Effects of Information Sharing on Collective Behaviors in Competitive Populations

2 authors:

Reiji Suzuki
Nagoya University

Takaya Arita
Nagoya University

Effects of Information Sharing on Collective Behaviors in Competitive Populations

Reiji SUZUKI and Takaya ARITA

Graduate School of Human Informatics, Nagoya University
Furo-cho, Chikusa-ku, Nagoya 464-8601, Japan
{reiji, ari}@info.human.nagoya-u.ac.jp

Abstract

This paper explores the effects of information sharing on diversity and adaptivity of behaviors in competitive populations. We focus on the information supplement of congestion status at the events or theme parks. We have conducted a multi-agent simulation, in which each agent visiting the attractions is able to avoid the crowded ones by using the shared information among agents with a certain probability. Experiments have shown that there exists the optimal probability that minimizes the congestion deviation among attractions. We also discuss the cause of a sudden decrease in this effect of information sharing, which has been observed in long-term experiments.

Keywords: information sharing, behavioral diversity, collective behavior, El-farol bar problem, Minority Game.

1 Introduction

The origin and maintenance of diversity have been explored in various fields concerning complex systems. Especially, behavioral diversity in social populations of agents has been discussed mainly in social and economic sciences, because it is one of the essential factors that determine the dynamics and adaptivity of competitive populations.

Arthur devised the El-farol bar problem [1] to study a competitive interaction of boundedly rational agents, in which each agent faces the binary choice of either attending or not a bar which is enjoyable only if it is not too crowded. He had shown that inductive reasoning of agents yielded a diversity of behavior among agents and made the average attendance self-organize to around the desirable capacity of the bar. Challet and Zhang also proposed a simple version of Arthur's model, which is known as the Minority Game [2]: N agents have to choose an action from 0 or 1. Those agents who have chosen the minority win, the others lose. Each agent possesses a finite set of strategies which are represented as mappings from possible M-length history of minorities' choice to its next action, and uses the one which would have been the most rewarding if it had been used since the beginning. Savit, Manuca and Riolo have found an environmental condition ($\rho = 2^M/N$) that minimizes the volatility (the standard deviation of the number of winners) which is smaller than that in the case when all agents randomly choose actions [3].

Diversity of information shared among agents is also an essential factor because it can directly or indirectly affect the diversity of collective behaviors. Hogg and Huberman constructed an abstract model which is composed of interacting agents choosing resources based on imperfect or delayed information about rewards which depend on the frequency of agents' choices [4]. In their model, the population dynamics becomes chaotic as the delays and the uncertainty of information increase. But if each agent has an additional delay or imperfection about information that are genetically defined, the population evolves to a heterogeneous genetic composition, and the chaotic behavior is completely freezed out. Akaishi and Arita focused on adaptive property of misperception that can increase the diversity of information that facilitates flocking toward a limited resource in a foraging task [5]. They had shown that diversity of information, which was increased by misperception, could also increase the diversity of behavior and adaptivity of population. These studies imply that sharing with the same information among individuals does not always yield a desirable result for whole population.

The purpose of this study is to explore the direct or indirect effects of information sharing on diversity and adaptivity of behaviors in competitive populations by focusing on the information supplement of congestion status at events or theme parks. In particular, we aim at clarifying the dynamic properties of these effects so as to understand them in more realistic situations. We have constructed a model in which each agent visiting the attractions is able to avoid the crowded ones by using the shared information among agents with a certain probability. By altering the probability of information sharing in our model, we consider the correlation between informational and behavioral diversities.

2 The Model

There exist N_a attractions on the event space that is represented by two-dimensional ($W_x \times W_y$) grid as shown in Figure 1. There are N_p agents (visitors) and at most N_e agents can enter the space from the entrance every time step with the restricted admission that the total number of agents in the event space should not exceed the maximum number N_m. Initially, each agent decides whether it will visit each attraction $A_i (i = 0, \cdots, N_a - 1)$ or not with a probability P_i respectively. P_i represents the popularity of each attraction. Each agent also chooses one from them randomly as a first destination to visit.

In every time step, the order of each agent's turn for action are randomly decided, and each agent can execute an action in its turn based on its current mode: *walking*, *waiting* and *experiencing*. In *walking* mode (initial mode for all agents), each agent can walk toward its destination with the probability $1-(n+1)/10$, where n is the number of neighboring cells within a 3 by 3 window that are already decided as next position of other agents or outside of the event space, except for attractions. This factor stands for the interference among agents caused by congestion. If the agent can walk, the x and y coordinates of the agent are updated by the following equations:

$$x \leftarrow x + rsgn(A_{i_x} - x), \tag{1}$$

$$y \leftarrow y + rsgn(A_{i_y} - y), \tag{2}$$

where A_{i_x} and A_{i_y} denote the x and y coordinates of the destination A_i. $rsgn(k)$ is a fuction which returns a randomly chosen value from $-1, 0$, or 1 with probability p_r; otherwise returns $-1, 0$, or 1 if $k < 0, k = 0$, or $k > 0$ respectively. If the agent is going to take an oblique direction, it is allowed to walk with an additional probability $2^{-0.5}$, which makes an average walking speed per step independent of its direction.

Agents who have arrived at their destinations enter into *waiting* mode, and wait for their turns at the tails of waiting lines until they have their turn. It is because that each attraction A_i is capable of giving entertainment at most C_i agents at once. Agents are in *experiencing* mode while they are going through the programs for L_i time steps. When an agent has finished going through the program there, it chooses next destination from its remaining attractions to visit using the information about congestion status of all attractions, and then enters into *walking* mode again. The information is provided for each agent with a certain probability r through an information equipment such as PDA. If an agent receives the information, it heads for the attraction with the shortest waiting line at present among its remaining attractions to visit; otherwise it heads for the nearest one from its current position in slant distance. The probability of information sharing r is the parameter which decides the informational diversity among agents in our model. The agent who has no remaining attractions to visit is eliminated from the event space. A simulation ends when all agents have been eliminated.

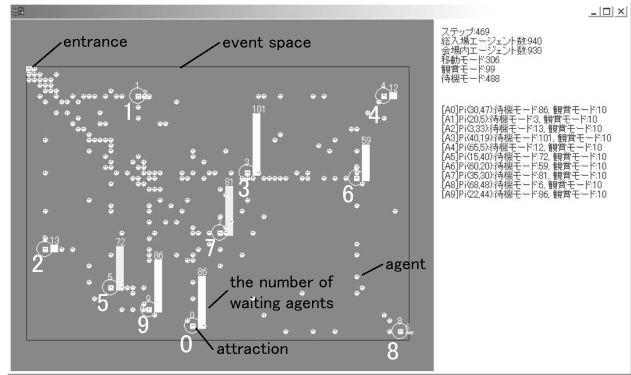

Figure 1: The screenshot of the simulation.

3 Experimental Results

3.1 Effects of Information Sharing on Behavioral Diversity

We arranged each attraction $A_i (i = 0, \cdots, 9)$ as shown in Figure 1 and adopted the same parameters for all attractions: $P_i = 0.7$, $L_i = 30$ and $C_i = 10$. We also used the following values as the other environmental parameters: $W_x = 70$, $W_y = 50$, $N_a = 10$, $N_p = 2000$, $N_e = 2$, $N_m = 1000$ and $p_r = 0.05$.

Firstly, we clarify the basic behavior of population caused by the environmental condition (arrangement of attractions). Figure 2 shows a typical trial in case of $r = 0$, in other words, no information is shared among agents. Horizontal axis shows the time step and each line shows the number of waiting agents (agents in *waiting* mode) at each attraction (the line "Ax" corresponds to the attraction x in Figure 1). In this paper, we consider behavioral diversity of whole population by focusing on these values.

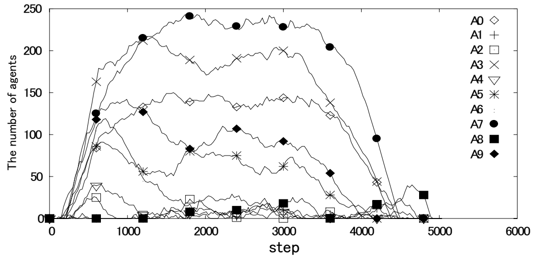

Figure 2: The number of waiting agents at each attraction ($r = 0.0$).

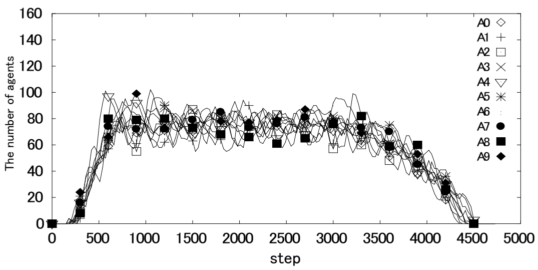

Figure 3: The number of waiting agents at each attraction ($r = 0.5$).

From the initial condition, many agents entered into the event space and headed for their destinations, then the number of waiting agents increased at all attractions. But there were large differences among their peaks through the trial. The centrally-located attractions on the event space (such as attraction 3 and 7) had many waiting agents. In contrast, peripherally-located attractions (such as attraction 1 and 8) had few waiting agents. The centrally-located attractions are close to many other attractions and they are preferentially selected by agents as next destinations, because each agent always chooses the nearest one from the remaining attractions to visit when $r = 0$. Thus, the centrally-located attractions tend to be crowded with agents. It means that the behavioral diversity among agents is decreased by the environmental condition in the sense that agents have an inclination to concentrate into certain attractions.

Next, we have conducted experiments using various probabilities of information sharing r. Figure 3 and 4 depicts the examples in case of $r = 0.5, 1.0$, and Figure 5 shows the standard deviation of the number of the waiting agents among attractions in various cases of r. As r increased, the transitions of the number of waiting agents dramatically got closer as shown in Figure

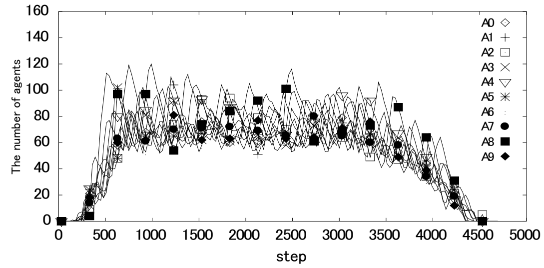

Figure 4: The number of waiting agents at each attraction ($r = 1.0$).

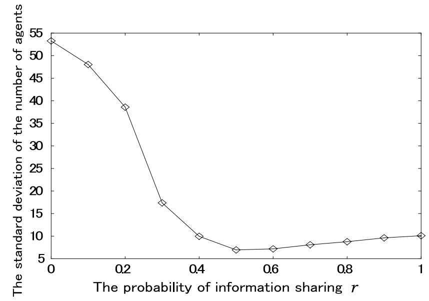

Figure 5: Correlation between r and the standard deviation of the number of waiting agents among attractions.

3, and then the deviation reached the minimum value when $r = 0.5$. However, as r increased, the deviation slightly increased when $r \geq 0.6$. Figure 4 ($r = 1.0$) tells us that it is caused by the large fluctuations in the number of waiting agents compared with Figure 3 ($r = 0.5$). This is due to the fact that sharing of the same information among too many agents rather causes new concentration of agents into another attraction that was not crowded a little time ago. Thus there exists an optimal informational diversity that maximizes the behavioral diversity that was basically decreased by the environmental condition.

3.2 A Dynamic Shift in the Effect of Information Sharing

Subsequently, we have conducted experiments using the condition: $r = 0.5, N_p = 20000$, so as to clarify how the effects of information sharing shown in previous section changes through long-term experiments. We have observed the dynamic shift in the effect of information sharing in about 50 percent out of 30 trials in this setting. Figure 6 shows a typical example of such a phenomenon. We can observe the sudden

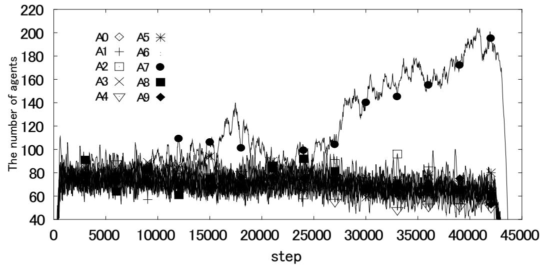

Figure 6: The number of waiting agents at each attraction ($r = 0.5, N_p = 20000$).

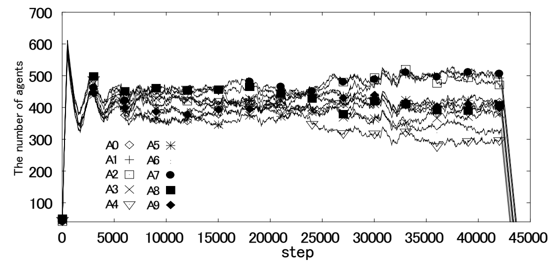

Figure 7: The number of agents who are due to visit each attraction ($r = 0.5$).

increase in the number of waiting agents at the attraction 7, from step 15000 to 20000 and after 25000.

The reason for such a decrease in the effect of information sharing is explained by the side effect of information sharing on future behavioral diversity. Agents who have received the information tend not to choice the centrally-located attractions such as the attraction 7. Thus, the deviation of the waiting agents among attractions was kept small in early period of the trial. However, at the same time, it gives rise to the gradual decrease in future behavioral diversity: the increase in the deviation of the number of agents who are due to visit each attraction (who have each attraction in their remaining attractions to visit) in the event space. Figure 7 depicts the number of agents who are due to visit each attraction in the same trial as Figure 6. Since the agents' destinations are chosen from their remaining attractions to visit, the deviation of these values reflects on the future behavioral diversity among agents. In fact, the number of agents who were due to visit the attraction 7 relatively got larger as time elapsed. This means that the future behavioral diversity was gradually decreased in the sense that more agents were due to visit the attraction 7 than other attractions. This decrease in the future behavioral diversity tends to make agents choose the attraction 7 even when they receive the information (especially in case where they have only the attraction 7 in their remaining attraction to visit). Then the concentration of agents into the attraction 7 occurred at last.

4 Conclusion

We have discussed how information sharing affects diversity and adaptivity of behaviors in competitive populations by focusing on the information supplement of congestion status at events or theme parks. By conducting multi-agent simulations, the following results were obtained: First, the behavioral diversity among agents is decreased by the environmental condition such as the arrangement of attractions on the event space. Second, there exists an optimal probability of information sharing that minimizes the standard deviation of congestion degree among attractions. Third, the dynamic shift in this effect in long-term experiments, the sudden increase of the waiting agents at a certain attraction, is caused by the side effect of information sharing, in other words, the gradual decrease in the future behavioral diversity among agents.

We believe that this series of study on the effects of information sharing would not only deepen our understanding of the collective behavior in human society but also could develop a new design principle for multi-agent robotic systems with a population of robots having complex interaction among them.

References

[1] W. B. Arthur, "Inductive Reasoning and Bounded Rationality," *American Economic Association Papers Proceedings*, Vol. 84, No. 2, pp. 406–411, 1994.

[2] D. Challet and Y. C. Zhang, "Emergence of Cooperation and Organization in an Evolutionary Game," *Physica A*, Vol. 246, pp. 407–418, 1997.

[3] R. Savit, R. Manuca and R. Riolo, "Adaptive Competition, Market Efficiency, and Phase Transitions," *Physical Review Letter*, Vol. 82, No. 10, pp. 2203–2206, 1999.

[4] T. Hogg and B. A. Huberman, "Controlling Chaos in Distributed Systems," *IEEE Trans. on Systems, Man and Cybernetics*, Vol. 21, No. 6, pp. 1325–1332, 1991.

[5] J. Akaishi and T. Arita, "Misperception, Communication and Diversity", *Proceedings of Artificial Life VIII*, 2002 (in press).