Improvement of Bias and Rising Threshold Algorithm based on Local Information Sharing

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Abstract: This paper improves BRT algorithm based on Local Information Sharing (BRT-Lis) to apply to the practical problems which locations related environments. We consider how to adjust the local parameters so that agreed behavior could be obtained optimally. We also examine how the Local Information Sharing influences the agreement with a simple position changing model.

1 INTRODUCTION

In a swarm, macro candidate behaviors are created by micro interactions among individuals, and the behavior of individuals is influenced by their macro behavior. The relationship between the micro interactions and the macro states is usually nonlinear. Thus, it is not easy to analytically obtain micro behaviors that lead to an appropriate macro state. Therefore, the principle and method leading to a bottom-up mechanism by the highly organized behavior found in social organisms is still attracting the attention of researchers. Therefore, the principle and method leading to a bottom-up mechanism by the highly organized behavior found in social organisms is still attracting the attention of researchers. Research on foraging behavior by ant and bee colonies has been undertaken for a long time, and excellent models have been proposed to assign individuals to feeding and resting roles. Tofts et al. (1992) introduced foraging-for -work (FFW) model in which individuals seek work and engage in task performance when they encounter a stimulus. Page et al. (1991) developed a model of task allocation in bees based on the threshold principle, where individuals are represented as boolean automata embedded within a network. However, they did not try to relate quantitatively their results to any specific experimental observation. Gordon et al. (1992) developed a model based on a connectionist model, which can be seen as a more complex and a more experiment-driven version of Page et al.'s boolean network. Bonabeau et al. (1998) introduced a simple mathematical model of the regulation of division of labor in social insects based on a fixed response thresholds. They showed that this simple model explains the experimental observation of Wilson (1984), it was possible to extend the model to a more complicated situation, explore its characteristics, and studied under conditions that could explain temporary multifaceted phenomena. Castello analyzed the simulation results using the adaptive respond threshold model (ARTM), and conducted experiments with real robots. And, in this study, SARTM, a simplified version of ARTM, was proposed in order to improve the adaptation and emergent capabilities of robotic swarms in which the response threshold is calculated dynamically.

On the other hand, there are cases where it is not possible to adjust the division of labor, so it is not possible to lead a swarm to attain the targeted macroscopic state. Thus, general models about how a swarm discovers, memorizes, and learns new micro interactions to enable the attainment of the desired macro state have not been proposed. This results in a bottleneck in the construction of swarm systems (Kubo et. el's reseach (2015)).

In previous work (Phungnhu et al., 2017), we have developed an agreement algorithm using a trial and error method at the macro level (BRT model, Bias and Rising Threshold model) based on the hypothesis that the opinion of a swarm is always made by agreements between the individuals while the agreement content changes on an hourly basis. In the conventional division of labor models, for example, fixed response thresholds model Bonabeau et al.'s research (1998), the swarm's tasks are fixed. They considered only one or some limited purposes of the swarm. In contrast, in the BRT algorithm, the swarm can create various

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responses against environmental changes and the like by switching its behaviors until discovering an suitable agreement behavior.

The BRT model is a model that expands the 2-choice consensus-building model proposed by Namatame bias model (Namatame, 2001) that can be used even in cases where more than two choices are available. In the BRT model, an agent determines its attitude by its own preference, in which the threshold is rising with time, and by looking at the ratio of the population. However, this ratio is the ratio of the number of agents who are choosing the same behavior to the total number. In other words, as shown in Figure 1 (A), the information sharing must be global. However, in reality, the global information sharing is impossible. Moreover, even if the information on the whole swarm can not be obtained, macro behaviors will be able created by local interaction among neighbors (Figure 1 (B)).

Thus, in this paper, we point out improving the original BRT algorithm in order to make it more realistic and practical based on Local Information Sharing. By using a simple position changing model, we also find out that the suitable macro behavior can be discovered more quickly than in the original BRT algorithm when the number of agents is very small.

This paper is organized as follows. Section 2 describes the original BRT algorithm, Section 3 introduces BRT-Lis, and then Section 4 shows the experimental results and discussions. Conclusions and future work are described in Section 5.

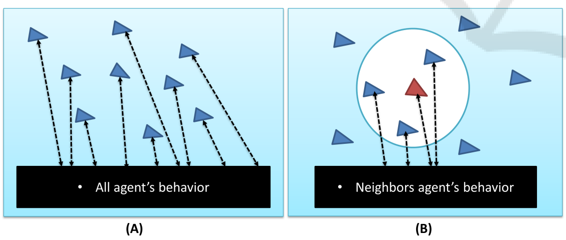

Figure 1: The image of (A) global information sharing in BRT and (B) local information sharing in BRT-Lis.

2 ORIGINAL BRT MODEL

The BRT model is a model that expanded from Namatame model. First of all, we will introduce this model.

2.1 Namatame Bias Model

Namatame got inspiration from the research in critical mass of Thomas Crombie Schelling. As shown

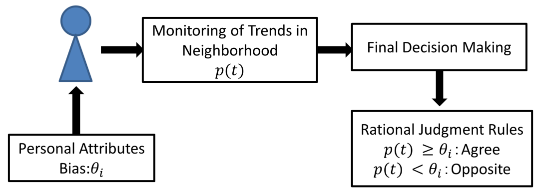

Figure 2: The role of social skin in individual decision-making (Namatame, 2001).

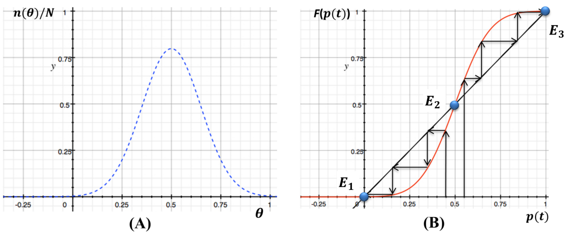

Figure 3: Bias design method. (A) Probability density function. (B) Cumulative distribution function and equilibrium point of collective consensus decision (E1 and E3 are stable points, E2 is an unstable point).

in Figure 2, he concluded that individual decision-making does not only depend on personal philosophy and personal preferences (bias θ_i), but it also depends on the atmosphere of the whole group $p(t)$. He proposed a decision-making framework based on the introduction of individual differences (bias value). An agent determines its attitude by its own preference and by looking at the ratio of the population in favor and opposite to it. As shown in Eq.(1), the agents disagree if the proportion of the consensus faction is less than the threshold and agrees if it exceeds the threshold.

$$\begin{cases} p(t) \geq \theta_i : Agree \\ p(t) < \theta_i : Opposite \end{cases} \quad (1)$$

Namatame investigated various distributions and clarifed that we distribute the bias value θ_i in a bell shape as shown on the left side of Figure 3, one unstable point and two stable points are generated, and all members smoothly move their opinions to ultimately agree or disagree, as shown on the right side of Figure 3. The number of iterations required to attain convergence depends on the bell shape of the distribution and not on the number of agents, so it is expected that prompt convergence can be achieved even with a large number of agents.

2.2 The BRT Model

Namatame bias model can only deal with two options that *agree* or *disagree* with an opinion. In the BRT model, we have proposed an algorithm that enables agreement to be achieved promptly even when there are multiple opinions ($M \geq 2$).

Now, we assumed that there are N agents $P_1, \cdots, P_i, \cdots, P_N$ ($1 \leq i \leq N$). $A = \{a_1, \cdots, a_j, \cdots, a_M\}$ is the set of agent candidate behavior with $M \geq 2$ ($1 \leq j \leq M$). $A_i(t) \in A$ is the behavior of agent P_i at time t. The agent P_i has a bias θ_i ($0 < \theta_i < 1$). $n(a_j)$ is the number of agents selecting behavior a_j. a_{goal} is the desirable candidate behavior ($a_{goal} \in A$). The agent does not know a_{goal}, in advance, only when all have agreed, and it is understood that a_{goal} is an agreed behavior.

At this time, the agent P_i decides on behavior $A_i(t+1)$ at the time t as follows: If

$$n(A_i(t))/N \geq \theta_i + \tau \cdot c \cdot (t - t_{i,last}(t)) \quad (2)$$

is satisfied, $A_i(t+1) = A_i(t)$. Otherwise, a behavior other than $A_i(t)$ is stochastically chosen and becomes $A_i(t+1) \in A \backslash A_i(t)$. Here, τ is a constant representing the increment in the number of proponents.

In addition, $t_{i,last}(t)$ is the time at which the agent P_i last changed its behavior, and $((t - t_{i,last}(t)))$ is the time over which the same action continues to be selected.

$$t_{i,last}(t+1) = \begin{cases} t+1 & A_i(t+1) \neq A_i(t) \\ t_{i,last}(t) & otherwise \end{cases} \quad (3)$$

$c(t)$ is a function that is equal to 1 when the desirable macro purpose is not achieved as follows:

$$c = \begin{cases} 0 & \forall i, A_i(t) = a_{goal} \\ 1 & otherwise \end{cases} \quad (4)$$

If the ratio of agents who select the same behavior as theirs is lower than $\theta_i + \tau \cdot c \cdot (t - t_{i,last}(t))$, the agent randomly selects a new behavior from other candidate behaviors.

3 BRT-LIS

3.1 Proposed Method: BRT-Lis

In BRT model, an agent knows all the behaviors of other agents. Therefore, it can know the number of agents who choose the same behavior ($n(A_i(t))$). Here, we assume that the agent gets only the information of neighbors that is within a fixed radius r. We call $NB_i(t)$ is the set of neighbors of agent P_i at time step t. $N_i(t)$ is size of this set (the number of neighbors).

Here, we also assume that there are N agents $P_1, \cdots, P_i, \cdots, P_N$ ($1 \leq i \leq N$). $A = \{a_1, \cdots, a_j, \cdots, a_M\}$ is the set of agent candidate behavior with $M \geq 2$ ($1 \leq j \leq M$). $A_i(t) \in A$ is the behavior of agent P_i at time t. The agent P_i has a bias θ_i ($0 < \theta_i < 1$). $n_i(a_j)$ is the number of neighbors selecting behavior a_j. a_{goal} is the desirable candidate behavior ($a_{goal} \in A$). The agent does not know a_{goal}, in advance, only when all have agreed, and it is understood that a_{goal} is an agreed behavior.

At this time, the agent P_i decides on behavior $A_i(t+1)$ at the time t as follows: If

$$n_i(A_i(t))/N_i(t) \geq \theta_i + \tau \cdot c \cdot (t - t_{i,last}(t)) \quad (5)$$

is satisfied, $A_i(t+1) = A_i(t)$. Otherwise, a behavior other than $A_i(t)$ is stochastically chosen and becomes $A_i(t+1) \in A \backslash A_i(t)$. Here, τ, $c(t)$ and $t_{i,last}(t)$ are same to BRT model.

In $NB_i(t)$, if the ratio of agents who select the same behavior as theirs is lower than $\theta_i + \tau \cdot c \cdot (t - t_{i,last}(t))$, the agent randomly selects a new behavior from other candidate behaviors.

3.2 Generation of the Bias Value θ_i

Here, we also use Gaussian distribution to generate the bias value θ_i.

The Gaussian distribution method:

$$\theta_i = min(1, max(0, G(\mu, \sigma_g^2))) \quad (6)$$

Where: $G(\mu, \sigma_g^2)$ is a random variable with a Gaussian distribution, μ is the expected distribution, σ_g^2 is the variance.

$$G(\mu, \sigma_g^2) = \frac{1}{\sqrt{2\Pi\sigma_g^2}} exp(-\frac{(x-\mu)^2)}{2\sigma_g^2}) \quad (7)$$

4 THE EXPERIMENTAL RESULTS

4.1 Experimental Setup

In this section, we present the details of the environment that are important for completely understanding our experimental setup. In this work, we use a simple position changing model. Picture of domain is shown in Figure 4. Black dot represents the agent P_i and the dotted circle represents the neighborhood of P_i at the center of the circle, light black dot represents a neighbor of P_i, blue dot represents an agent who is not the neighbor of P_i. Red arrows represent 4 behaviors of agent ($M = 4$), behavior a_1 is *Turn Left* (move to the left side of the domain), behavior a_2 is *Go Up*, behavior a_3 is *Turn Right*, behavior a_4 is *Go Down*.

The experimental settings for variables are given in Table 1. We chose the variables that yielded the best results in our previous research on BRT model

[8]. The domain is toroidal. This means that agents that move off one edge of our domain reappear on the opposite edge moving in the same behavior.

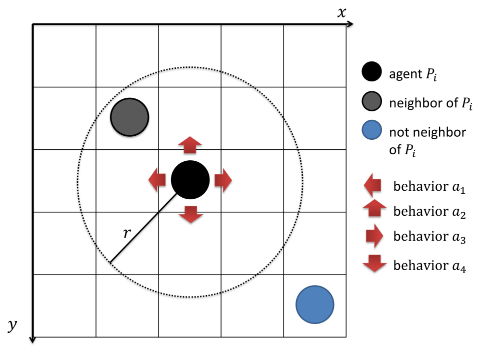

Figure 4: Image of the simple position changing model. The black dot represents the agent P_i and the dotted circle represents the neighborhood of P_i at the center of the circle, the light black dot represents a neighbor of P_i, the blue dot represents an agent who is not the neighbor of P_i. The red arrows represent 4 behaviors of agent ($M = 4$), behavior a_1 is *Turn Left* (move to the left side of the domain), behavior a_2 is *Go Up*, behavior a_3 is *Turn Right*, behavior a_4 is *Go Down*.

Table 1: Experimental setting for variables.

Variable	Value
domain *height*	600
domain *width*	600
units moved by each agent per time step	1
the number of candidates behavior M	4
the expected distribution μ	$1/M$
the variance of Gaussian distribution σg	$1/(3M)$
the increment value τ	0.001

4.2 Confirmation of Behavior

In the following, we describe computer experiments that were used to show how the agreement state can be switched as a function of the BRT-Lis. In order to observe the behavior-switching more clearly, we assume that there is no desirable behavior (a_{goal}) in the set of agent candicate behavior A.

For this experiment, the number of agents was set at $N = 1000$. We show the candidate behaviors selection over time where all members started from an agreed behavior at the initial time when the radius r is $r = 20, 50, 100, 200$.

Figure 5 shows an example of agents, which are randomly located in the domain, at the initial time. Figures 6 $\sim$ 9 show a transition example of each case of radius values. The horizontal axis represents time step and the vertical axis represents $n(a_i), i = 1,2,3,4$, which is the number of agents who choose behavior a_i. As can be seen in Figure 6, agreement by all individuals has never been emerged with too small radius r ($r = 20$). In Figure 7, we see that the number of agents who choose behavior a_4 increases rapidly in first 1200 time steps and reachs 1000 instantaneously several times. Thus, it can not be said that the agreement behavior has be emerged. However, as can be seen in Figure 7, when the radius r is set in high value ($r = 100$), the number of agents choosing the same behavior is beginning to be maintained at a certain and high value. This means that although the agreement is unstable, it has been emerged. When the radius r is set in very high value ($r = 200$), which means the agent can share the information with about one-third of all individuals ($\pi r^2/(width * height)$), all individuals choose the same behavior for nearly constant time. We found that all individuals switched behavior by agreeing with a behavior.

Thess results show that the higher radius value we set, the more clearly the agreement can be seen. In the next subsection, we will examine the influence of the radius r in more details.

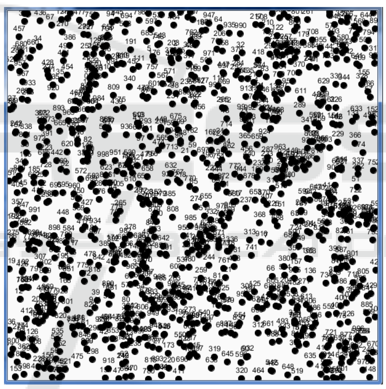

Figure 5: An example of agents at the initial time.

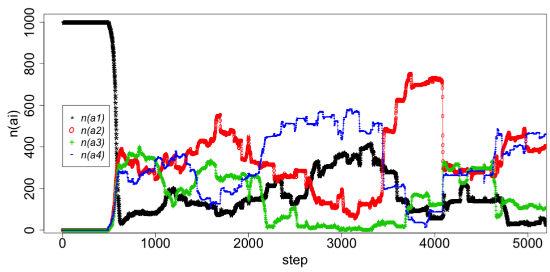

Figure 6: Swiching behavior when $r = 20$.

4.3 Searching Ability of the Desired Behavior and Its Features

In this subsection, we show that it is possible to discover the desired behavior using computer simulations.

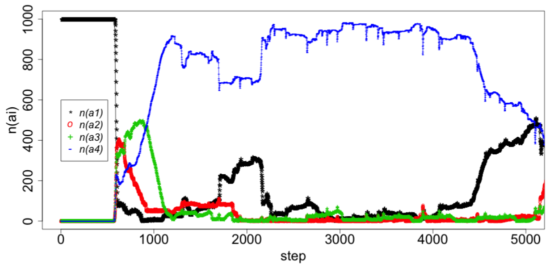

Figure 7: Swiching behavior when $r = 50$.

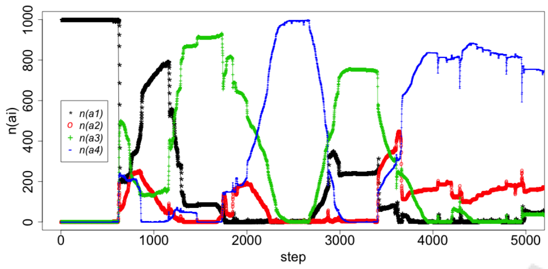

Figure 8: Swiching behavior when $r = 100$.

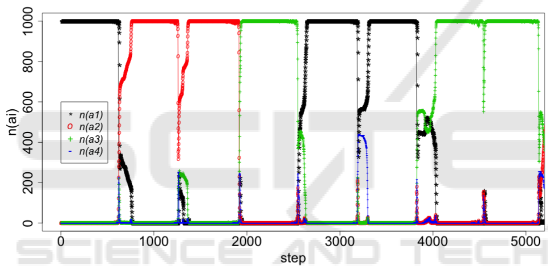

Figure 9: Swiching behavior when $r = 200$.

4.3.1 Influence of the Radius r

We conduct the experiment with the number of agents $N = 100$. Assuming that all the agents selects an agreed behavior at the initial time, we verified whether it is possible to reach the desired behavior by changing the radius r. We selected behavior a_4 and set it as the desired behavior ($a_{goal} = a_4$). Then, we changed the radius r and counted the cases where all of the agents were able to select a_4, conducted 100 trials on each parameter set, and determined the probability of discovery and average of time required to reach the desired behavior from an agreed state. We set time limit is 30000, and if this time limit was reached the trial was stopped. These experimental results are shown in Figure 10 and 11.

Figure 10 shows the changing of the success ratio and average of time required to reach the desired behavior from an agreed state in the initial time. The vertical axis on the left is the ratio at which behavior a_4 was successfully agreed (blue line), the vertical axis on the right is average of time required to do that (red bar), and the horizontal axis is value of the radius r. As we can see, the success ratio increased with a decrease in r and when r was set to $r = 200$, the success ratio was close to 100%. This means that BRT-Lis model could achieve the same result as BRT model, which is equivalent to BRT-Lis model with $r = 400$. On the other hand, we can see that the higher radius value we set, the more rapidly the desired behavior be discovered with a proportion.

Figure 11 shows the cumulative distribution of ratios that reached the desired behavior from an agreed state in initial time. As a result, it is found that when the radius r was too small, the desired behavior could not be discover any time. When the radius r is set to the bigger value (about $50 \sim 100$), the number of cases discovering the desired behavior increases. When the radius r is set to even bigger value (around 200), the desired behavior is reached promptly in all cases.

From the above, it can be concluded that BRT-Lis model could discover the desired behavior in the same as of BRT model with an suitable radius r.

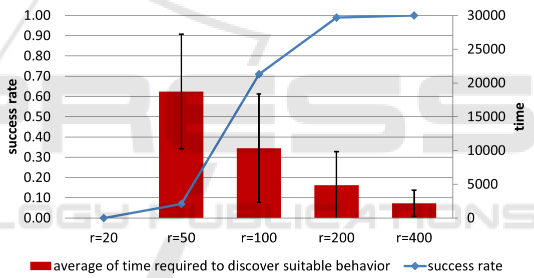

Figure 10: The changing of the success ratio and the average of time required to discover the desired behavior from an agreed state in the initial time. $r = 20, 50, 100, 200$.

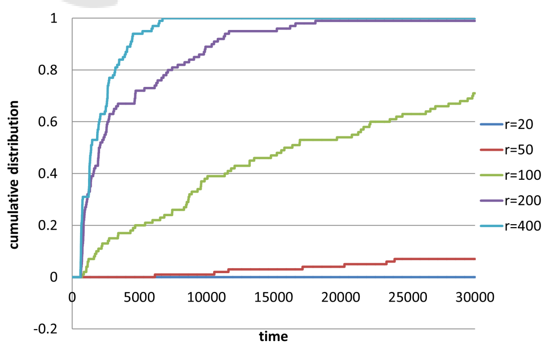

Figure 11: The cumulative distribution of ratios that reached the desired behavior from an agreed state in initial time.

4.3.2 Influence of the Number of Agents N

Here, we make clear how the number of agents influence the searching ability of the desired behavior. We set $r = 100$, $a_{goal} = a_4$. Assuming that all the agents selects an agreed behavior at the initial time. We changed the radius r and counted the cases where all of the agents were able to select a_4. Figure 12 shows the results of performing 100 trials for a number of agents $N = 4, 8, 16, 64, 256$. A trial is terminated at time step 30000.

The vertical axis on the left is the ratio at which behavior a_4 was successfully agreed (red line), the vertical axis on the right is average of time required to do that (blue bar), and the horizontal axis shows the number of agents N. As can be seen, when the number of agents is set a very small value (about 4 $\sim$ 16), the success ratio surprisingly decreased with an increase in N. It is considered that the number of agents is too small, and there is almost no neighbor. Therefore, each agent makes decisions without being affected by other agents. At this time, the probability of selecting the desired behavior a_4 by all individuals could be $1/(3N)$. Thus, the smaller the number of agents N is, the higher success ratio could be. Howerver, when the number of agents is set a bigger value, the density of agents in the domain increases and the number of neighbors of each agents increases too. Therefore, the probability that individual information is indirectly conveyed to everyone increases. As can be seen, the success ratio increases when $N \geq 16$.

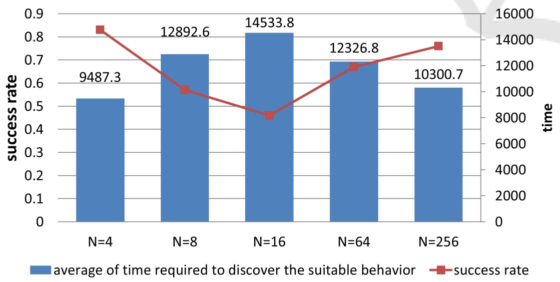

Figure 12: The changing of the success ratio and the average of time required to reach the desired behavior from an agreed state in the initial time. $N = 4, 8, 16, 64, 256$.

5 CONCLUSIONS

In this paper, we introduced the improved BRT algorithm based on Local Information Sharing (BRT-Lis) and considered how to adjust the local parameters so that the desired behavior could be obtained optimally. We conducted the experiments that confirm the behavior switching function of BRT-Lis with a simple position changing model. We also examined how the Local Information Sharing influences the searching ability of the desired behavior. The experimental result revealed that the following implications: (1) BRT-Lis model can discover the desired behavior in the same as of BRT model with an suitable radius r and (2) the extremely low density or high density of agents in the domain is the condition of high success ratio of searching the desired behavior.

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