behavior in ant colonies that is very similar to what we made in [Numaoka and Takeuchi 93, Numaoka 93]. This report caught our attention and we decided to investigate if the model that we originally devised for globally communicating robots can still apply to locally communicating robots, with a slight modification.

The rest of this paper is organized as follows. In the next section, we describe the essence in a model of collective alteration of strategic type. In Section 3, we show the results of the two types of simulation and, in Section 4, we overview some related work. Finally, we conclude the paper in Section 5.

2 A Model of Collective Decision-Making Behavior

In [Numaoka and Takeuchi 93], we proposed a model of collective decision making behavior in which all robots change their strategic type when a relatively small number of the robots perceive a disadvantage in their current strategic type and change it. This model has two features. One is that every robot decides its current strategy based on its own interests. The other is that such robots can collectively choose one particular strategic type. In the rest of this section, we will explain these two features.

2.1 Self-interested behavior

Every robot determines its behavior based on its own interest. In our model, we assume that all the robots share a restricted set of primitive interests, that are

[2] The lead ant has recruited a follower to go with it to a food item too large for one ant to retrieve. (from pp.310 of [Alcock 89])

[3] Ants that have found prey lay a pheromone trail from the prey back to the nest, stimulating others to join them. (from pp.312 of [Alcock 89])

represented as *strategies.* To choose the favorite strategy, they use a payoff as an indicator to measure the worth of a strategy. In a given interval, the robots decide their strategy for any type based on the payoff calculated by a payoff function and distribute it to the environment. The range to which the information of the decision can reach depends on the case. In [Numaoka and Takeuchi 93, Numaoka 93], as a particular case, we assumed that the range is infinite. Namely, each robot can receive information from all the other robots with communication delay, regardless of its position.

The payoff function used by the robots is defined as follows:

$$P_i(\mathbf{n}(t)) = (U - \Gamma n_i(t))(P_0 + Cn_i(t)) - Dn_i(t) \sum_{j \notin type(i)} n_j(t), \tag{1}$$

where $n_i(t)$ is the number of robots taking the i-th strategy at time t and U, Γ, P_0, C, and D are positive parameters. *type(i)* is a function that returns the same set of strategies as the i-th strategy. The second term is introduced to represent the loss incurred in mixing different strategic types.

The interpretation of parameters U, Γ, P_0, C, and D fully depends on the application domain of the robot team that we need. Take a foraging team as an example. Robots have both foraging and harvesting strategies. In this case, U represents the utility of the strategy, Γ is the positive amount by which the payoff decreases as each additional robot adopts the strategy, P_0 is the payoff accrued in the absence of any cooperation, C is the extra benefit due to cooperation, and D is a coefficient to amplify the loss of mixing different strategic types. In every simulation we made, we gave the same set of parameters to every strategy of every robot.

For simplicity, we neglect any negative payoffs yielded by Equation (1). Thus, instead of Equation (1), the following payoff function, which replaces negative payoffs with a small positive constant value, is used:

$$P_i(\mathbf{n}(t)) = \max((U - \Gamma n_i(t))(P_0 + Cn_i(t)) - Dn_i(t) \sum_{j \notin type(i)} n_j(t), \quad P_{min}). \tag{2}$$

This payoff function has the following feature:

Proposition 2.1 *The payoff function defined in Equation (2) has multiple equilibrium states. Each equilibrium corresponds to one strategic type that is the only strategic type chosen in the equilibrium.*

2.2 Collective alteration of strategic types

Our primary goal is to show that a group of robots with multiple strategic types has dynamics such that a change in the strategic type in a small number of robots, in a special mode called *instigator*, causes the same change throughout the whole group. This implies, in the underlying dynamics, that a group of robots moves from one equilibrium to another by being triggered by the migration of a small number of robots. Such dynamics give powerful adaptability to a group of robots since even a small change in the environment, recognized by a small number of robots, can cause a global change in the strategic type.

Two important phenomena, at least, are required for collective change of the strategic type. They are:

1. serious change in the strategic types of the instigators, and

2. the widely acknowledged perception of the ineffectiveness of the current strategic type.

Neither of these can itself be the reason for causing a global change of strategic type, but, if these two are perceived simultaneously they constitute a good reason for global change.

To realize the first phenomenon, we introduce *instigator* mode robots, which keep choosing a strategy of a particular type no matter what payoffs they receive. Suppose that, in the environment, there is a change which the robots can sense and which, in the light of their current strategies, they perceive as being disadvantageous. Under such circumstances, robots enter the instigator mode. For example, in the case of a foraging team, if robots find a food source, they enter instigator mode by reducing Us of all foraging type strategies to 0 in Equation 2 while keeping the Us of all harvesting type strategies unchanged. The payoff to every foraging type strategy becomes P_{min}. This produces a great gap between foraging and harvesting strategies. As a result, almost no robots choose foraging strategies.

The second phenomenon is realized by a special signal issued by instigator mode robots and by a momentary reduction of parameter U of every strategy by all robots except for instigators. The robot entering instigator mode broadcasts a special signal. When a robot receives this signal, the robot reduces the value of U to every strategy as if the robot's capability of perceiving the real utility is atrophied, although we do not want to convince that this solution is realistic.

3 Simulations

Based on the model described above, we made two types of simulation. First, we simulated a group of robots with an assumption of global communication. This was reported in [Numaoka and Takeuchi 93]. In this paper, for comparison, we briefly describe an example to show the phenomenon that we want to realize. Second, we investigated the case of locally communicating robots. In both simulations, our purpose was to investigate the dynamics of the collective behavior of autonomous robots where multiple equilibrium states exist. Especially, we were interested in the case where partial behavior of the system eventually influences and changes the behavior of the total system.

For both simulations, we provided 200 simulated robots and two strategic types. One type has three strategies, while the other has two strategies. For convenience, we call the former *foraging* strategies and the latter *harvesting* strategies. In each interval, a robot gets the chosen strategy from other robots and tries to change its strategy at rate α, the *decision rate*. For simplicity, when the strategy changes, robots choose the i-th strategy with probability [4]:

$$\rho_i = \frac{P_i}{\sum_{j=1}^{M} P_j}, \quad {}^{5} \tag{3}$$

where M is the total number of strategies.

[4]In [Numaoka 93], I explain full details of a procedure that robots take for decision making.

[5]This probability has a normal distribution in proportion to payoffs. In Ceccatto and Huberman's work [Ceccatto and Huberman 89], on the other hand, the probability of choosing the next strategy involves a temperature-like parameter β. This actually corresponds to *certainty-ness*: perfect knowledge implies $\beta = \infty$ and maximal uncertainty is denoted by $\beta = 0$.

3.1 Globally communicating robots

Robots broadcast their current decision on strategy at given intervals. In this broadcasting, we presuppose the existence of a communication server that lies between robots and the communication server. The server has N queues if N robots exist, thus it can receive information from the i-th robot at the i-th queue. The communication server behaves as follows:

1. The server investigates whether it has received information from all robots or not. If not, it waits until the condition is satisfied.
2. When the server has gathered information from all robots, it sums up the number of robots for each strategy.
3. The server sends the information on the number of robots choosing every strategy to all the robots.

In our simulation, for simplicity, we assume that robots send information synchronously in a given interval and that the round-trip time between robots and the communication server is constant, which is τ time units. In this case, the communication server can get information from the queues in a given interval but with a certain communication delay.

Again, the dynamics that we want to realize is that in which all robots collectively change their strategic type in response to a change by the instigators. In [Numaoka and Takeuchi 93, Numaoka 93], we evaluated some aspects of this dynamics. One attractive study is to investigate the critical ratio of instigators needed to cause the dynamics. We determined in theory in [Numaoka and Takeuchi 93, Numaoka 93] that at least 14.4 % robots should be instigator to cause the desired phenomena. This has been confirmed by our simulation.

In terms of reducing utility, for simplicity, all robots use the following step function as parameter U in Equation 2:

$$U(t) = \begin{cases} \mathit{80} & \text{if } t_1 \leq t \leq t_2; \\ \mathit{200} & \text{otherwise,} \end{cases} \tag{4}$$

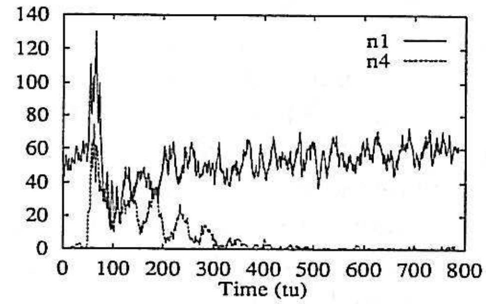
where t is 0 when the robot receives a special signal issued by any *instigator* robot.

To investigate this, we begin simulations with an initial distribution of 67, 67, 66, 0, and 0 to five strategies (the first three are foraging strategies and the remaining two are harvesting strategies). Namely, robots assume equilibrium for the foraging strategy. This state is assumed to have existed continuously for at least 50 time units. This is because we introduce a communication delay of 50 time units. The values of parameters C, Γ, P_0, and D are 0.1, 1.0, 0.2, and 0.1, respectively.

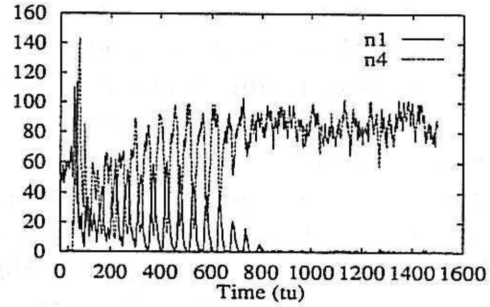
Figures 1 (a) and (b) show the cases for 27 and 28 instigators, respectively, where the communication delay is 50 time units, decision rate α is $\frac{1}{6}$, and t_1 and t_2 in Equation 4 are 20 and 120 time units (tu). It is clear from these figures that 28 instigators is the number required to indicate the boundary if global transition is to take place. The oscillation observed in Figure 1 (b) becomes sluggish and converges quickly as the number of instigators increases.

3.2 Locally communicating robots

In this case, we do not assume the existence of a communication server. Instead, robots have LEDs, the color of which indicates the strategy, and sensors, that can count the number of LEDs of each color. In every interval, robots decide their strategy based on the information acquired by the sensor.



(a)



(b)

Figure 1: Globally Communicating Robots: Figure 1 shows the transitions of the number of robots choosing a foraging strategy (n_1, solid line) and a harvesting strategy (n_4, dotted line). The condition is that $C = 0.1$, $\Gamma = 1.0$, $P_0/C = 0.2$, $P_{min} = 0.0001$, U/Γ=200, $\tau = 50.0$(tu), and $\alpha = 1/6$ with (a) 27 instigators or (b) 28 instigators. In (a), after restoring the value of utility U at 120 (tu), n_1, which is for a foraging strategy, gradually increases up to around 60, which is the state before reducing the value of U. On the other hand, in (b), n_4, which is for a harvesting strategy, gradually increases up to around 80 after oscillations.

In contrast to globally communicating robots, the communication delay in local communication is negligible. Thus, we ignore communication delay in this type of simulation. Instead, we focus 1) on a process in which the effect of a local change of strategic type becomes widespread, and 2) on the pattern that is formed in the process.

To investigate these issues, we arranged 200 robots in a 10 × 20 rectangular formation. We assumed a situation where they are collectively moving while foraging but keep their position in relation to their neighbors. The distance between the centers of two robots is 25 units, each robot having a sensing area forming a circle 30 units in radius. [6]

In simulation of globally communicating robots, the values of parameters were

[6] This type of physical setting is not intrinsic in this simulation. In an investigation of locally communicating robots, it is sufficient to think of there being a static neighbor relation along which information is exchanged. Study on harvesting by a group of robots [Goss and Deneubourg 92] provides an excellent example. In harvesting, ant-like robots forage by using sensing beacons to make chains. The simulation settings we used here were made in the hope that the result of our simulation can be applied to such a harvesting robot group.

determined by considering the total number of robots which a robot can determine at any instant. In the case of locally communicating robots, the number of robots that any robot can perceive depends on the location of that robot. The dynamics of collective behavior fully depends on the form of the payoff function, that is, on the form being determined by the values of parameters. Therefore, the payoff function shown in Equation (2) requires a slight modification as follows:

$$P_i(\mathbf{n}(t)) = \max((U' \times N(t) - \Gamma n_i(t))(P_0' \times N(t) + Cn_i(t)) \\ -Dn_i(t) \sum_{j \notin type(i)} n_j(t), \quad P_{min}). \tag{5}$$

Here, U' is a utility for perception of one robot and P_i' is a payoff for perception of one robot. [7] $n_i(t)$ is the number of robots choosing the i-th strategy, perceived at time t. $N(t)$ is $\sum_{i=1}^{5} n_i(t)$. [8]

In terms of reducing utility, for simplicity, all robots use the following step function as parameter U' in Equation 5:

$$U'(t) = \begin{cases} 0 & \text{if } t_1 \le t \le t_2; \\ 1 & \text{otherwise.} \end{cases} \tag{6}$$

Again, t is 0 when the robot receives a special signal issued by any *instigator* robot.

We can suspect that it is not fair to use Equation 5 for the payoff function of locally communicating robots. In the case of globally communicating robots, it was an aggregation model since n_i is large. On the other hand, in the case of locally communicating robots, n_i is quite small, at the most 10 in our simulation. In practice, this fact affects the result of simulation. We had to set parameters in Equation 5 so that the function indicated by the equation is monotonic in the effective area with respect to $n_i(t)$. Otherwise, we would never have observed the result we wanted.

We, again, began simulations with an initial distribution of 67, 67, 66, 0, and 0 to five strategies. Namely, the robots assume the equilibrium of a foraging strategic type. The values of parameters C, Γ, P_0', and D are 1.0, 1.0, -0.3, and 0.1, respectively. Here, note that P_0' is a negative value and D is relatively small.

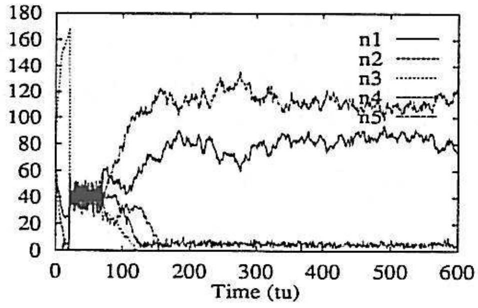
Figure 2 shows three transient decision making behaviors. In Figure 2 (b), the case with 28 instigators succeeds but, if t_1 and t_2 are 20 and 40 (tu), it fails. Clearly, success or failure depends on the pattern of distribution of strategies at the instant that the value of U' is restored.

Figure 3 shows the characteristic patterns formed by the transient decision making behavior shown in Figure 2. Instigators are arranged from left to right and in top-down order. In these figures, a star '*' indicates that a robot at that position chooses a foraging type strategy and a space ' ' indicates that a robot at that position chooses a harvesting strategy.

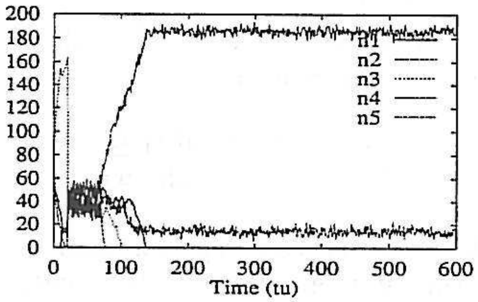
We can observe one distinctive characteristic from these figures. After the value of U' is restored (generation 72), in the failure case, lines, in which the type of strategy being chosen by the instigators is dominant, appear alternately. On the other hand, in the successful case, at generation 72, a nucleus colony of the

[7] U' and P_i' are approximately U/N and P_i/N, respectively. Here, U, P_i, and N are those in Equation 2.

[8] In this simulation, robots in the middle of the rectangle can perceive 9 robots including themselves at any instance. Robots at the north, east, south, and west edges can normally perceive 6 robots, and robots in the north-east, north-west, south-east, and south-west positions can perceive 4 robots.



(a)



(b)

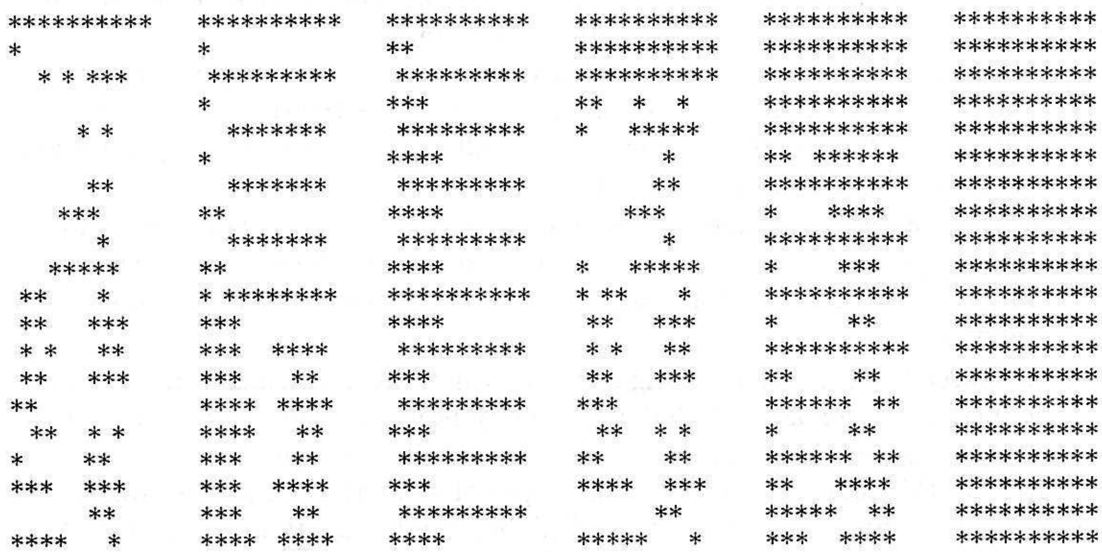
Figure 2: Locally Communicating Robots: Figure 2 shows the transitions of the number of robots choosing strategies under the condition that C = 1.0, Γ = 1.0, P_0'/C = -0.3, P_{min} = 0.0, and U'/Γ=20.0. t_1 and t_2 are 20 and 70 (tu) from the beginning. In (a), there are 10 instigators. In (b), there are 28 instigators. n_i indicates the number of robots choosing the i-th strategy. n_1, n_2, and n_3 are for foraging strategies whereas n_4 and n_5 are for harvesting strategies. In (a), it is found that, after restoring the value of U', n_1 for a foraging strategy increases along with n_5 for a harvesting strategy. Since two strategic types are mixed, this is an example of failure. On the other hand, in (b), only n_4 for a harvesting strategy increases and converges whereas all foraging strategies have disappeared. Therefore, this is an example of success.

target strategic type is formed around the instigators. From this nucleus colony, the influence spreads to the state shown in Figure 3 (f).

4 Related Work

Autonomous robots have the advantage of being adaptable and robust in a dynamic environment. On the other hand, they have the disadvantage of not being fully controllable from outside, although it is possible to give direction to emergent behaviors. In a sense, they are self-interested entities pursuing their own interests. Because of this self-interested nature, it is questionable whether they would be able to cooperate as a group.

Deneubourg and Goss's work on ant-like robots [Deneubourg *et al.* 91] provides one encouraging example where such self-interested and primitive entities



(a) (b) (c) (d) (e) (f)

Figure 3: Patterns of Strategy Distribution: Figure 3 shows the patterns in generations 72, 100, and 600. (a) through (c) depict the distributions for 10 instigators, which is an example of failure. (d) through (f) depict the distributions for 28 instigators, which is an example of success. In (d), we can find the formation of a nucleus colony in the top three lines. Based on the colony, the effect is distributed over the robot team ((e) and (f)).

can adopt cooperative and beneficial behavior, where ant-like robots sort objects into piles of the same type. This is a good example of the kind of robotic system that we would like to realize.

Beckers, Deneubourg, Goss, and Pasteels also reported on the quite attractive collective behavior [Beckers *et al.* 90] seen in real ant colonies. This is a trail recruitment system for selecting between two food sources. Pheromone is used as the communication medium. In their paper, Beckers et al. discuss the necessity of direct transmission, in this case, worker-to-worker transmission of the food location. They say that, without direct transmission, a newly discovered source can never attract ants working at an old food source. Thus, a forager must actively invite nest-mates on the principal trail to deflect them to the new source.

5 Concluding Remarks

Our long-range goal is to construct teams of robots that engage in tasks that require mass effect such as foraging, fire-fighting, forest rescue work, poisonous gas detection in factories, or mine detection in deserts. To progress toward this goal, we are now concentrating on discovering any meaningful collective behavior and inventing a technology to realize such collective behavior in a team of autonomous robots.

In this paper we first described a model of collective alteration of strategic types. This model makes it possible for all other robots to follow and choose that type when a small number of robots, called *instigators*, change and fix their strategic type. This model is characterized as follows:

- Each robot's interests are represented as strategies. Strategies are grouped into strategic types. The power of an interest is relative to its payoff, as calculated by a payoff function. The payoff function reflects the populations of robots choosing given strategies.
- Robots, if they perceive a critical state in their environment, enter an *instigator* mode. Instigators always choose only one particular strategic type. The role of the instigator resembles that of the recruiter in the ant colony described above.
- To spread the effect of instigators choosing one particular strategic type, a special trigger is used that is probably issued by the instigators, all the robots control one parameter U in their payoff functions.

Based on this model, we devised two types of simulation. The first simulation was devised to investigate the effect of global communication on the collective alteration of strategic types. As the results show, we found a *critical ratio* that causes a collective alteration of strategic type. This ratio was also proved in a theory described in [Numaoka and Takeuchi 93]. Furthermore, although we did not present it in this paper, we found that communication delay seems to play an important role in transition between the equilibrium points in a multi-stable system [Numaoka and Takeuchi 93].

Some would claim that the assumption of global communication in a team is not realistic. There may be many reasons for making such a claim. Some would mention the technological issue. I would respond to this claim by saying that it is, in principle, realistic if we consider satellite communication, although many issues still require consideration. One consideration would be the issue that the communication server would form a bottleneck. Actually, the communication server would be required to conduct pipeline processing. Another issue would that of the robustness of the communication server.

We would like to say, nevertheless, that the assumption is still realistic if we look at an example in human society. In fact, we benefit from such global communication, especially in the stock market. People in the stock market decide whether they should sell or buy a stock based on the information indicated on the board. This is the mechanism that we would like to realize in a team of robots.

The purpose of the second simulation was to investigate the phenomena in collective decision making under local communication conditions. Unlike globally communicating robots, a communication delay in a restricted neighborhood relation is not so problematic. Thus, we can neglect the factor of communication delay in this simulation. Instead, we are interested in examining the relation between the patterns that appear in the transition of collective decision making and the results of collective alteration of strategic type.

Through the second simulation, we determined that one important factor makes the result successful. This is a form of the payoff function with particular parameter values. In the first simulation, the payoff function is non-monotonic in [0, 200] with respect to the number of robots choosing the i-th strategy, n_i. On the other hand, in the case of locally communicating robots, the payoff function seems to monotonically increase the effective area with respect to n_i, thus producing successful results. The effective area is, for example, [0, 9] if the number of perceived robots is 9. If the payoff function is non-monotonic, the population distribution tends to level off across all the strategies. Therefore, the set of parameter values is chosen such that it makes the payoff function monotonically increase in the effective area.

The second simulation revealed the following fact about the relation between patterns and results. Namely, it is necessary for robots to collectively alternate their strategic type such that a nucleus colony forms around instigators where all robots in the sensing area choose the same strategic type.

We were also interested in a well-balanced distribution of populations between multiple strategies in a chosen strategic type. In global communication, we succeeded in realizing a well-balanced distribution. However, in local communication, a well-balanced distribution was not realized. This point requires further analysis in the future.

The simulated robots we investigated here do not have any learning capability. By introducing a learning capability, the performance of collective work would be improved. We are now investigating how we can introduce reinforcement learning technology (e.g. [Lin 91, Kaelbling 92]) into our model.

Finally, we would like to note a critical distinction between globally communicating robots and locally communicating robots. The dynamics of decision making behavior by globally communicating robots are sustained by aggregate effect. With respect to this viewpoint, analysis such as that done by Huberman and Hogg in their model of computational ecosystem is possible. We suspect, however, that it is difficult to view the case of locally communicating robots as an aggregate system. We speculate that a modeling using cellular automata [Wolfram 86] or percolation [Grimmett 89] would be appropriate for analyzing the case of locally communicating robots. An attempt to make such a model would also be fruitful future work.

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