An Information Distribution Method for Avoiding Hunting Phenomenon in Theme Parks

Extended Abstract

Hiroaki Yamada
Fujitsu Laboratories Ltd.
Kawasaki, Japan
yamadah@fujitsu.com

Naoyuki Kamiyama
Kyushu University / JST, PRESTO
Fukuoka, Japan
kamiyama@imi.kyushu-u.ac.jp

ABSTRACT

In this study, we propose an indirect control method of pedestrian flows in theme parks using congestion forecasts and information distribution. Specifically, we propose a simulation-based algorithm for the problem of finding the optimal information distribution policy of congestion forecasts satisfying user equilibrium conditions.

KEYWORDS

pedestrian simulation, congestion forecast, simulation optimization, user equilibrium

ACM Reference Format:

Hiroaki Yamada and Naoyuki Kamiyama. 2020. An Information Distribution Method for Avoiding Hunting Phenomenon in Theme Parks. In *Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), Auckland, New Zealand, May 9–13, 2020,* IFAAMAS, 3 pages.

1 INTRODUCTION

In theme parks, congestion is ubiquitous. It is caused by popularity concentration for rides and attractions. If we can reduce congestion, we can reduce the waiting time of visitors, thus improving visitor satisfaction. Furthermore, because we can avoid accidents caused by congestion, it is one of the most important issues in theme park management. Of course, it is not difficult to observe that if we regulate visitors' movement, we can easily reduce congestion. However, restricting freedom of wandering considerably reduces visitor satisfaction. Thus, when we control congestion in theme parks, we must consider the trade-off between reducing congestion and restricting freedom.

In this study, we consider an indirect control of pedestrian flows in theme parks by, e.g., route recommendation, information on congestion, and coupons. The interest in such indirect control methods, which can handle the trade-off, seems to be increasing because of the spread of mobile devices which can individually distribute suitable information (e.g., smartphones). Especially, we consider the problem of finding an optimal policy on supplying congestion information, which is one of the indirect control methods of pedestrian flows. In our policy, we have to determine what type of information is supplied and whom it is supplied to. If we simply supply congestion situations in real time to everyone, then visitors will avoid crowded attractions and crowded periods of time. Such behavioral changes cause new congestion in places that are not expected to be crowded and reduces congestion in the places which are expected to be crowded. Furthermore, such a situation may be repeated. This situation is called a hunting phenomenon (see, e.g., [2]). Therefore, to reduce congestion by information distribution, we have to avoid the hunting phenomenon.

We focus on a user equilibrium to control visitors' behavior by congestion forecasts. User equilibrium is a situation in which players want to maximize their utility functions, but they cannot increase their utility function by individually changing their strategies. That is, there does not exist an incentive to change their behavior. Thus, if we can supply a user equilibrium as congestion forecast, then we can make the situation as the forecast. We call this reproducible congestion forecast a *congestion forecast satisfying user equilibrium conditions*. If we can find multiple congestion forecasts satisfying user equilibrium conditions, we can choose the optimal forecast minimizing congestion.

We propose a simulation optimization method that can find an optimal policy by avoiding the hunting phenomenon. In the simulation optimization, typically we enumerate a small number of alternatives and evaluate all the policies using simulation. Then, we select the best policy based on the results of the simulation (see, e.g., [1]). However, in this type of research, the authors mainly focus on direct control methods [6]. As previous work of indirect control methods, in the situation where visitors strategically behave, Masuda and Tsuji [5] studied the effect of priority tickets (i.e., fast passes) on congestion equilibrium. However, we cannot apply this kind of theoretical approach to information distribution because the approach is based on strict assumptions.

2 SIMULATION MODEL AND ALGORITHM

We use the pedestrian simulation model proposed in [3], which can treat the effect of congestion information on visitors' behavior. Ohori, Iida, and Takahash [3] modeled visitors' choice by multinomial logit utility function and reproduced congestion in theme parks. More precisely, the utility $U_i(a, p)$ of a visitor i at a position p for each attraction a is defined by

$$U_i(a, p) := \alpha_i(a) + \beta_1 d_i(a, p) + \beta_2 c_i(a),$$

where $\alpha_i(a)$ is a real number representing the preference of the visitor i for the attraction a, $d_i(a, p)$ is the travel cost for the visitor i from the current position p to the attraction a, c_i is the current congestion cost of the attraction a for the visitor i, and β_1 and β_2 are parameters balancing the travel cost and the congestion cost, respectively. The values $\alpha_i(a)$, $d_i(a, p)$, and $c_i(a)$ take real numbers between 0 and 1.

Proc. of the 19th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2020), B. An, N. Yorke-Smith, A. El Fallah Seghrouchni, G. Sukthankar (eds.), May 9–13, 2020, Auckland, New Zealand.

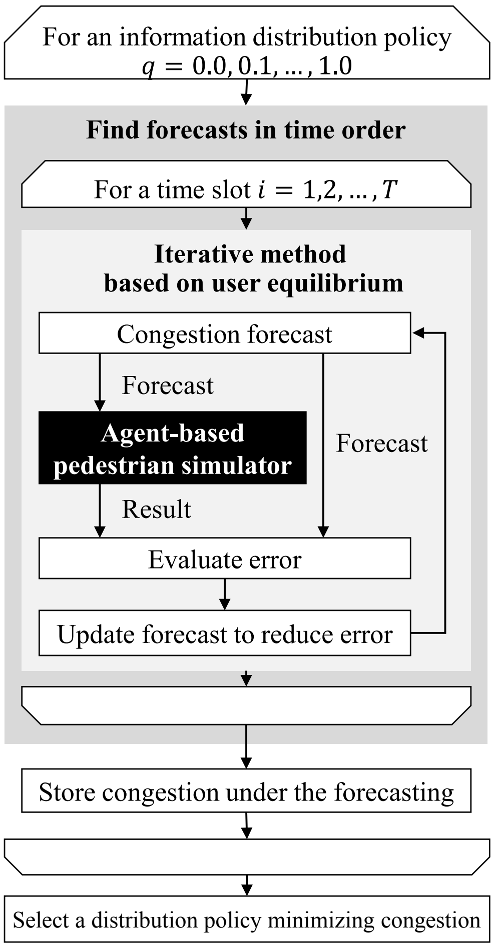

Figure 1: Overview of the algorithm. The trapezoid represents the start and end of the For loop.

An attraction consists of one queue lane and several service units. For example, a service unit represents a vehicle of a roller coaster. If some visitors are waiting in the queue lane for some attraction, then a new visitor lines up at the end of the line. Otherwise, the new visitor can ride on a vacant service unit. Each unit has capacity and time required as the parameters. In short, a theme park is modeled as a queueing network.

Our algorithm is based on algorithms for computing equilibrium traffic assignment in road networks [4] (see Figure 1). In this algorithm, we first fix the information distribution policy q (i.e., how many visitors we distribute the congestion forecast to). Then, we sequentially optimize the policy from earlier time steps to later time steps. In each iteration of each time step, we update the current forecast by the realized congestion of this step.

3 NUMERICAL EXPERIMENTS

In our numerical experiments, the number of visitors is 500, the number of attractions is 3 with only 1 unit, and the simulation period is from 8:00 a.m. to 12:00 p.m. Each time slot of the forecast is one hour, and each time step corresponds to a minute. The arrival time of an agent is stochastic, and it obeys normal distribution with 8:30 a.m. as the expected value and a standard deviation of 60 min. The geography is a simple structure consisting of only one zone with one popular attraction $\{a_1\}$ and two normal attractions $\{a_2, a_3\}$. There exist 3×4 parameters for optimization. For simplicity, we assume that $d_i(a, p) = 0$ for every agent i, every attraction a, and every position p.

In the numerical experiments, we fix an information distribution policy as 0.5 (i.e., $q = 0.5$). Table 1 shows the result of our algorithm. The matrix F represents the obtained congestion forecast. The maximum queue length was improved from 130 to 104 (i.e., if we do not use our algorithm, the maximum queue length is 130). The number of iterations on $q = 0.5$ is 142. Figure 2 shows the effect of optimal congestion forecasting. The congestion at the popular attraction a_1 is reduced by forecasting. Furthermore, the forecast is the same as the situation. Even if we apply our algorithm for all information distribution policies in $q \in \{0.0, 0.1, \ldots, 1.0\}$, the number of total iterations is 1190, and the total calculation time is 0.5 h.

Table 1: Result of our algorithm. Information distribution policy q is fixed at 0.5.

Parameters	Values
$F = \begin{pmatrix} F(1,a_1) & F(1,a_2) & F(1,a_3) \\ F(2,a_1) & F(2,a_2) & F(2,a_3) \\ F(3,a_1) & F(3,a_2) & F(3,a_3) \\ F(4,a_1) & F(4,a_2) & F(4,a_3) \end{pmatrix}$	$\begin{pmatrix} 1. & 0.6804 & 0.6622 \\ 1. & 0.7241 & 0.7828 \\ 1. & 0.6659 & 0.6589 \\ 1. & 0.6679 & 0.6261 \end{pmatrix}$
Maximum queue length	104 (130)
Iteration ($q = 0.5$)	142
Total iterations	1190
Total calculation time	0.5 hours

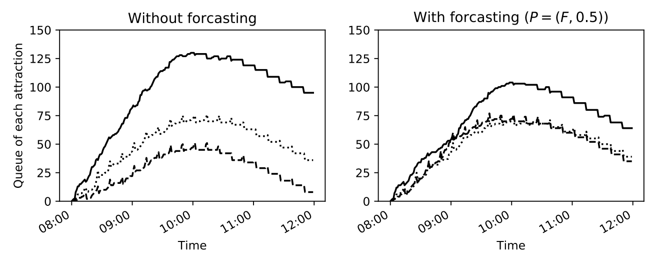

Figure 2: The left figure shows the transition of the length of the waiting queue of each attraction without supplying congestion forecast. The right figure shows the transition of the length of the waiting queue of each attraction with supplying the congestion forecast computed by our algorithm.

ACKNOWLEDGMENTS

This research was supported by JST, PRESTO Grant Number JPMJPR1753, Japan, and Fujitsu Laboratories Ltd. The authors would like to thank Hiroaki Iwashita, Takuya Ohawa, and Kotaro Ohori for useful discussion.

REFERENCES

[1] N. De Bufala and J.-D. Kant. 2019. An Evolutionary Approach to Find Optimal Policies with an Agent-Based Simulation. In *Proceedings of the 18th International Conference on Autonomous Agents and Multiagent Systems*. 610–618.

[2] T. Imai and K. Nishinari. 2015. Optimal information provision for maximizing flow in a forked lattice. *Physical Review E* 91, 6 (2015), 062818–1–062818–7.

[3] K. Ohori K, M. Iida, and S. Takahashi. 2013. Virtual Grounding for Facsimile Model Construction Where Real Data Is not Available. *SICE Journal of Control, Measurement, and System Integration* 6, 2 (2013), 108–116.

[4] L.J. LeBlanc, E.K. Morlok, and W.P. Pierskalla. 1975. An efficient approach to solving the road network equilibrium traffic assignment problem. *Transportation Research* 9, 5 (1975), 309–318.

[5] Y. Masuda and A. Tsuji. 2019. Congestion Control for a System with Parallel Stations and Homogeneous Customers Using Priority Passes. *Networks and Spatial Economics* 19, 1 (2019), 293–318.

[6] S. Shigenaka, S. Takami, Y. Ozaki, M. Onishi, T. Yamashita, and I. Noda. 2019. Evaluation of Optimization for Pedestrian Route Guidance in Real-world Crowded Scene. In *Proceedings of the 18th International Conference on Autonomous Agents and Multiagent Systems*. 2192–2194.