Collective Dynamics

Effectiveness Verification of Evacuation Guidance Including Underground Passages Using Multi-objective Optimization

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Abstract In this study, we approach the optimization problem of evacuation guidance assuming major terminal stations in Tokyo using crowd simulation and optimization algorithms. We propose a method to optimize multiple indicators with various guidance variables, including underground passages, and evaluate multiple scenarios obtained through optimization. The results of experiments using three algorithms: Random search, NSGA-II, and MOTPE, showed that MOTPE can be used to search for high-quality solutions quickly. Additionally, scenarios with guidance shortened the total evacuation time and reduced the congestion levels compared to scenario without guidance.

Keywords Multi-objective optimization · multi-agent simulation · evacuation guidance

1 Introduction

Japan is one of the most disaster-prone countries in the world, as it constantly experiences storms, torrential rains, floods, and earthquakes. Therefore, disaster prevention measures are crucial to reduce the risk of disasters. Evacuation guidance is an effective disaster-prevention measure. In general, there is an urgent need to formulate organized evacuation guidance plans that can effectively reduce disaster risks.

In recent years, underground spaces in Japan have been constructed rapidly and extensively [1]. It is necessary to formulate more sufficient evacuation guidance plans, especially for terminal stations. As concerns exist regarding underground space, active research is being conducted to evaluate underground safety considering these concerns [2–5]. However, many underground facilities are structurally robust and suitable for safely evacuating people. Thus, in this study, we obtain desirable evacuation scenarios using multiple guidance variables, including the use of underground passages for large-scale earthquakes in urban areas.

Evacuation guidelines are generally verified through demonstrations [6, 7]. However, these are difficult to implement in public spaces because of the large number of people in these places. Therefore, we use a crowd simulation to verify the guidance in various real-world scenarios at a low cost.

Multiple indicators are available for evaluating evacuation behavior, such as efficiency and safety [8, 9]. However, because these evaluation indicators have a trade-off relationship, it is necessary to consider a multi-objective optimization problem in which a solution is determined based on multiple evaluations. In this study, we set the overall evacuation completion time and the degree of congestion as objective functions, and use three multi-objective optimization methods to obtain a desirable evacuation scenario.

2 Related research

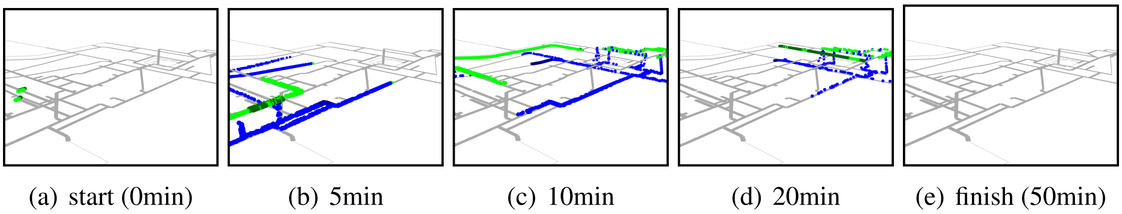
2.1 Verification of evacuation guidance using crowd simulation

Previous works have mainly focused on evacuation simulations assuming fire [2, 3] and flood scenarios [4, 5] in urban underground passages and subways. In most previous studies, underground spaces have generally been assumed to be dangerous, and it has been assumed that people evacuate from them. However, Wang et al. [10] mentioned that underground facilities offer advantages, including increased space and clarity, in selecting evacuation routes. Therefore, underground passages may be indispensable for emergency evacuations in urban areas, except in the case of fires or flooding. To date, few studies have verified the evacuation guidance effects including underground passages as evacuation routes. In this study, we verify the effectiveness of evacuation guidance using multiple guidance variables, including underground passages.

2.2 Improvement of multi-objective optimization algorithm

NSGA-II [11] is one of the multi-objective optimization algorithms based on genetic algorithms. It requires thousands of evaluations to converge, making it inefficient for real-world objective functions [12].

Therefore, in recent years, optimization algorithms have been improved to enable them to solve real-world multi-objective optimization problems. Ozaki et al. proposed a multi-objective tree-structured Parzen estimator (MOTPE) [12], which extends the tree-structured Parzen estimator (TPE) [13] to a multi-objective optimization method. In addition, it converges faster than existing methods for several benchmark problems. However, it has not been evaluated on real-world problems. In this study, we apply MOTPE to a real-world evacuation guidance problem and assess its capability and performance compared with existing algorithms.



(a) start (0min) (b) 5min (c) 10min (d) 20min (e) finish (50min)

Figure 1 Evacuating simulation of CrowdWalk. Green dots show evacuees on the ground and blue shows those underground. The color changes to dark representing increasing levels of congestion.

3 Verification methods for evacuation guidance

We explain the process of multi-objective optimization for evacuation guidance using a crowd simulation. The desired evacuation scenarios are obtained through two processes of evaluation iterations. The first process is involves calculating the objective function values using a crowd simulation. The second process involves evaluating the objective function values using an optimization algorithm.

3.1 Evacuation guidance simulation

We simulate the flow of pedestrians during evacuation using the pedestrian simulator CrowdWalk (Commits on Aug 17, 2023) [14] to verify underground passages. CrowdWalk is a multi-agent simulator that specifically assumes crowd movement. All agents' positions are updated the Social Force Model, which is a pedestrian movement model. It places movement paths in a single dimension, thereby enabling large-scale and high-speed simulations. Each evacuee leaves their starting point for the destination at a specific time. The flow of the evacuees is controlled through guidance at multiple locations and the objective function values are calculated based on the simulation results.

3.2 Multi-objective optimization algorithm

This subsection explains the methods for updating the guidance variables using a multi-objective optimization algorithm. We use three algorithms for verification: Random search, NSGA-II, and MOTPE. Random search is an algorithm that generates parameters using a random number generator, and it can be implemented either asynchronously or in parallel. NSGA-II is an algorithm that has been expanded from a genetic algorithm to an algorithm that handles multi-objective optimization problems. It updates variables through three steps: ranking, selection, and generation. Although NSGA-II requires time to converge, it can employ mechanisms such as mutations to update the variable $\boldsymbol{x}$ and thereby avoid falling into the local minima. MOTPE it is a Bayesian optimization algorithm that extends TPE to a multi-objective optimization problem. It updates the variables in three steps: dividing the solution, building surrogates, and maximizing the acquisition function. While updating $\boldsymbol{x}$, MOTPE converges quickly by evaluating the expectation of the hypervolume; nonetheless, it quickly falls into the local minima.

4 Experimental setup

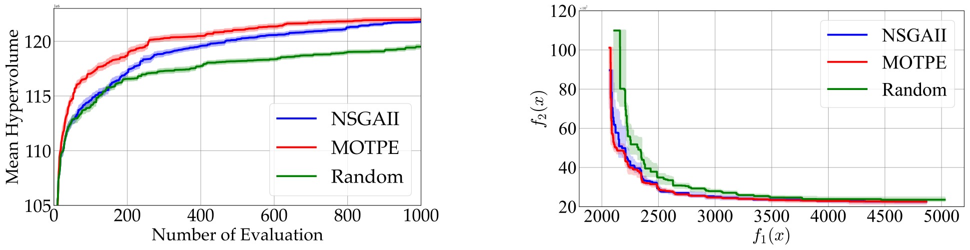
In this study, we simulate the process of evacuation from a major terminal station in Tokyo to an evacuation site through the main street. We assume a major terminal station in Tokyo with multiple ticket gates on both the east and west sides as well as on the ground and underground. The starting points for the evacuees are set at each ticket gate of the station and the destination is set as the safe evacuation site on the ground. The expected number of evacuees is set to 6,900.

4.1 Guidance variables

The variables that are considered as guidance are divided into the following three categories: western-side guidance (x_1,x_2), the time difference from departure (x_3), and underground guidance (x_4,x_5). The five guidance variables are defined as $\boldsymbol{x} := (x_1, x_2, x_3, x_4, x_5)$. To guide evacuees from the east ticket gate above ground to the west ticket gate, the ratio of the three flow lines connecting east and west is defined as $x_1[\%]$ (center and south side) and $x_2[\%]$ (north side). $x_3[\text{sec}]$ refers to the time difference between the departure times of the evacuees at each ticket gate divided into two groups. Half of the evacuees depart at the exact starting time, whereas the other half remain in a temporary refuge shelter for a given time. To guide evacuees on the ground to the underground space, the proportions of stairs that are used on the flow line connecting the east and west ticket gates and the evacuation area are defined as $x_4[\%]$ (east side) and $x_5[\%]$ (west side). Additionally, the five guidance variables are mutually independent, with $0 \leq x_1 \leq 100$, $0 \leq x_2 \leq 100$, $0 \leq x_3 \leq 2000$, $0 \leq x_4 \leq 100$, $0 \leq x_5 \leq 100$.

4.2 Objective functions

Two objective functions are set. The multi-objective optimization of the two objective functions is defined as $\min f(\boldsymbol{x}) := (f_1(\boldsymbol{x}), f_2(\boldsymbol{x}))$. The first objective function f_1 is the traveling time of all evacuees. The overall traveling time of the evacuees is calculated as $f_1(\boldsymbol{x}) = D_N - O_1$. where N is the number of all evacuees, and O_n and D_n are the departure and arrival times of the n-th evacuee, respectively. The second objective function $f_2(\boldsymbol{x})$ represents the population density of each evacuee and is calculated as $f_2(\boldsymbol{x}) = \sum_{t=1}^{T} \sum_{n=1}^{N} \mathbb{I}(d_n > d^{\text{threshold}})$. The local population density around the n-th evacuee, d_n, is defined as $d_n = \sum_{i=1}^{N} \mathbb{I}(0 < ||\boldsymbol{p}_n - \boldsymbol{p}_i|| \leq 1)$. where $\boldsymbol{p}_i$ is the position vector of the i-th evacuee, and $\mathbb{I}(\cdot)$ is the indicator function. T denotes the evacuation completion time [min];and $d^{\text{threshold}}$, which represents the threshold of overcrowding, is defined based on the standard-level services defined by Fruin [15]. People generally tend to have negative impressions of underground spaces [16]. Thus, agents tend to feel greater anxiety about pedestrian congestion in underground spaces. Therefore, the threshold level of the underground space is higher than that of the ground space. The threshold levels are 2.17 and 1.08 [ped/m^2] for the underground and ground spaces, respectively. Additionally, the walking speed when using staircases is half the default speed.



(a) (b)

Figure 2 (a) Hypervolume and (b) Pareto front

4.3 Parameters and evaluation indicators

We use Optuna [17] to implement the multi-objective optimization. The evaluation budget (including the initial evaluations) is 1,000 iterations for all algorithms. For each method and setting, 20 optimization experiments are conducted using the default parameters. The hypervolume is used as an evaluation indicator to evaluate the convergence, uniformity, and spread [18, 19], which determine the effectiveness of the algorithm. It is used as an indicator to evaluate the effectiveness of the algorithm. The arbitrary reference point is $r = (7500, 25000)$.

5 Results

5.1 Comparison of algorithm performance

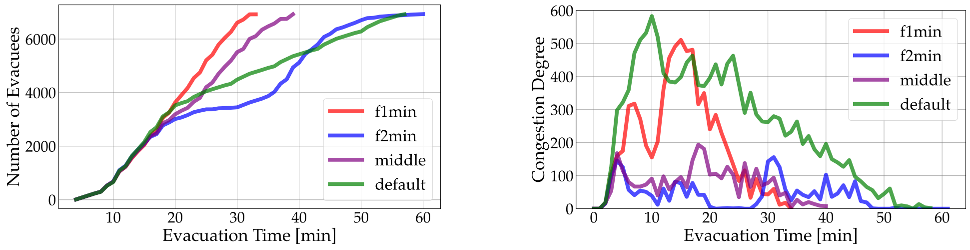
Fig. 2(a) shows the average value of the hypervolume per number of evaluations for each method. The light shaded color indicates the standard error. MOTPE could obtain stable solutions for approximately 600 evaluations and converged the hypervolume faster than the existing methods, achieving the highest hypervolume value in all evaluations. Thus, MOTPE can be used to search for high-quality solutions. 2(b) shows the 50% attainment surfaces. The light shaded color indicates the Pareto fronts obtained from the best and worst trials. The Pareto front of MOTPE is the curve closest to the Pareto optimal solution because it aimed to minimize both objective functions f_1 and f_2. Therefore, MOTPE clearly outperformed the existing methods.

5.2 Verification results of guidance variables

This section describes the evaluation using the Pareto solutions obtained from the trials with the best hypervolumes for MOTPE. Three scenarios on the Pareto solutions and the default scenario without any guidance were evaluated. Table 1 lists the guidance variables and objective function values for the scenarios in the evaluation. The three scenarios for the Pareto solutions are categorized as follows: the minimum time to complete the evaluation f_1 ($f_1$min), the minimum congestion f_2 ($f_2$min), and the middle of the f_1 and f_2

Table 1 Guidance variables and objective function values of each scenario

scenario	x_1[%]	x_2[%]	x_3[sec]	x_4[%]	x_5[%]	f_1	f_2
$f_1$min	40.0	0.0	493	79.0	53.0	1980	6921
$f_2$min	42.0	49.0	1608	38.0	2.00	3619	2289
middle	42.0	12.0	843	87.0	13.0	2386	3009
default	0.0	0.0	0.0	0.0	0.0	3478	14176



(a) (b)

Figure 3 (a) Cumulative number of evacuated evacuees and (b) Congestion degrees.

(middle) scenarios. The middle scenario was selected using the distance-to-limit method of knee-point selection [20], which selects sparse solutions from the Pareto solutions. In the default scenario without any guidance, the evacuees evacuated from the departure point to the destination through the shortest route. Fig. 3(a) shows the cumulative number of evacuees who arrived at the safe evacuation site. The time to complete the evacuation $f_1$min and middle scenarios were shorter than those for the default scenario. In Table 1, the variables x_4 and x_5 in the $f_1$min and middle scenarios are larger than those in the other scenarios, indicating that the available passages, including those underground, were effectively utilized in these two scenarios. Fig. 3(b) presents the degree of congestion for each evacuation time in each scenario. In the $f_1$min scenario, the degree of congestion was higher than that in the default scenario for a specific period. However, all scenarios with guidance exhibited lower overall congestion than that in the default scenario.

6 Conclusions

In this study, we proposed a method to optimize multiple evaluation indicators in trade-off relationships using crowd simulation and optimization algorithms. We obtained evacuation scenarios incorporating underground passages, not previously considered as guidance variables. Optimization was conducted using three algorithms, with MOTPE demonstrating the best performance for the proposed method. Additionally, we showed that scenarios with guidance can more effectively reduce evacuation completion time and congestion compared to scenario without guidance. We assumed that all evacuees were evacuated to a single destination to simplify the problem. However, the simulation should resemble real-world practical scenarios more closely. It is necessary to improve the accuracy of the initial values by setting multiple destinations and obtaining actual pedestrian data.

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