A Fuzzy Model-based Virtual Theme Park Simulator and Evaluation of Agent Action Models

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Summary
Agent-based simulation is a promising approach to social system analysis. This paper considers a fuzzy model-based virtual theme park simulator, in which each agent has a unique preference and acts with its own rule defined by a fuzzy model. Each agent model is designed to imitate a human subject whose responses to a questionnaire are used in defining the action rule of his/her agent. Experimental results demonstrate that the proposed simulator can reproduce situations reflecting the answers of many human subjects. The validity of the simulation model is also checked by human subjects through an experiment that compares the results of the simulation with their expectations.

Key words:
Social simulation, multi-agent, fuzzy modeling

1. Introduction

How to control the availability and reliability of resources within a community, in such a way that both community managers and users can be satisfied without stressful constraints, is an important problem. Computer-based simulation is a useful approach for analyzing complex human systems such as those that occur in economics, psychology, and other social sciences. Agent-based simulation [1] is a discrete simulation approach, in which individual entities in the model are directly represented and possess internal states and sets of behaviors or rules that determine how each agent acts at the next step. In order to extend agents' strategies, soft computing techniques have been applied to agent model design. Genetic algorithms [2,3] have been shown to be useful for evolving strategies for the iterated Prisoner's Dilemma game [4]. The fuzzy systems approach has also been introduced to computer-based simulation, for example, in a road traffic simulator [5,6].

This paper considers a fuzzy model-based community simulator for behavior analysis in a virtual theme park. A number of agents with various tastes act autonomously according to their action rules defined by a fuzzy model-based decision rule in a virtual theme park consisting of many attractions. The action pattern of each agent is modeled based on the answers to a questionnaire obtained from a human subject, and the optimal action for each agent is selected at each step, so that each agent's satisfaction is maximized.

By means of an experiment, it is demonstrated that the proposed simulator can reproduce situations reflecting the answers of many human subjects. The validity of the simulation model was also checked by human subjects, via an experiment examining the extent to which they believed that their own behavior would match that of their corresponding agent.

2. Fuzzy Model-based Virtual Theme Park Simulator

2.1 Simulation Environment

In the simulator, guests are represented by agents, which act autonomously according to their action rules in a multi-agent system. A number n of agents ($i = 1,2,...,n$) enter the virtual theme park one by one and stay in the park until closing time. The agents choose an attraction to ride and line up in its queue when they enter the theme park or finish with another attraction.

The theme park contains m attractions ($j = 1,2,\ldots,m$). The opening hours are specified as T minutes ($t = 1,2,...,T$). In our simulation, we do not assume a transition time for guests to move from one attraction to another, i.e., transition times are considered to be constant and are included in riding times. Two guests can ride any particular attraction at the same time. All rides start every two minutes and their riding times are specified as two minutes. The attractions in the theme park are classified as follows: (A) high-speed and thrilling attraction, (B) ride, (C) theater or live entertainment, (D) horror and panic attraction, (E) game, (F) fantasy and fairy tale attraction, (G) attraction for kids and families.

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Guests can access information about the waiting time for each attraction w_j^t, i.e., the waiting time for attraction *j* at time *t*.

2.2 Agent Model

In the simulation model, the situation for each guest is categorized into three cases: C_1: it takes little time to ride any attraction, C_2: it takes a long time to ride the most favorite attraction, C_3: it takes a long time to ride the top three favorite attractions. Each agent obtains satisfaction s_{ik}^t according to case C_k.

The action of agent *i* at iteration step *t* is inferred from the waiting times using a model with fuzzy if-then rules [7-9]. Here, the attraction index *j* is ordered based on the agent's preference ratio, i.e., *j* = 1 for the most favorite attraction, *j* = 2 for the second one, etc. Assume that the attitudes of guests towards queue length is represented by two fuzzy sets ``*short*'' and ``*long*'' shown in Fig. 1, in which ``*LONG*'' is a model parameter. When ``*LONG*'' is large, guests are patient and don't mind waiting a long time for their turn.

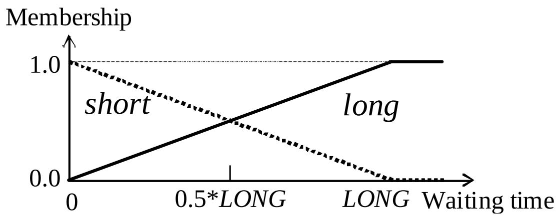

Fig. 1. A fuzzy partition of the waiting time

The action rules are as follows:

Rule R_1:

If w_1^t is *short* then C_1, (1)

Rule R_2:

If w_1^t is *long* and w_2^t or w_3^t is *short* then C_2, (2)

Rule R_3:

If w_1^t, w_2^t and w_3^t are *long* then C_3, (3)

where R_k is the label of the fuzzy if-then rule, C_k is a consequent case, and *k* is the case index. The action of each agent for each case is defined based on the answer to questionnaires on preferences and action rules given by a human subject. The confidence μ_{ik}^t for inputs (w_1^t, w_2^t, w_3^t) with the fuzzy if-then rule R_k is defined as follows:

$$\mu_{i1}^t = M_{1short}(w_1^t) \cdot s_{i1}^t, \quad (4)$$

$$\mu_{i2}^t = \min\{M_{2long}(w_1^t), M_{2short}(w_2^t), M_{2short}(w_3^t)\} \cdot s_{i2}^t, \quad (5)$$

$$\mu_{i3}^t = \min\{M_{3long}(w_1^t), M_{3long}(w_2^t), M_{3long}(w_3^t)\} \cdot s_{i3}^t, \quad (6)$$

where $M_{k\,short}(\cdot)$ denotes the membership function of the antecedent fuzzy set M_k. The value s_{ik}^t is the satisfaction rate for case C_k of agent *i* and is obtained from a questionnaire response. The fuzzy rule is selected by the maximum operator as follows:

$$R_i^t \quad \text{where} \quad \max\{\mu_{i1}^t, \mu_{i2}^t, \mu_{i3}^t\}. \quad (7)$$

Using the above action rules, the simulator involves many agents, each of whom has its own unique action rules. Figure 2 shows a screen shot of the virtual theme park simulator, in which the color bar of each attraction represents its queue length of guests waiting for the ride at iteration step *t*.

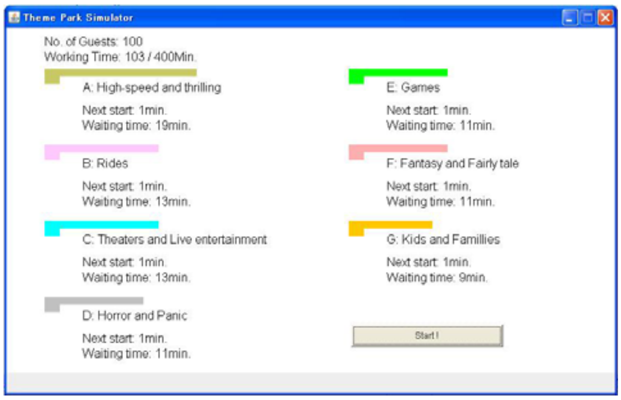

Fig. 2. A screen shot of the theme park simulator

3. Experimental Results

3.1 Simulation Settings and Answers to Questionnaires

Before simulations, questionnaires on attraction preferences (top three favorite attractions) and action rules (actions for $C_1, \cdots, C_3$) were administered to 224 human subjects (students from two universities in Osaka) [10].

The result for answers to the first question concerning the top three favorite attractions is shown in Table 1. The high-speed and thrilling attraction was the most popular, and the attraction preferences were highly biased.

Table 1: Top Three Favorite Attractions

	Attraction Type	*1st*	*2nd*	*3rd*
A	high-speed and thrilling attraction	124	31	17
B	ride	28	35	54
C	theatre or live entertainment	22	45	56
D	horror and panic attraction	10	28	41
E	game	31	61	34
F	fantasy and fairy tale attraction	2	9	5
G	attraction for kids and families	7	15	17

The second question is related to the case C_1: when it takes little time to ride any attractions, which action would you like to take? The answers are summarized in Table 2. There was a tendency for guests to choose favorite attractions but they did not necessarily choose the most favored one.

Table 2: Action Rules for Case C_1

	In case C_1, I ride …	*# subjects*
A	The most favorite attraction only	14
B	The most favorite attraction frequently	90
C	The top three favorite attractions equally	42
D	All attractions equally	78

The third question is related to the case C_2 : which action would you like to take in case C_2? Table 3 summarizes the answers and shows that guests obtained sufficient satisfaction by choosing other attractions when there was a long wait for the most favorite attraction.

Table 3: Action Rules for Case C_2

	In case C_2, I ride …	*# subjects*
A	The most favorite attraction only	7
B	The most favorite attraction once and then others equally afterwards	136
C	All attractions equally, except for the most favorite attractions	80
D	No attraction and leave the theme park without refund	1

The fourth question is related to the case C_3 and the answers are summarized in Table 4. The table indicates that guests try to obtain satisfaction by choosing various attractions when there is a long wait for the top three favorite attractions.

Table 4: Action Rules for Case C_3

	In case C_2, I ride …	*# subjects*
A	The top three favorite attractions only	31
B	One of the top three favorite attractions once and then others equally afterwards	138
C	All attractions equally, except for the top three favorite attractions	50
D	No attraction and leave the theme park without refund	5

The next question is related to the satisfaction level for cases C_2 and C_3. The answers are summarized in Table 5. The table shows that guests obtained a certain amount of satisfaction by not riding the favorite attractions. The results indicate that the theme park simulator should consider ``second choice situations'' for agents, i.e., guests can obtain sufficient satisfaction by avoiding serious decreases in satisfaction that occur from having to wait in long queues.

Table 5: Satisfaction level for Case C_2 and C_3 against C_1

Satisfaction level (%)	*case C_2*	*case C_3*
0-20	3	9
20-40	2	46
40-60	13	62
60-80	104	84
80-100	102	23

3.2 Simulation Results

Then, in order to carry out the experiment, the results of the questionnaires were applied to the simulation, *i.e.*, each of 224 agents was designed corresponding to a human subject, and action rules were defined based on his/her answers. The parameter ``*LONG*'' was set as ``*LONG* = 40''.

For comparison, a simulation was first operated only with the case C_1 action rule, i.e., `` first choice only situation''. Figure 3 shows the trajectory of queue lengths of the 7 attractions for 400 time slots. Because an attraction of type ``A (high-speed and thrilling attraction)'' was much the most popular, it always had a long queue. In this simulation, the total amount of satisfaction obtained by all agents during the hours of operation (the sum of $\max\{\mu_{i1}^{t}, \mu_{i2}^{t}, \mu_{i3}^{t}\}$ in Eq. (7)) was 762.9.

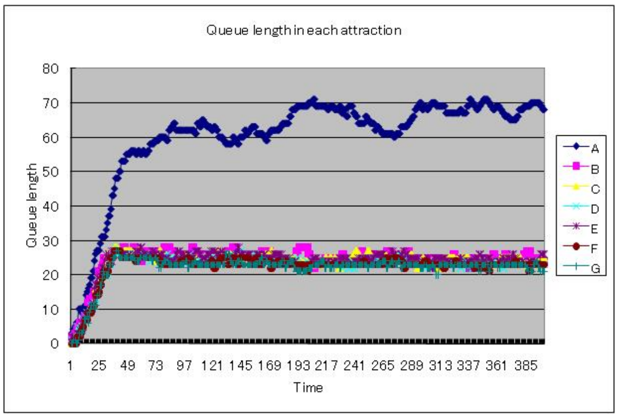

Fig. 3. Trajectory of queue lengths in the `` first choice only situation''

Next, a simulation was operated with the proposed agent action model, in which the ``second and third choice situations'' are also considered. Figure 4 shows the trajectory of queue lengths. The figure indicates that many guests selected the ``second or third best choice'' of cases C_2 and C_3, thus avoiding significant losses of satisfaction. With this simulation the long queues disappeared, and the total amount of satisfaction increased to 849.7.

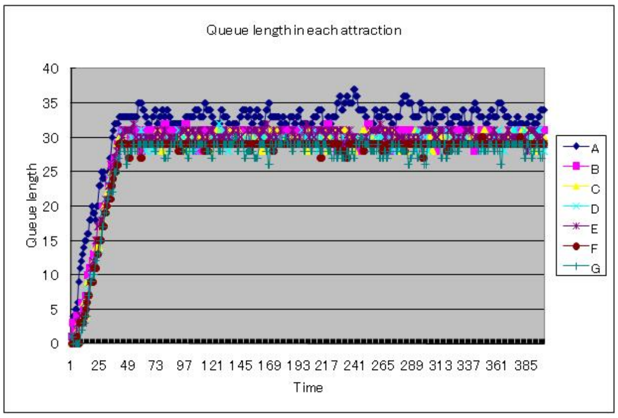

Fig. 4. Trajectory of queue lengths for the proposed agent action model

The above results imply that the proposed simulator can reproduce ``second choice situations'' reflecting answers of many human subjects and that it can be useful for analyzing human behavior in complicated social systems.

3.3 Validation of Agent Action Model

Next, the validity of the proposed agent action model was evaluated by the human subjects through a comparative experiment, in which each human subject was asked to select an agent with behavior most resembling their own.

In this experiment, two agents were indicated by ``blue'' and ``red'' marks in queues during simulations and the task for each subject was to select his/her agent from the two candidates (i.e., to distinguish his/her agent from anther randomly selected agent) only from the visual information of agent actions shown on a PC monitor. A screen shot of the queue information is shown in Fig. 5. In order to reduce the load on subjects, the number of agents and the operation time were decreased to $(n,T)=(112,200)$.

Although 56 human subjects tried the task, only 30 subjects could successfully select his/her agent. The success ratio was 54%. At first glance, the low accuracy seems not to support the validity of the proposed method because the result indicates almost random selection. It can be said that human action is very ambiguous and that the task of this experiment is not so easy. That may be because human action is based not only on the consistent first choice rule but also on other second or third choices that are implicit in most cases.

Fig. 5. A screen shot in agent model validation

We might also expect that accuracy would be improved if agents' inner feelings could be explicitly represented, i.e., each subject had his/her own rules that are situation dependent, and that agent actions should be considered along with these situations.

Then, the same experiment was performed by representing the agent's situation of ``first or second or third choices''. In order to dynamically represent the agent's situation, a visual signal using character pictures was added to the simulation display. Figure 6 shows the character pictures for the three cases of C_1, C_2 and C_3. One of the pictures was dynamically displayed for both blue and red agents, and each human subject tried to select his/her agent considering both agent actions and their feelings. Using the visual signal, the success ratio was increased to 61% (34 out of 56).

This result implies that human action is severely influenced by situations and seems not to be consistent at first glance. However, such complicated actions are based on certain rules and can be explicitly formulated by considering counter plans in a consistent manner. The proposed simulator is a realization of such community activity. We could confirm the efficiency of the proposed fuzzy model-based method in community simulations.

C_1 : satisfactory C_2 : ordinary C_3 : unsatisfactory

Fig. 6. Character pictures for three cases

4. Conclusions

This paper has proposed a virtual theme park simulator that can be used for behavior analysis of humans in communities. In the proposed agent-based simulator, action rules for each agent are designed based on a fuzzy inference-like model. By reflecting the answers to questioners by human subjects, we can reproduce the behavior of human subjects in the simulator.

In an experiment, 224 agents were constructed, each of which had a set of action rules reflecting a human subject's answers. Then, it was demonstrated that the simulator was able to reproduce situations reflecting the answers of many human subjects.

In another experiment, the validity of the proposed simulator was evaluated from the viewpoint of the degree to which the behavior of their corresponding agent matched their expectation. It was confirmed that the consideration of counter plans contributes to more successful understanding of complicated human actions.

The proposed simulator can be used in many community analyses. A potential future study is an analysis of the influence of a variety of user preferences or attraction features. In the experiment, counter plans contributed to the removal of long queues, even when user preferences were highly biased. However, it is possible that counter plans might fail to absorb much higher preference biases. Another future study includes the introduction of other mechanisms into the simulator. For example, in order to extend the virtual theme park into a network community simulator, some user guidance models should be introduced because user preferences and attraction features are not explicitly indicated in network communities. Such simulations may contribute to construction of an environment in which anyone can produce any content they wish and in which content can be accessed while still ensuring reliability of service and resources [11].

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