Paper

Investigation of Global Performance Affected by Congestion Avoiding Behavior in Theme Park Problem

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We focus on the simple theme park problem, where there are two attractions and visitor agents which select their destination attraction based on congestion disregarding behavior and congestion avoiding behavior. According to the computer simulation, the result shows that the growth of individual congestion avoiding behavior is not always effective for improving global performance, and this phenomenon is caused by the oscillation of successive selection switching of the same destination by many congestion avoiding agents. Although the model and setting of this paper is simpler than other related works, we consider each phenomenon in those works has the same characteristic based on the ineffectiveness caused by the homogeneity of congestion avoiding behavior and information sharing.

Keywords: Multiagent, Mass User Support, Theme Park Problem, Information Sharing, Scheduling

1. Introduction

Recent technological progress in ad-hoc network environments related to Personal Digital Assistant (PDA), cellular phone, and wireless LAN use has indicated the increasing importance of ubiquitous computing environments [(1)(2)]. In a ubiquitous computing environment, various independent communication devices, sensors, and processors are distributed in the user environment for supporting the user's daily activities. Moreover, the information technology for supporting such personal activity might include technology for airline, bus, and railway scheduling and reservations, car navigation, or hotel and services reservation.

The information technology for supporting a user's daily activities needs a new type of artificial intelligence based on the linkage between the digital information space and the real world situation, and certain infrastructures of information processing based on agent architecture and sensing technology have been studied as a base of such an artificial intelligence [(3)]. In particular, a new type of artificial intelligence called mass user support has been studied [(4)~(6)]. Its goal is not only to optimize individual utility but also to support a social system comprised of a group of individuals. Mass user support research aims to develop a dynamic social resource allocation mechanism that increases social welfare without reducing individual utility.

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One important research area related to mass user support is a flow control in which there are many people and each person has individual utilities based on one's preference and restrictions of daily activities. Our purpose is to construct a personal user support system that is interconnected and optimizes both global performance and individual utility, e.g., an interconnected car navigation system including global traffic flow control without sacrificing each individual utility, or a personal guidance device with a reservation system for individual urban activity. If we can reduce a small percentage of traffic congestion by the concept of mass user support, its profit for the environment and our future is very large. For the realization of such a system, one of the most important technologies is a control for reducing congestion based on global information. When we can obtain current transportation congestion information, we may be able to avoid congested routes by prediction of congestion occurrence or may not change own route due to some restrictions. If most people avoid congestion based on such information, can we achieve a reduction of global congestion?

In a related work, Suzuki et al. proposed a multiagent model of visitor flow in a virtual event hall [(7)]. This model consists of visitor agents who intend to go to several event booths in the hall. There are two types of agents; one agent decides a destination based on current congestion information, and another agent does not take any thought of such information and merely goes to the nearest booth. In their paper, they investigated the relationship between congestion occurrence and congestion avoiding behavior with information sharing. Shiose et al. constructed a simple multiagent traffic model with a Vehicle Information and Communication System [(8)] (VICS) which gives users congestion information and a recommended route [9]. His model also has two types of agents; one avoids congestion based on VICS information and another disregards it. They studied the relationship between congestion avoiding behavior and global performance. Moreover, Tanahashi et al. developed an elaborate macro model traffic simulator, and studied the effectiveness of a traffic information system using the simulation of Toyota City in Japan [10].

Although these models are different from each other, their simulation results commonly show the important finding that the existence of moderate congestion avoiding behavior contributes to reducing global congestion. However, an excessive increase of congestion avoiding agents spoils global performance. Namely, it is not always effective for increasing congestion avoiding behavior. This is a critical characteristic for considering mass user support, but these models are rather complicated and it is difficult to analyze the relationship between congestion avoiding behavior.

Therefore, we focus on the theme park problem [11], a multiagent model for studying individual visiting activity and global performance, and clarify the relationship between global performance and congestion avoiding behavior. In the theme park problem of this paper, there are two attractions providing services. An agent selects a destination attraction from the two choices and goes along a road to the destination. Each attraction has its capacity, and overflow agents have to wait for the previous agents to finish. In addition, there are two types of agents, i.e., a congestion avoiding agent, and congestion disregarding agent. A congestion avoiding agent does not like congested situations and avoids them by using current congestion information. A congestion disregarding agent does not take notice of congestion and merely decides on his/her preferred choice. The aggregated global performance of such agents is measured by the average wait time of the agents. The reason for adopting a multiagent model [13] rather than a macro-simulation model is to treat individual preference and restrictions with bounded rational and not completely controllable behavior. The theme park situation in this paper is considered as a dynamically extended model of the route selection problem considered by Knight [12], which is a simple static situation, and in which many rational selectors simultaneously choose a highway to minimize individual travel time.

2. Theme Park Problem

The theme park problem is one example of mass user support research [11], that consists of two kinds of elements, a spatial component and a software agent. The spatial component of the theme park may be one of several types; attraction, road, plaza, entrance, and exit. The software agent represents a visitor to the theme park, and it has individual preferences regarding each attraction. The objective of the theme park problem is to develop an algorithm that dynamically coordinates agents' visiting behavior in order to reduce congestion and increase an individual visitor's satisfaction. In other words, the theme park problem is a dynamic resource allocation problem that needs to coordinate many individual behaviors and optimize individual and group satisfaction by using distributed information.

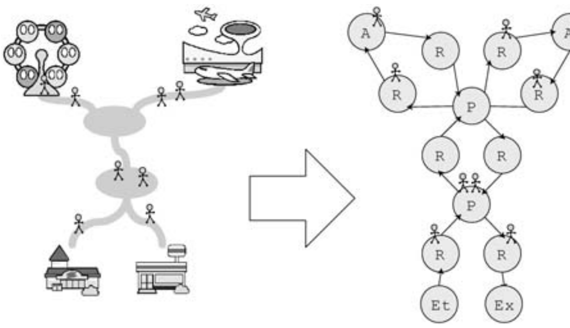

Fig. 1. Example of a small theme park. The left figure shows the image of theme park, and the right shows the directed graph representation of it. In the right graph representation, A, R, P, En, and Ex represent an attraction, road, plaza, entrance and exit component, respectively

We used a theme park situation as a research topic for the following reasons.

- The problem is closed; namely, only information related to the theme park has to be considered, and it is possible to model the individual agent's visiting activity and preferences for the attractions.
- It is possible to measure the effectiveness of coordination based on the degree of congestion, wait time for admission to the attractions, and throughput.
- The number of agents takes the order of $10^2 \sim 10^5$, and should be large enough for the initial study of mass user support.
- It is possible to compare the problem's solutions with real theme park data.
- The outcome of this study should be implementable in a real theme park with IT devices.

In this paper, we concentrate on clarifying the relationship between visitors' congestion avoiding behavior and global performance, i.e., wait time for attraction.

The theme park problem is constructed from N spatial components that provide a particular kind of service for the visitor agents. Component i has one of five types of service defined as attraction, road, plaza, entrance, and exit. It also has two static attributes, c_i and st_i, and each type of component is characterized by these parameters. Parameter c_i represents the service capacity of component i, which means the maximum number of visitors that can be served in component i at once. st_i is the service time for a visitor agent. The agent requires st_i to receive its service in the component i; e.g., the agent requires st_i to move through a road component. The theme park is defined as a directed graph in which the components are represented as nodes and each component is connected by directed edges. An example of a theme park that consists of two attractions, two plazas, one entrance and exit is shown in Fig. 1. The visitor agents transit these components according to the directed edges.

In the theme park, n agents visit attraction components through road and plaza components. The visitor agent j has a preference p_{ji} which represents the agent j's degree of preference for component i. Each p_{ji} is a real value between 0 and 1 that has been determined in advance. For example, a higher value of p_{ji} indicates that agent j strongly hopes to visit component i. Preference values for components other than attraction are set to 0.

The dynamical definition of the model is as follows. Let t be the time step of the simulation. The simulation is iterated until t reaches the termination time t_{max}. The agent j has five dynamical attributes, $cs_j, pt_j, vt_{ji}, wt_j$, and mt_j. cs_j represents the component where the agent j is on at time t. The agent j belongs to only one component at any time, and starts from the entrance component when arriving at the theme park. The past time pt_j represents how long the agent j spends in component i. This variable is increased by one when the time step of the simulation proceeds, and cleared when the agent leaves the component. The visiting time vt_{ji} is the number of times agent j has visited node i. wt_j and mt_j represent the total wait time and total moving time of the agent j, respectively.

Component i has the set of agents a_i and the queue q_i as dynamical attributes, a_i consists of agents visiting component i at time t. The queue consists of agents that desire to visit component i when the service capacity of component i is full. The priority order of a queue is based on First-In First-Out (FIFO) buffers, and an earlier agent has admittance priority over that of a later one. When agent j goes inside component i, agent j is erased from queue q_i.

The simulation procedure proceeds as follows. At time t, agent j acts in turn according to agent number. For simplification, let i be the current component of agent j, namely, corresponding to cs_j. The agent can choose the next component to transit to if the following condition is satisfied.

$$st_i \le pt_j \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (1)$$

The condition indicates that the service of current component i has finished. Otherwise, agent j spends more time in the current component until the service has finished.

Next, suppose that agent j satisfies the above condition and chooses component k as the next one. In the simulation, the next component is chosen based on the agent behavior explained later. If the following condition is also satisfied, agent j can transit from the current component i to the next component k.

$$|a_k| + 1 \le c_k \text{ and } |q_k| = 0, \cdots\cdots\cdots\cdots \quad (2)$$

or,

$$|a_k| + 1 \le c_k, |q_k| \ne 0 \text{ and}$$
$$\text{agent } j \text{ is the first priority in } q_k. \cdots\cdots\cdots \quad (3)$$

The notation $|\cdot|$ means the cardinality of elements.

When agent j moves to the next component after satisfying condition 2 or 3, the total wait time of agent j is updated as

$$wt_j \leftarrow wt_j + (pt_j - st_i) . \cdots\cdots\cdots\cdots \quad (4)$$

Moreover, if component i is road or plaza component, the total moving time is updated as

$$mt_j \leftarrow mt_j + st_i . \cdots\cdots\cdots\cdots\cdots \quad (5)$$

After updating, agent j moves to component k by changing the current component cs_j to k, and pt_j is reset to zero. If the agent does not satisfy condition 2 or 3, agent j is added to queue q_k and waits until component k is available for agent j.

The pseudo code for simulating the theme park problem is shown in Fig. 2.

```
procedure Theme_Park_Problem()
  initialize();
  while (t < t_max) do
    agent_activity();
    t ← t + 1;
  end while
  output evaluation();
end procedure

procedure agent_activity()
  for each agent j do
    if the agent j is active
      pt_j ← pt_j + 1;
      i ← cs_j;
      if (st_i ≤ pt_j)
        k ← next_component_navigation();
        if the condition 2 or 3 is satisfied
          wt_j ← wt_j + pt_j − st_i;
          if the component i is a road or plaza
            mt_j ← mt_j + st_i;
          endif
          cs_j ← k;
          vt_k ← vt_k + 1;
          pt_j ← 0;
          delete the agent j from a_i;
          delete the agent j from q_k;
          add the agent j to a_k;
        else if j is not registered in q_k
          add the agent j to q_k;
        end if
      end if
    end if
  end for
end procedure
```

Fig. 2. The pseudo-code for simulating the theme park problem

3. Simulation Setting

For computer simulation, we prepared a simple theme park model shown in Figure 3. In this model, there are two attractions; attraction 1 and attraction 2. The difference between the two is only service time. A preference value for each agent p_{ji} is randomly given from 0 to 1. In this case, both attractions are equally preferred by the agents. An agent arrives at the entrance according to the Poisson Distribution with the average arrival rate λ, and the agent has to select an attraction at the fork of the entrance. After selecting one way, the agent goes to the destination attraction along a road. If the destination is congested by many agents, the agent has to wait for its turn in accordance with the FIFO rule.

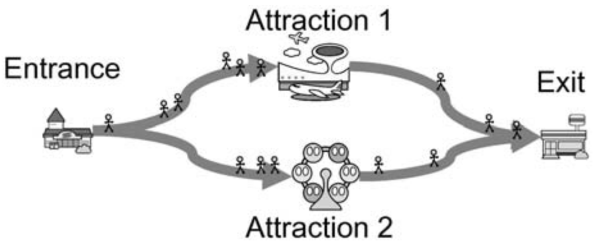

Fig. 3. The situation of the theme park for simulations

When all the previous agents in the queue have finished receiving their service, the agent receives its service and goes out by the exit.

To select a destination attraction, we prepared two types of agents; a Congestion Disregarding (CD) agent and a Congestion Avoiding (CA) agent. A CD agent simply chooses a more preferred destination that has a higher preference value for the agent. On the other hand, a CA agent observes the state of congestion in both attractions, and chooses the destination according to the estimated wait time. The estimated wait time is simply calculated by the equation (the estimated wait time) = (the number of waiting agents)×(the service time)/(the capacity), and the agent chooses the attraction which has the shorter estimated wait time. This estimated wait time is calculated based on the current state and does not include a prediction, therefore, the choice may be wrong upon arrival because the situation dynamically changes for the agent after going along a road. If the estimated wait time of both attractions is equal, this agent simply selects the more preferred attraction.

The behavior of the CA agent is very simple but we consider this modeling is not misdirected because it is generally difficult for a person to correctly predict future congestion based on the current situation and he/she may merely avoid the current congestion in most cases. For the simulation, we varied the ratio of each type of agents in order to investigate the effectiveness of congestion disregarding behavior and congestion avoiding behavior.

The main difference between our model in this paper and the route selection model of Knight is as follows.

- In the route selection model, all the agents simultaneously choose a route for maximizing individual utility using predictions of others' selection. However, in our model, agents dynamically arrive at the theme park according to the Poisson Distribution and make choices based on the current state. Namely, the route selection model is static and our model is dynamic.
- The route selection model supposes a rational agent which can perfectly understand the static model situation, and iteration of rational selection leads global behavior to converge an equilibrium of ideal load distribution. On the other hand, in our model the agent is imperfect and boundary rational, and the agent reactively makes a decision since it is difficult to optimize its behavior in a dynamic situation in which a decision takes effect at a later time. Accordingly, it is necessary to study what the optimum state of our model is and how to resolve this dynamic problem.

Table 1. The parameter settings

The simulation step, t_{max}	$10,000$
Total number of agents, n	$1,000$
The capacity of roads	∞
The service time of roads	100
The capacity of attractions, c_1 and c_2	10
The service time of attraction 1, st_1	100
The service time of attraction 2, st_2	$50 \sim 100$
The average arrival rate, λ	0.3

We used the parameter settings shown in Table 1. In this setting, we fixed the service time of attraction 1 and varied the service time of attraction 2 because the balance of service time strongly influences the load distribution of attractions, and it is necessary to clarify the relationship between the congestion and balance. In addition, we set the ratio of CA agents from 0 to 1 to investigate the optimum global performance. Other parameters were decided on the basis of preliminary experiments to emphasize the points at issue in this work. Each result of simulations is averaged over 500 trials.

4. Experimental Results

The ratio of agents which selects attraction 1 at various service time settings of attraction 2 is shown in Fig. 4. The X axis indicates the value of R_{CA}, the ratio of CA agents. The setting $R_{CA} = 0$ means there are only CD agents, and $R_{CA} = 1$ means there are only CA agents. In each service time setting, the ratio of agents that select attraction 1 is about 0.5 at the point that $R_{CA} = 0$ because all agents randomly selects their preferred destination with no consideration of congestion. In the case of $st_2 = 100$, namely the equal service time case, the ratio of agents that select attraction 1 is about 0.5 independently of the value of R_{CA} because attractions 1 and 2 are the same with respect to services. In the cases of $st_2 < 100$, according to increase of R_{CA}, the ratio of agents to select attraction 1 decreases and agents' choices shift to the shorter service time attraction. The ratio change of selection is clearly affected by the increase of congestion avoiding behavior. Additionally, the longer service time of attraction 2 increases the ratio to select attraction 1.

The normalized average wait time for attraction 1 and 2 is shown in Fig. 5. In each service time setting st_2, it is remarkable that the wait time decreases to a certain value of R_{CA} and increases from that value. Namely, the optimum value of R_{CA} for minimizing the average wait time exists in each case. This result of the simple theme park simulation may agree with some related works such as the event hall simulation and traffic simulation [7][9][10]. Additionally, in the cases that the service time of attraction 2 is similar to that of attraction 1, excessive numbers of CA agents spoil the global performance compared with the case of only CD agents. This result suggests that the global performance aggregated by only congestion avoiding behavior might be inferior

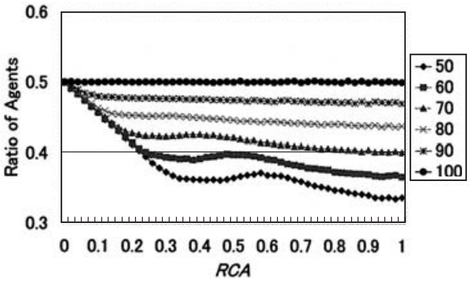

Fig. 4. The ratio of agents which selects attraction 1. The X axis indicates R_{CA}, the ratio of CA agents, and the Y axis indicates the ratio of agents that selects attraction 1. Each number indicator corresponds to the setting of st_2, the service time of attraction 2

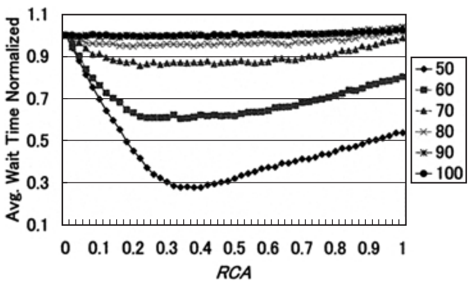

Fig. 5. The average wait time for the attractions. The X axis indicates R_{CA}, the ratio of CA agents, and the Y axis indicates the average wait time of whole agents. For normalization, each wait time is divided by the wait time of the case $R_{CA} = 0$. Each number indicator corresponds to the setting of st_2, the service time of attraction 2

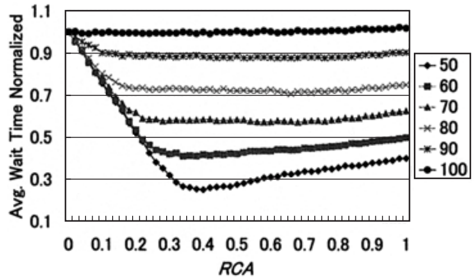

Fig. 6. The average wait time of agents which selected attraction 1. The X axis indicates R_{CA}, the ratio of CA agents, and the Y axis indicates the average wait time. For normalization, each wait time is divided by the wait time of the case $R_{CA} = 0$. Each number indicator corresponds to the setting of st_2, the service time of attraction 2

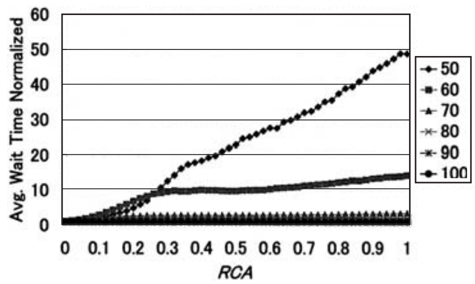

Fig. 7. The average wait time of agents which selected attraction 2. The X axis indicates the ratio of CA agents, R_{CA}, and the Y axis indicates the average wait time. For normalization, each wait time is divided by the wait time of the case $R_{CA} = 0$. Each number indicator corresponds to the setting of st_2, the service time of attraction 2

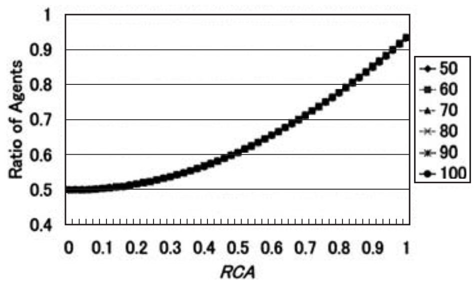

Fig. 8. The ratio of agents which selected the same attraction as the previous agent selected. The X axis R_{CA}, indicates the ratio of CA agents, and the Y axis indicates the ratio

to the performance of only random selecting with no intelligence.

The graphs of average wait time at attraction 1 and 2 are shown in Figs. 6 and 7, respectively. Each wait time is also normalized by the wait time of the case $R_{CA} = 0$. The number of agents selecting attraction 2 increases according to the increase in the value of R_{CA} as shown in Fig. 4, and Fig. 7 correspondingly shows the increase of the average wait time at attraction 2. In other words, the queue length of attraction 1 becomes shorter and that of attraction 2 becomes longer in response to the number of CA agents. It means that this result is caused by the ratio change of CD and CA agents, and the load distribution shifts to the shorter service time attraction in response to congestion avoiding behavior. The average wait time shown in Fig. 5 is based on the result of attractions 1 and 2 in Figs. 6 and 7.

The ratio of agents that select the same attraction as the previous agent selects is shown in Fig. 8. A larger value of this ratio means that more agents sequentially select the same attraction as the previous agent. The ratio to follow the previous agent is about 0.5 in the case $R_{CA} = 0$ because all the agents randomly select destinations independently of the previous agent. According to the increase of R_{CA}, the ratio is a larger value, and is grater than 0.9 in the case $R_{CA} = 1$. Fig. 4 indicates that the ratio to select attraction 1 maintains a certain value in the case of a grater R_{CA} value, while the result of Fig. 8 means that the frequency of switching the attractions becomes less rather than most agents selecting identical attractions. Moreover, the ratio of agents in Fig. 8 draws almost same line in each setting of st_2. This result indicates that a dynamic state of congestion caused by more CA agents does not change in the short term and CA agents consecutively select the same attraction by comparing estimated wait times at two attractions. After the estimated wait time of two attractions is reversed the order and the congestion avoiding agents switch the destination to the shorter estimated wait time attraction, the agents which have

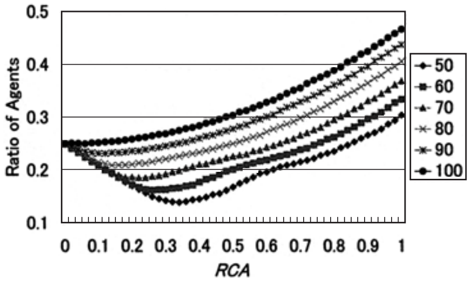

Fig. 9. The ratio of agents which selected attraction 1 following the previous agent. The X axis indicates R_{CA}, the ratio of CA agents, and the Y axis indicates the ratio of agents selecting attraction 1 following the previous agent. Each number indicator corresponds to the service time of attraction 2

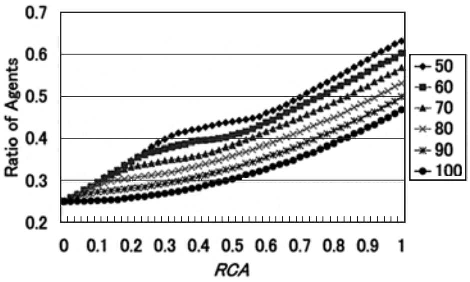

Fig. 10. The ratio of agents that selected attraction 2 following the previous agent. The X axis indicates R_{CA}, the ratio of CA agents, and the Y axis indicates the ratio of agents selecting attraction 2 following the previous. Each number indicator corresponds to the service time of attraction 2

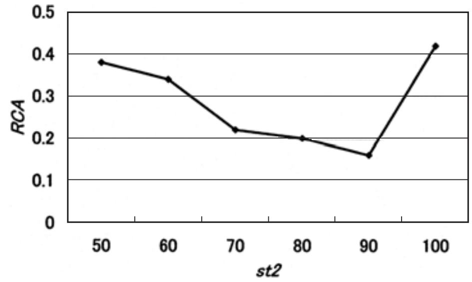

Fig. 11. The CA agents' ratio which shows the best performance in each attraction 2 setting. The X axis indicates st_2, the service time of attraction 2, and the Y axis indicates R_{CA}, the ratio of CA agents

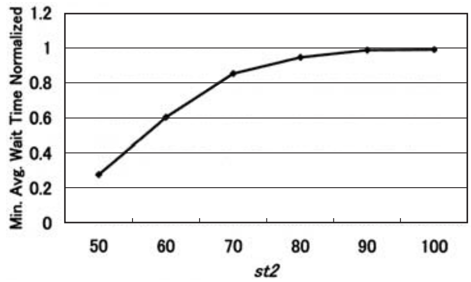

Fig. 12. The minimum wait time at each attraction 2 setting. The X axis indicates the service time of attraction 2, and the Y axis indicates the minimum average wait time

already selected the another attraction arrive for some time. Namely, the effect that congestion avoiding agents switch the destination to the shorter estimated wait time attraction works later by the length from the turning point to the destination, and the frequency that congestion avoiding agents switch the destination is strongly affected by the length of road rather than the setting of service time. This phenomenon is caused by the simple theme park setting with only two attractions, and it is expected to be more complex for the other settings with more attractions and complicated road structure.

The ratio of agents selecting attractions 1 and 2 following the previous agent is shown in Figs. 9 and 10, respectively. Namely, the values shown in Fig. 8 are analyzed into these graphs. It is remarkable in these graphs that the ratio of agents continuously selecting attraction 1 falls and rises in accordance with the value of R_{CA}. On the other hand, the ratio of agents selecting attraction 2 increases according to R_{CA}. The result in these graphs supports the idea that the cluster size of agents that consecutively select the same destination becomes larger over a certain value of R_{CA}.

The optimum R_{CA} value for minimizing the average wait time in each st_2 setting is shown in Fig. 11. In the case $st_2 = 50$, the optimum value is about 0.4, and this value decreases according to increases in st_2. This result shows that more congestion avoiding behavior is not effective where the condition of choices is similar. In addition, the optimum R_{CA} of the case $st_2 = 100$ is a larger value and is not important because the attractions have no difference in this case, and the difference in performance between each R_{CA} is small.

The optimum wait time in each st_2 is shown in Fig. 12. These values are normalized by the wait time in $R_{CA} = 0$. The optimum wait time approaches 1 according to an increase in the value of st_2. This result indicates that congestion avoiding behavior becomes effective for largely different choices and it is not effective for slightly different choices.

Since the settings of theme park model and the behavior of agents are fixed and not controllable in this simulation, it is not possible to directly control the parameter R_{CA} and achieve the optimum wait time. However, these results indicate the possibility for controlling the average wait time by introducing new ideas, e.g., attraction facilities dynamically changing the contents according to congested situation, intelligent information board that predicts the estimated wait time and implicitly controls the macro agents' behavior, and dynamic traffic regulations with one-way traffic for a kind of event. Such control mechanisms are applications of mass user support, and it is necessary for realizing mass user support to implicitly adjust the macro behavior which can not be directly controlled.

5. Discussion

In the experimental simulations, we have shown the relationship between the congestion occurrence in the simple theme park and the macro settings of agents' attitudes including congestion disregarding behavior and congestion avoiding behavior. The result shows one possibility that the growth of individual congestion avoiding behavior is not always effective for improving global performance. This phenomenon is caused by the oscillation of many congestion avoiding agents successively selecting the same destination. In other words, many congestion avoiding agents are forced to continuously determine the same choice by using the magnitude of estimated wait time, the growth of cluster size, which affects the length of queue in each attraction, and the increased wait time. Although the model and setting of this paper is simpler than other related works, we consider that each phenomenon in these works has the same characteristic based on the ineffectiveness caused by the homogeneity of congestion avoiding behavior and information sharing. In addition, the delay time between decision-making and the emergence of its effect is an important factor related to the phenomena. Our study recognizes it as the length of road from the entrance and attractions. It is necessary to investigate the time delay effect on global congestion.

Although we supposed there are only two kinds of agent behavior and the macro settings are fixed for the experimental simulations, a real user recognizes the environment and decides his/her own behavior based on his/her observation, utility, preference, and restrictions. Moreover, the real user have inductively learned whether own decision-making is right or not in his/her daily life. It is an important question whether or not the aggregation of non-cooperative user's bounded rational behavior based on inductive learning leads to user equilibrium, in which all users select individual best behaviors and no user may heighten his utility through unilateral selection, or the system equilibrium, in which all the resources are optimally distributed to the users. For the fixed iterated simple situations, some multiagent simulation research shows that the agents can achieve user equilibrium by inductive learning. B. Arthur shows that the classifier-type learning agents can achieve user equilibrium for the El Farol Problem [14], a kind of Minority game. Y. Sasaki also gives a result that reinforcement learning agents can achieve user equilibrium for the traffic route selection problem with a simple traffic network [15].

However, if the users can inductively learn such simple situations, can the users achieve user equilibrium in a large theme park they visit for the first time or a dynamically changeable traffic network? Our previous study shows it is difficult to optimize individual behavior in the complicated theme park model because optimal behavior is easily changed by the theme park setting [11]. In a real environment, the users may not be able to understand how to recognize the environment and how to measure the effectiveness of choices in their real lives, and they may not be able to achieve user equilibrium, much less system equilibrium. Therefore, the purpose of mass user support is to design an indication mechanism with incentives to receive system information and to prove acceptance of system indication to be effective for each individual, moreover, to bring the user equilibrium to the system one. Namely, it is necessary for the mass user support to reform the dynamic problem structure by informing the users of reliable and effective information.

For realization of such a system, it is necessary to study a coordination service that focuses on many fickle users and considers each individual user's utility, preference and restrictions in dynamic complex networks. The users desire to be able to change their own activities easily and we should consider a flexible reservation system [16] rather than a perfect, ideal and inelastic one. Moreover, it is very important that the system fairly supplies the coordination service, that is, it must be prohibited that the system informs different indications to users in the same or similar situations based on some kind of stochastic calculation. We can find many studies of congestion avoidance in computer network theory but these results and approaches can not be directly applied to mass user support due to the above discussion.

6. Conclusion

We supposed the simple theme park problem where there are two attractions and visitor agents choose the destination attraction one based on congestion disregarding behavior and congestion avoiding behavior. According to the computer simulation, the result shows that the growth of individual congestion avoiding behavior is not always effective for improving global performance, and this phenomenon is caused by the oscillation of many congestion avoiding agents successively selecting the same destination. In addition, the delay time between decision-making and the emergence of its effect is one of important factor related with the phenomena, and it is necessary to investigate time delay effect on global congestion.

This is the beginnings of study mass user support. We will investigate the characteristics of this problem and study the coordination and reservation system for achieving mass user support.

Acknowledgment

A part of this research is financially supported by Encouragement of Young Research (B), Grant-in-Aid for Scientific Research, Japan.

(Manuscript received Dec. 9, 2003,
revised June 4, 2004)

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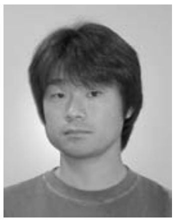

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