Evaluation of Optimization for Pedestrian Route Guidance in Real-world Crowded Scene

Extended Abstract

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ABSTRACT

In this paper, we proposed evaluation index considering safety of pedestrian. This evaluation index, it is possible to evaluate all of pedestrian traveling time, unfairness and congestion degree. We also confirm that the guidance control method optimized by CMA–ES can realized better than real guidance.

KEYWORDS

CMA-ES; RMSE; pedestrian simulation

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1 INTRODUCTION

Multi–Agent Simulation(MAS) is widely used in fields, such as tourism, transportation, and town planning, during large-scale events. In general, these studies are used for evacuation [1][2][3][4] and cost management [5][6][7], and are not widely used for safety considerations such as at alleviating congestion and guiding pedestrians to safety in the event of a disaster. In recent years in Japan, the Tokyo Olympic are about to begin in 2020. Large facilities such as stadiums will be used for Olympic games; such facilities require safe and efficient management. However, in order to realize them, it is necessary to evaluate the real (manual) guidance control method, and resolving the optimization problem for the high dimensional space of the MAS is very important.

Typically, performing large-scale optimization in a high dimensional space is difficult. Parameter search has been used for manual search, grid search, and random search [8]. To efficiently determine an optimal mathematical solution, researchers have proposed solutions such as Bayesian optimization [9] and Covariance Matrix Adaptation Evolution Strategy(CMA–ES) [10]. To improve the performance of the machine-learning classifier, Ozaki et al. evaluated hyperparameter optimization [11]. They prove that the Nelder–Mead method [12], a direct search method, is superior to other methods. However, in general, the Nelder–Mead method is used to quickly find a local solution. Bayesian optimization and CMA–ES are known to have superior performance in global optimization. In this research, to control the flow of tens of thousands of people, we used an optimization method using CMA–ES, which is superior to the global optimal solution search.

Additionally, by proposing evaluation index considering safety, it is possible to evaluate all of pedestrian traveling time, unfairness and congestion degree. We also confirm that the guidance control method optimized by CMA–ES can realize better induction than the real guidance control method.

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2 METHOD

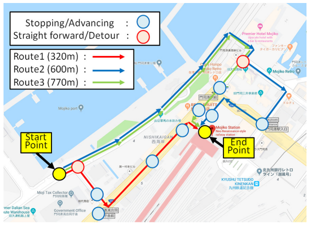
2.1 Guidance control method

Fig. 1(a) shows guidance control location of the event staff. This guidance controls system implemented the “stopping / advancing” control at eight locations and the “straight forward / detour” controls at two locations; i.e., there were controls at 10 locations. **Fig. 1(b)** shows the state of the simulation using this guidance control. Green dots show that people are moving smoothly and red dots show that people are caught up in congestion.

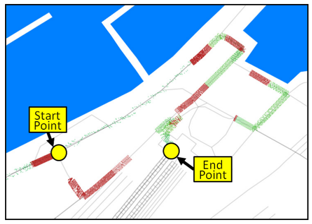
In general, complicated rules such as “After proceeding for 2 min, stop for 3 min, then proceed for 5 min and stop for 2 min” are not realistic owing to a high probability of confusion. In this research, to apply guidance control commands in the field, we divided the total induction time into sections of N. Within that section, guidance control information was expressed by repeating “stopping / advancing” or “straight forward / detour” at *Open* min and *Close* min. We called these commands the guidance control method. In the guidance control method, the control time of the n-th section of the control location $p = \{1, 2, \cdots, P\}$ was represented by $Open_{np}$ and $Close_{np}$. In optimization of the guidance control method for fireworks display, parameter used a two-type command time ($Open_{np}$, $Close_{np}$) with ten control points (P = 10) and three control divisions (N = 3).

2.2 Evaluation of the guidance control method

In general, in a congested environment, stress levels increase when the wait time is long. We defined the delay time as the difference between the average arrival time $Travel_c(t)$ of people during a fixed period and the arrival time $MinT_c$ of people on each route in the absence of congestion. However, this delay time does not



(a) Guidance control locations in 2016



(b) Simulation after the fireworks display.

Figure 1: Map showing the layout of the fireworks display

consider the place where people wait, and waiting in front of the goal is deemed better. Therefore, in this research, each route was divided into S_c sections, and the delay time was calculated as the square of the difference ($Regret_{s,c}(t)$):

$$Regret_{s,c}(t) = (Travel_{s,c}(t) - MinT_{s,c})^2. \tag{1}$$

The Root Mean Square Regret (RMSR) of the evaluation index was calculated as follows:

$$RMSR = \sqrt{\frac{\sum_{c=1}^{C}\sum_{t=1}^{T} Flow_c(t) \times \sum_{s=1}^{S_c} Regret_{s,c}(t)}{\sum_{c=1}^{C}\sum_{t=1}^{T} Flow_c(t)}}. \tag{2}$$

RMSR is extended equation of the Root Mean Square Error(RMSE). The number of people arriving at the station through the route c at the time t is $Flow_c(t)$. RMSR were optimized through CMA-ES using the 60 ($2 \times 10 \times 3$)-dimensional parameters.

The real guidance and our optimized guidance are compared with the following three criteria: $E(t)_{ave}$, $E(t)_{dif}$, and $E(t)_{crowd}$. $E(t)_{ave}$ evaluates the average time it takes for all people to walk to the station:

$$E(t)_{ave} = \frac{\sum_{c=1}^{C} Travel_c(t) \times Flow_c(t)}{\sum_{c=1}^{C} Flow_c(t)}. \tag{3}$$

$E(t)_{dif}$ evaluates the maximum value of time difference between routes:

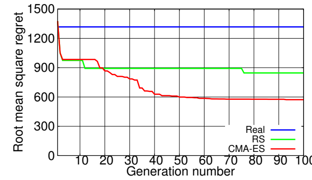
$$E(t)_{dif} = \{\max_{c\in\{1,\dots,C\}}(Travel_c(t)) - \min_{c\in\{1,\dots,C\}}(Travel_c(t))\}. \tag{4}$$

This value indicates unfairness. $E(t)_{crowd}$ is the number of people in the high density area:

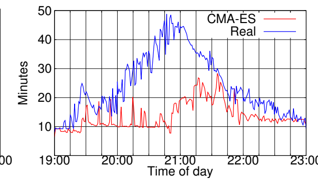
$$E(t)_{crowd} = \sum_{c=1}^{C}\sum_{n=1}^{Flow_c(t)} \begin{cases} 1 & (\text{if } Density_n(t) > 1.08) \\ 0 & (\text{otherwise}) \end{cases}. \tag{5}$$

This criterion represents the number of people at risk.

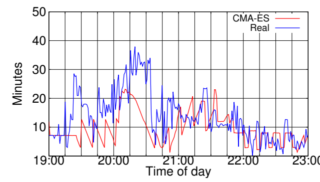
Where, $Density_n(t)$ represents the population density of the n-th person. The high density was defined as 1.08 [ped / m^2] or more based on Fruin's standard level services [13].



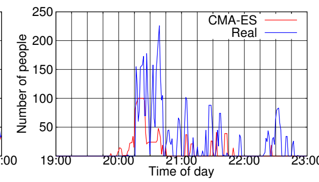
(a) Optimization results



(b) Average time



(c) Difference time



(d) People in crowded

Figure 2: RMSR of optimization results and compare of the real guidance and the best solution guidance

3 EXPERIMENT AND DISCUSSION

In this experiments, we simulated the crowd flow at the Kanmon Strait fireworks display in 2016 using the pedestrian simulator CrowdWalk[14]. The distribution of the initial crowd at the end of the fireworks was measured using the stereo cameras and handy GPSs. **Fig. 2(a)** shows the result of the optimization of the guidance control method. The horizontal axis shows the generation number, and the vertical axis shows for **Eq. (2)**. For each generation result of **Fig. 2(a)**, we describe the best value among the calculation results obtained in the past. CMA–ES is represented by red, and the random search is represented by green. The real guidance control method is represented by blue. Random search and CMA–ES could find a better guidance method than the real guidance control method in 1 generation (i.e., 100 trials). In other words, the real guidance control method is still a result that can be improved. Using CMA–ES, we could find a better guidance method than the guidance control method in used in random search in 20 generation (i.e., 2000 trials). Also, the calculation result of the 100th generation by CMA–ES, RMSR became approximately 1/2 that of real method, it became approximately 2/3 of random search(100th generation).

Next, we comparisoned of real guidance and the best solution of CMA–ES. The horizontal axes of three the graphs in **Fig. 2(b)–(d)** show the time. The vertical axes of **Fig. 2(b)**, **(c)**, and **(d)** shows, **Eq. (3)**, **(4)**, and **(5)** respectively. The red line denotes the best guidance control method in CMA–ES. The blue line denotes the real guidance method. When comparing the simulation results with the real guidance method, simulation results are superior than real guidance in all comparison results.

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REFERENCES

[1] E. Mas, A. Suppasri, F. Imamura, and S. Koshimura, "Agent-based Simulation of the 2011 Great East Japan Earthquake/Tsunami Evacuation: An Integrated Model of Tsunami Inundation and Evacuation," Journal of Natural Disaster Science, vol. 34, no. 1, pp. 41–57, 2012.

[2] H. Wang, A. Mostafizi, L. A. Cramer, D. Cox, H. Park, "An agent-based model of a multimodal near-field tsunami evacuation: decision-making and life safety," Transp. Res. Part C: Emerg. Technol, vol. 64, pp. 86–100, 2016.

[3] T. Takabatake, T. Shibayama, M. Esteban, H. Ishii, and G. Hamano, "Simulated tsunami evacuation behavior of local residents and visitors in Kamakura, Japan," International Journal of Disaster Risk Reduction, vol. 23, pp. 1–14, 2017.

[4] J. Bangate, J. Dugdale, E. Beck, and C. Adam, "SOLACE a multiagent model of human behaviour driven by social attachment during seismic crisis," In 4th International Conference on Information and Communication Technologies for Disaster Management (ICT-DM). pp. 1–9, 2017.

[5] A. Horni, K. Nagel, and K. W. Axhausen, "The Multi-Agent Transport Simulation MATSim," Ubiquity Press, 2016.

[6] T. Morstyn, A. V. Savkin, B. Hredzak, and H. D. Tuan, "Scalable energy management for low voltage microgrids using multi-agent storage system aggregation," IEEE Transactions on Power Systems, vol. 33, no. 2, pp. 1614–1623, 2018.

[7] L. Ma, N. Liu, L. Wang, J. Zhang, J. Lei, Z. Zeng, C. Wang, and M. Cheng, "Multi-party energy management for smart building cluster with PV systems using automatic demand response," Energy Build, vol. 121, pp. 11–21, 2016.

[8] J. Bergstra and Y. Bengio, "Random Search for Hyperparameter Optimization," Journal of Machine Learning Research, vol. 13, pp. 281–305, 2012.

[9] J. Mockus, "On Bayesian Methods for Seeking the Extremum," Optimization Techniques IFIP Technical Conference Novosibirsk, pp 400–404, 1974.

[10] N. Hansen, and A. Ostermeier, "Completely Derandomized Self-Adaptation in Evolution Strategies." Evolutionary Computation, vol. 9, no. 2, pp. 159–195, 2001.

[11] Y. Ozaki, M. Yano, and M. Onishi, "Effective Hyperparameter Optimization Using Nelder-Mead Method in Deep Learning," IPSJ Transactions on Computer Vision and Applications, Nov. 2017.

[12] J. A. Nelder, and R. A. Mead, "A Simplex Method for Function Minimization," The Computer Journal, vol. 7, pp. 308–313, 1965.

[13] Fruin - levels of service [Online].
Available: http://www.gkstill.com/Support/crowd-flow/fruin/LoS.html

[14] T. Yamashita, T. Okada, and I. Noda, "Implementation of Simulation Environment for Exhaustive Analysis of Huge-Scale Pedestrian Flow," SICE Journal of Control, Measurement, and System Integration, vol. 6, no. 2, pp. 137–146, 2013.