https://doi.org/10.20965/jdr.2024.p0248

Paper:

Development of a Real-Time Crowd Flow Prediction and Visualization Platform for Crowd Management

Kensuke Yasufuku† and Akira Takahashi

Cybermedia Center, Osaka University
5-1 Mihogaoka, Ibaraki, Osaka 567-0047, Japan
†Corresponding author, E-mail: yasufuku.kensuke.cmc@osaka-u.ac.jp
[Received September 29, 2023; accepted December 20, 2023]

Crowd management at large-scale events and specific facilities is a critical issue from the perspectives of safety and service quality improvement. Traditional methods for crowd management often rely on empirical knowledge, which has limitations in quickly grasping the on-site situation and making decisions on the spot. In this study, we developed a real-time crowd flow prediction and visualization platform incorporating an agent-based crowd simulation and an advanced crowd management system called crowd management platform as a service. In a case study focused on the area around the Tokyo Dome, we demonstrated that capturing pedestrian flow allows for accurate predictions of congestion at the nearest train station up to 10 min in advance. Moreover, the time required to predict the situation 20 min ahead for 3,000 agents was 1 min and 35 s, confirming the feasibility of real-time processing. To enhance the accuracy and reliability of the simulation results, a sensitivity analysis considering errors in pedestrian flow measurement revealed that simple linear models cannot capture the complexity of crowd dynamics adequately. Notably, the agent-based simulation replicated stop-and-go wave patterns observed in actual measurements under specific crowd conditions, confirming the advantage of using agent-based simulations. Finally, we proposed a method that enables facility managers and security personnel to conduct a more comprehensive evaluation. This method integrates their existing experience with the aggregated display of multiple simulation results, which includes consideration of errors in pedestrian flow measurement through a visualization platform.

Keywords: crowd flow prediction, crowd management, agent-based simulation, visualization

1. Introduction

In events such as sports, concerts, and exhibitions, where large numbers of people gather, crowd security is routinely implemented to ensure safety. When these events end, congestion occurs not only within the facility but also on the pedestrian streets that lead to public transportation. One important measure is to ease the concentration of congestion, such as by implementing regulated exits. However, most planning for such measures is based on accumulated experience and expertise, and there is a growing expectation for the incorporation of findings from the latest scientific research [1]. Among these, agent-based crowd simulation [2] is effective in aiding the decision-making process of advanced crowd management and beginning to be applied at large-scale events [3]. Additionally, by monitoring crowd conditions on the day of an event and cross-referencing them with an advanced crowd management plan, it is possible to assess the risk of accidents before they occur and implement early-stage security measures.

Advancements in video recognition, smartphone location data utilization, Internet of Things technology, and machine learning have enabled the near-real-time measurement of congestion [4, 5]. Recently, simulation technologies that virtually replicate physical objects in cyberspace based on data collected through advanced measurements and observations have gained attention. These are often referred to as cyber-physical systems or digital twins [6, 7]. Methods for utilizing digital twins in urban spaces combined with crowd measurement technology have been proposed to simulate pedestrian flows.

Since 2020, Japan's Ministry of Land, Infrastructure, Transport and Tourism has been advancing Project PLATEAU, which is aimed at the development, utilization, and open data conversion of 3D urban models that replicate real cities [8]. Concurrently, municipal-level discussions have commenced, and Tokyo is conducting pilot projects targeting the realization of a digital twin by 2030 [9]. Among these pilot projects, the visualization of real-time pedestrian flow, including subterranean spaces, is under consideration. However, the focus has remained limited to the visualization of crowds. In Europe, the IoTwins project [10] is also conducting research and development on crowd management as a testbed in facility management, such as at stadiums; however, it has not reached the stage of real-time crowd flow prediction [11]. Nevertheless, numerous methods utilizing machine learning have been proposed to estimate future crowd congestion based on real-time pedestrian flow data [12–14]. Furthermore, by integrating an agent-based crowd simulation, the behavior of individuals and the geometric shapes of complex spaces can be replicated [15]. Agent-based crowd simulations enable the visualization of crowd movement and changes in density distribution within target areas. This approach promotes an intuitive understanding of the simulations, even for those who are not experts in the field. However, there have been no discussions about the implementation of real-time crowd flow prediction systems or the specific challenges involved.

This study aimed to develop a real-time crowd flow prediction and visualization platform that incorporates agent-based crowd simulation and an advanced crowd management system. We applied this system to the environment around a stadium at the end of large-scale events to clarify the technical challenges. Specifically, to predict congestion 10 min ahead in real time and simulate crowd movement and density changes, it is crucial to address several technical challenges. These include managing the incomplete initial position information of crowds at the beginning of the simulation, assessing the impact of errors in the input data necessary for simulations involving sensing and time-series prediction, and determining whether the simulation's computational time is compatible with the demands of real-time prediction. In addition, to utilize the results of these simulations, it is vital to have a mechanism for sharing information among stakeholders and security personnel in various positions [16, 17]. We propose a visualization platform to achieve this.

2. Method

2.1. Agent-Based Crowd Simulation

An agent-based crowd simulation models individual humans as agents whose movements are governed by a set of rules. The simulation reproduces crowd behavior through local interactions among agents or with their environments. In this study, we employed Pathfinder [18], a commercial software package, for the agent-based crowd simulation.

A key feature of this software is the use of a navigation mesh for spatial modeling and route choice. A navigation mesh [19] represents the areas through which agents can move as a collection of 3D meshes (triangles), making it suitable for accurately reproducing the spatial geometry (**Fig. 1**). In Pathfinder, functionality is provided for importing generic 3D CAD data and automatically creating a navigation mesh derived from the geometric properties of the data [18]. This navigation mesh consists of a continuous series of triangular surface data that can be configured to mirror the shape of the geometry created from the 3D CAD data. In the process of selecting a route, each triangle is regarded as a node, and the connections between neighboring triangles are viewed as connections within a network configuration. Costs, such as the distance to a destination, are calculated to determine a route using a search algorithm [20]. When an agent has multiple destination candidates, the destination with the minimum cost is selected.

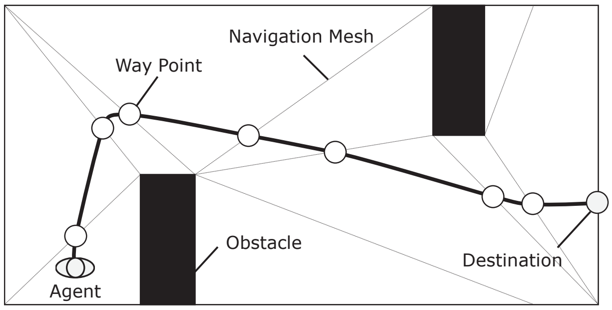

Fig. 1. Movement of an agent on a navigation mesh.

Once a destination is determined through the route choice, the agents obtain a series of waypoints on the edges of the navigation mesh (**Fig. 1**). A path to the agent's destination was formed based on these points. To smooth this path, Pathfinder utilizes a method called string pulling [21]. This method adjusts the agent to turn only at the corners of the obstacles, maintaining a distance at least equal to the radius of the agent from the obstacles. In addition, the software uses a physics-based model for collision avoidance between agents and obstacles or among the agents themselves.

2.2. Real-Time Crowd Flow Prediction

2.2.1. Acquisition of Pedestrian Flow Data

To acquire pedestrian flow data, we utilize the crowd management system developed in this project [22]. Crowd management platform as a service (CMPaaS) is equipped with functions to aggregate pedestrian flow data at specific locations. It conducts various simulations based on these data and stores the results for use in crowd control. Although the system is still under development, some of its features are available for this study.

Various types of data can be downloaded through the Web API provided by CMPaaS. The pedestrian-flow data used in this study were obtained from cameras installed on the target premises. These cameras capture the number of people crossing a predefined line (referred to as a "detection line") in the footage, which is collected in a time series at one-minute intervals.

2.2.2. System of Real-Time Crowd Flow Prediction

Real-time crowd flow prediction involves obtaining the most recent pedestrian flow data from CMPaaS and using an agent-based crowd simulation to predict potential congestion situations in the near future. As Pathfinder is an agent-based crowd simulation tool and lacks real-time simulation functionality, we utilized a Python script for real-time control, including the editing of Pathfinder's simulation input files, external execution of the simulation, and extraction of simulation results. The system flow is illustrated in **Fig. 2**.

A simulation input file refers to a text file containing all information required to run a simulation in Pathfinder.

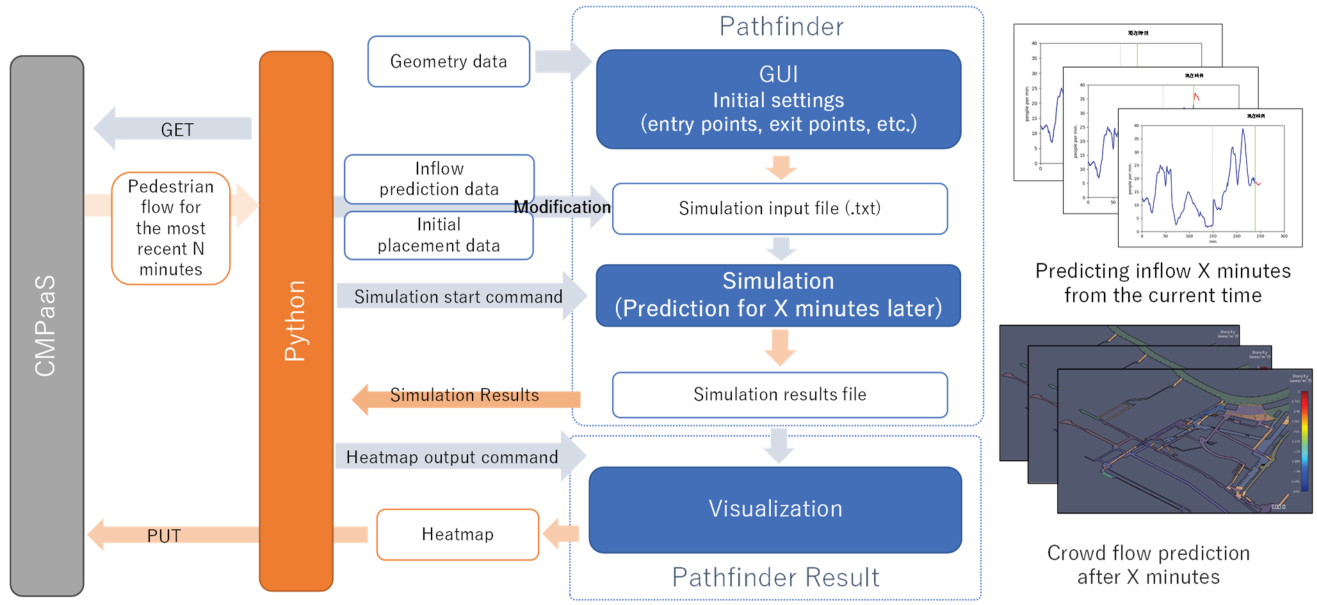

Fig. 2. System flow of real-time crowd flow prediction.

While Pathfinder was originally a graphical user interface-based software, the use of this input file enables simulation execution via a command line. To perform real-time crowd flow prediction, a Python script initially accessed CMPaaS using a Web API to collect the pedestrian flow for the most recent N minutes. Based on these data, the inflow data for individuals expected to enter the target area were predicted in a time-series manner. This time-series prediction of pedestrian flow was then written into the simulation input file, and the simulation was executed using Pathfinder via the command line. Future congestion conditions were extracted as heatmap images based on level of service [23] from the Pathfinder's simulation results using the Python script.

2.2.3. Technical Challenges in Real-Time Crowd Flow Prediction

In real-time crowd flow prediction, several technical challenges arise concerning (1) errors in the predicted input data, (2) replication of the initial placement of the crowd, and (3) simulation computational time.

(1) Errors in crowd flow prediction refer to the need to supplement the inflow data with an agent-based crowd simulation in the near future, which inherently contains errors. It is important to clarify the technical challenges regarding how these errors in the predicted values affect simulation results using methods such as sensitivity analysis and error propagation.

(2) Replication of the initial placement of the crowd refers to reproducing the initial positions of the agents at the start of the simulation. The pedestrian flow data obtained from CMPaaS are based on the number of people crossing the designated detection lines and insufficient to accurately set the initial positions of the agents. Therefore, this study employed a method that sets the initial positions of each agent using data interpolated through an agent-based crowd simulation. The interpolated data represent the initial position data at the current time, obtained by starting the simulation N minutes prior to the current time. However, the value of N entails a tradeoff with the computational time of the simulation.

(3) The simulation computational time must be assessed for its suitability for real-time prediction and whether the increase in computational time is acceptable with the scaling of the simulation. The computer used in this study had an Intel Core i9-13900KF (24 cores) CPU and 128 GB of main memory.

2.3. Case Study

2.3.1. Target Area

In this case study of crowd flow prediction, we focused on the area around the Tokyo Dome, specifically considering the period immediately after the end of a baseball game. The target area is shown in **Fig. 3**. The subject facility has a building area of 46,755 m^2 and can accommodate 55,000 people. It serves diverse purposes, ranging from hosting professional baseball games to concerts and various events. Considering the surrounding area, the total area was approximately 133,000 m^2.

Multiple cameras are installed in the target area to measure the pedestrian flow, and **Fig. 3** shows the lines where the flow is detected (note that the numbering of these detection lines is not sequential, as they also exist outside the target area). The scope of the agent-based crowd simulation extends from the stadium to the entrance of the railway station. Within this range, we aimed to predict the number of people passing over a pedestrian bridge monitored by the detection line LINE04. The arrows in **Fig. 3** indicate

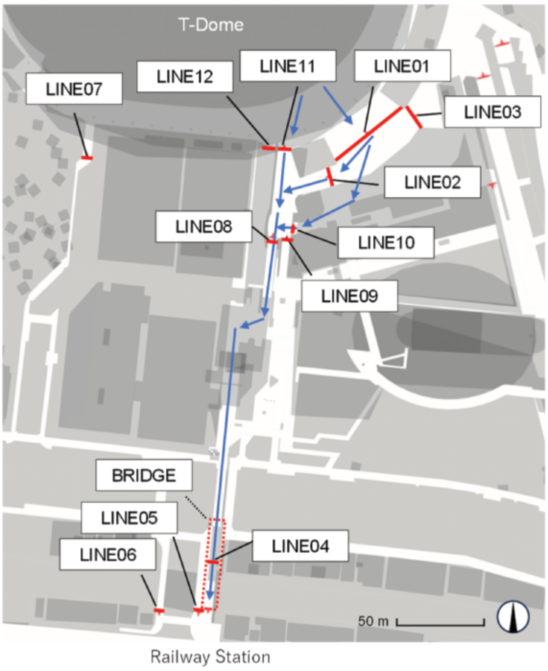

Fig. 3. Plan of the target area and location of detection lines.

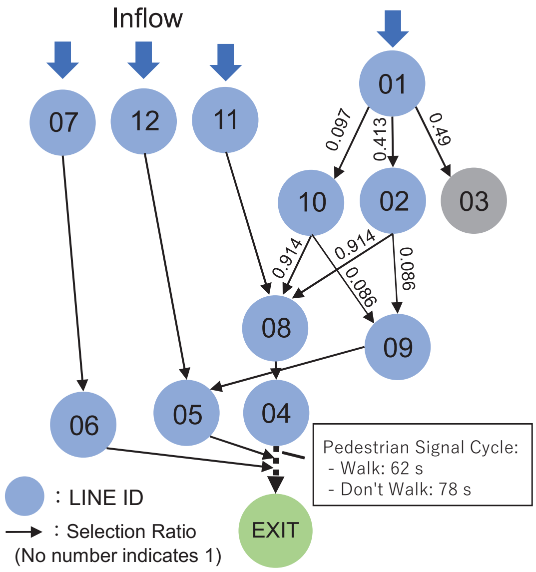

Fig. 4. Branching of pedestrian flow between detection lines.

routes leading to the pedestrian bridge. We assumed that people moving from the stadium toward the railway station would first pass the detection lines LINE01 and LINE11, and we used this flow data as the input for the simulation. Additionally, the inflow from detection lines LINE07 and LINE12 was considered in the agent-based crowd simulation, as these lines represent people merging from different routes toward the end of the pedestrian bridge at the station.

2.3.2. Parameter Settings

A crucial parameter in agent-based crowd simulation is the maximum walking speed. In this study, based on observational data in the target area, each agent was assigned a maximum walking speed of 1.36±0.21 m/s. Regarding the reduction in maximum walking speed as crowd density increases, we set the reduction rate to zero for densities up to 0.55 persons/m^2 and to 85% for densities above 2.2 persons/m^2, with linear interpolation for densities in between. This rate was set based on trial and error during simulation. We also introduced a personal distance parameter aimed at maintaining a certain distance between agents, and set it to 0.33 m. This value was derived from the average crowd density observed on the pedestrian bridge in the target area (1.87 persons/m^2). Although Pathfinder can modify a vast number of other parameters, default values were used.

If the agent selected more than one route to a destination, it was set to a predefined percentage. Additionally, there are alternative routes from the target stadium to railway stations. **Fig. 4** shows the branching of the pedestrian flow between the detection lines and the ratio of the route choices set in the simulation. The selection ratios for LINE01 to LINE10, LINE02, and LINE03 were set based on the actual sensed traffic volume ratios for LINE10, LINE02, and LINE03 during the identical 20-minute interval in the simulation. The traffic volume proportions for LINE08 and LINE09 were calculated for the selection ratios from LINE10 to both LINE08 and LINE09, as well as from LINE02 to LINE08 and LINE09. For practical reasons, identical selection ratios were assigned to each group. Between LINE04 and the entrance of the station, there is a crosswalk where impassable conditions can occur because of signal cycles.

2.3.3. Crowd Flow Prediction Scenario

In this case study, a specific time point was defined as 0 min, which coincided with the end of a baseball game. The congestion status of the pedestrian bridge at 10 and 20 min was predicted. The flow data obtained from CMPaaS, based on sensing, used the past 10 min of data. The data for the subsequent period from 0 to 20 min had to be based on a time-series prediction.

However, the primary objective of this research was to evaluate the performance of agent-based crowd simulation in real-time crowd flow prediction. Consequently, instead of employing time-series predictions, it used historical sensing data. However, it was assumed that the sensing and time-series prediction data required for real-time prediction would contain errors. The impact of these errors on the results of the agent-based crowd simulation had to be systematically examined. To facilitate this, errors of −20%, 20%, 50%, and 100% were uniformly applied to the original flow data, resulting in the creation of separate datasets. Another error dataset was generated using the moving average of the original data. The generated error datasets were used to predict crowd flow, and a sensitivity analysis of the results was conducted. This sensitivity analysis allowed for a comprehensive examination of the impact of errors on the simulation results from the perspectives of accuracy and robustness. Such an analysis has

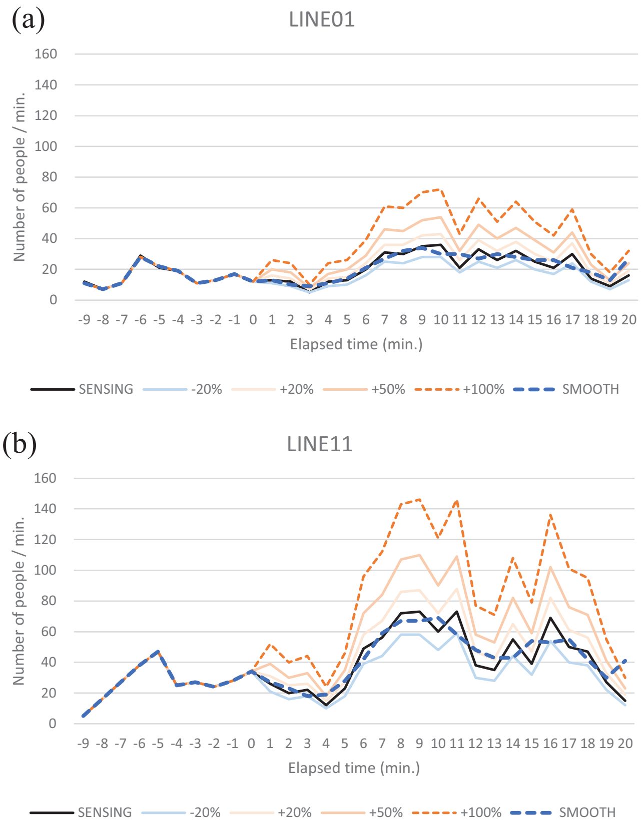

Fig. 5. Pedestrian inflow data from the detection lines (a) LINE01 and (b) LINE11.

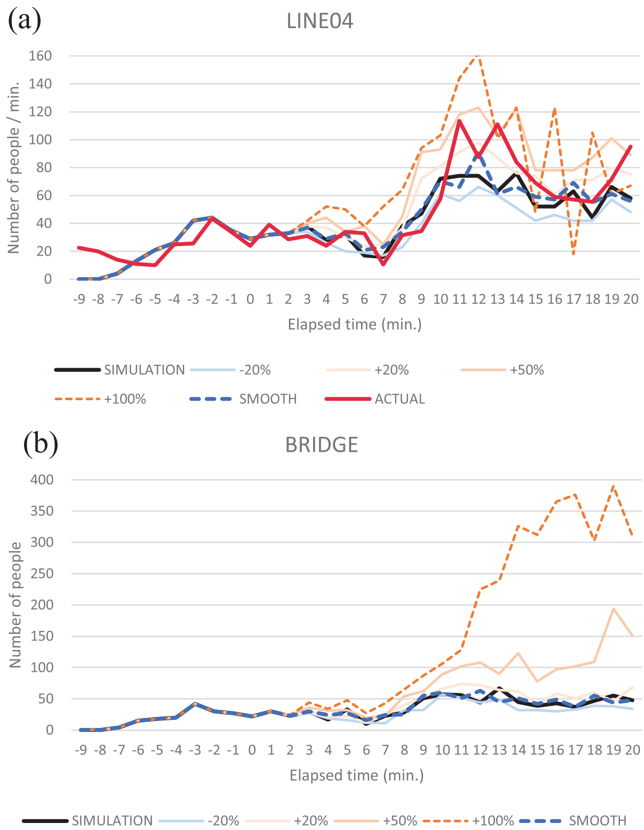

Fig. 6. The simulation results for (a) the number of people passing through LINE04 and (b) the number of people on the pedestrian bridge (BRIDGE).

the potential to provide insight into an acceptable range of errors and parameter optimization.

3. Results and Discussion

3.1. Case Study Results

In the case study for real-time crowd prediction simulations, a simulation was conducted over a 30-minute period, spanning from 10 min before to 20 min after a specific time. This simulation focused on crowd movement from the area surrounding the Tokyo Dome to the nearest train station. **Fig. 5** shows the pedestrian inflow data (SENSING) from detection lines LINE01 and LINE11, downloaded from CMPaaS. These data, which represent the number of people passing through the detection lines per minute, served as the input for the simulation. In the real-time prediction, six different input datasets were used when simulating a specific time period (0 min to 20 min later). These datasets accounted for uniform errors of −20%, 20%, 50%, and 100%, and moving average time-series data. The time step of the simulation was 0.025 s, and if the pedestrian inflow data was input in one-minute increments, the agents were spawned at constant equal time intervals.

The results of the crowd flow prediction are shown in **Fig. 6**, which displays the time-series data (SIMULATION) of the number of pedestrians passing over and present on the pedestrian bridge in front of the station at one-minute intervals. The number of people crossing the pedestrian bridge corresponded to the number of people traversing the detection line LINE04, as shown in **Fig. 6(a)**. Compared to the actual observed values (ACTUAL), the numbers generally aligned well. Specifically, the Nash–Sutcliffe coefficient [24] for accuracy from 0 to 10 min was 0.797. The Nash–Sutcliffe coefficient is an index used to evaluate the accuracy of a model by considering the magnitude of errors in the flow rate. A value closer to 1 indicates a higher model accuracy. Generally, a model is considered to have high reproducibility if the Nash–Sutcliffe coefficient is greater than 0.7.

Meanwhile, from 11 to 20 min, the Nash–Sutcliffe coefficient significantly decreased to −1.11. The simulation indicates fewer individuals passing from the 11th minute, with a peak error of −43.2% observed at the 13th minute. Possible reasons for this could be as follows: (1) as the pedestrian flow exceeds a certain scale, the accuracy of the input data decreases, owing to the influence of errors in the sensing data; (2) an increasing error over time. A further analysis of the impact of these errors was conducted.

3.1.1. Sensitivity Analysis of Predicted Input Data

As shown in **Fig. 5**, six types of data with systematically introduced errors in the detection lines LINE01 and

LINE11 were used as input data for the simulation. However, the data appearing in detection line LINE04 and the number of people on the pedestrian bridge, as illustrated in **Fig. 6**, exhibit greater variability than the introduced errors. The errors uniformly applied over time to the input data did not manifest proportionally in the data from LINE04 and the pedestrian bridge (BRIDGE). This observation suggests that the pedestrian flow at detection lines LINE01 and LINE11 does not maintain a simple linear relationship, as people may merge along the way or choose different paths.

In particular, after 10 min, a triangular waveform appeared at detection line LINE04 when input errors of 50% and 100% were applied, as shown in **Fig. 6(a)**, with a focus on the waveform. This waveform was also present in the actual measurement results and parts with large discrepancies between the actual measurements, and the simulation closely aligned with the results when an input error range of 20% and 50% was applied. Although the waveforms in the input data from detection lines LINE01 and LINE11 may have an impact, the increase in amplitude as the error increased suggests another underlying cause. To comprehend the specific phenomena that occurred, confirmation of the results through simulation visualization is necessary (refer to Section 3.2).

Conversely, when focusing on time-series graphs with errors introduced by the moving average, the output results of the simulation were not significantly smoothed, even when the input data were smoothed. The Nash–Sutcliffe coefficient for up to 20 min from 0 min was also high at 0.882, indicating a relatively minimal error impact.

Next, when examining the graph of the number of people on the pedestrian bridge (BRIDGE) for times after 10 min, as shown in **Fig. 6(b)**, a significant error emerged in the simulation results when an input error of more than 50% was applied. However, when the error range was between −20% and 20%, the results fell within this margin of error. This observation can be attributed to the fact that when the crowd density on the pedestrian bridge allows for free movement, the distance between the agents remains constant. This phenomenon is discussed in Section 3.2, along with the triangular wave observed at detection line LINE04, using the visualization results.

3.1.2. Replication of the Initial Placement of the Crowd

The reason for conducting the agent-based crowd simulation starting from −10 min is to set the initial placement of the crowd in the target area by time zero, using past sensing data. **Fig. 6** shows that in the graph for the detection line LINE04, the pedestrian flow is zero between −10 min and −8 min. This indicates that the inflow of people from detection lines LINE01 and LINE11 arrives at LINE04 approximately 2–3 min after the start of the simulation. The subsequent reduction in the difference between the SIMULATION and ACTUAL values confirms that starting the simulation 10 min in advance is sufficient to effectively set the initial positions of the agents.

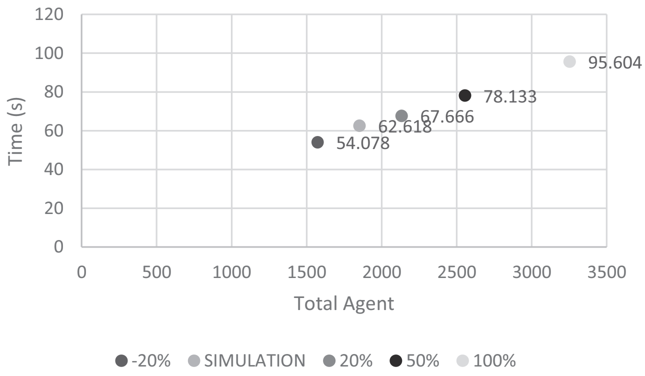

Fig. 7. Number of agents and simulation computational time.

3.1.3. Simulation Computational Time

The total number of agents generated for each simulation in the case study and the time required for the simulation are summarized in **Fig. 7**. The simulations were designed for real-time crowd flow prediction, where the observed data were used from 10 min before the simulation start time to 0 min, and the simulation was run until 20 min thereafter (30 min in total). Even in the case with the largest number of agents generated (3,254), the simulation was completed in approximately 1 min and 35 s, which is practical for real-time crowd flow prediction. In addition, the relationship between the number of agents and the simulation computational time was nearly linear. This allows for a rough estimate of the simulation time, depending on the scale of the task and the required prediction time.

3.2. Analysis Through Visualization

In the analysis conducted in Section 3.1.1, triangular waves were observed in the actual data of the detection line LINE04, as well as when the input pedestrian flow data were subjected to an error of more than 50%. Moreover, when the pedestrian flow data were doubled (error of 100%), prominent triangular waves appeared between the 13th and 19th minutes on the detection line LINE04. To explore the cause of this, we considered this issue through visualization.

The visualization results of the simulation predicting 18 min and 30 s after a certain time (time 0) are shown in **Fig. 8**. At the crosswalk in front of the pedestrian bridge, there is a convergence of the crowd that passed through detection lines LINE04 and LINE05, leading to congestion. The crosswalk is signal-controlled, and the crowd begins to move when the signal turns green. When the pedestrian flow doubles, stop-and-go waves [25] occur at that location. When the stop wave reaches detection line LINE04, the number of people passing through it drops sharply. This repetitive process generated triangular waves. Stop-and-go waves were also confirmed in the observational results and were conditionally reproduced in the real-time crowd flow prediction. Phenomena such as stop-and-go waves can be replicated using agent-based crowd simulations, highlighting the significance of using such simula-

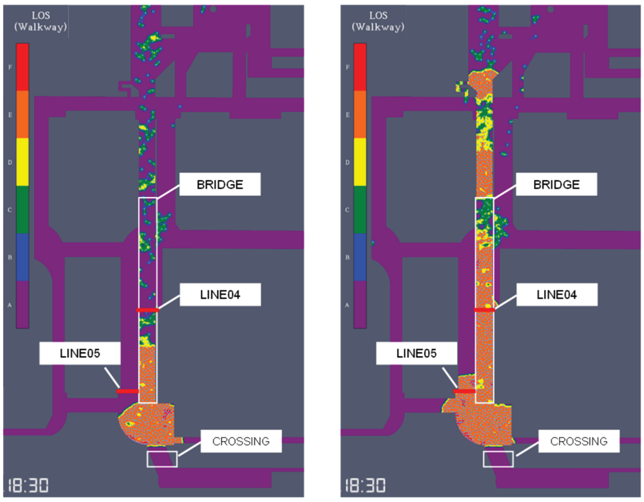

Fig. 8. Visualization of simulation patterns.

tions for real-time crowd flow prediction. Improving the timing accuracy of the emergence of these waves is a future challenge.

The graph in **Fig. 6(b)** shows the temporal fluctuations in the number of people on the pedestrian bridge. This increasing trend is particularly notable when the error exceeds 50%. The visualization results depicted in **Fig. 8** represent the time at 18 min and 30 s later when the number of people on the pedestrian bridge peaked and substantial congestion occurred. Although these figures are based on input data with errors of 50% and 100%, the real-time prediction data also contain errors. By visualizing congestion scenarios for multiple patterns that account for such errors, evaluations that consider the experiences of facility managers or security personnel can be made.

4. Conclusions

In this study, we developed a real-time crowd flow prediction system that utilizes current pedestrian flow data to predict imminent congestion scenarios through agent-based crowd simulation. The efficacy of this system was tested using a scenario following a large-scale event in the vicinity of the Tokyo Dome. The key conclusions are summarized as follows.

In a case study on real-time congestion prediction around the Tokyo Dome, a comparison between simulation predictions and observed values confirmed that the number of pedestrians on a pedestrian bridge could be accurately predicted up to 10 min in advance.

Using the number of people exiting the Tokyo Dome as input data and introducing a certain percentage of error, the simulation results indicated that the number of people passing over the pedestrian bridge did not have a simple linear relationship. However, when the error from the moving average of the time series data was incorporated into the input, the simulation exhibited a similar trend.

The effectiveness of a method for conducting an agent-based crowd simulation based on sensing data from 10 min prior was ascertained for the initial placement of agents during real-time congestion prediction.

The simulation started with observational data from 10 min prior and predicted up to 20 min after (a total of 30 min). With 3,254 simulated agents, the simulation was completed in 1 min and 35 s, verifying the practical computational time for real-time congestion prediction.

The abrupt change in the number of people on the pedestrian bridge was attributed to the stop-and-go wave phenomenon in the crowd, which was influenced by traffic signals near the closest station. These waves were confirmed by actual observational results at a pedestrian bridge. This phenomenon was validated through visualization and replicated in an agent-based crowd simulation under specific conditions.

The input data for simulations during real-time prediction inherently contain errors. Acknowledging this, we proposed a method for visualizing multiple congestion scenarios by considering the impacts of these errors.

In the future, it will be imperative to continue enhancing the accuracy of the simulation while concurrently expanding its scope to encompass the entire area around the Tokyo Dome. Furthermore, this study discussed the scalability of the system and introduced a framework that demonstrates its applicability beyond the Tokyo Dome. Owing to its high versatility, this system could be applied to various domestic and international crowd-attracting facilities and large-scale events.

Acknowledgments

This work was supported by the JST-Mirai Program Grant Number JPMJMI20D1 and JSPS KAKENHI Grant Number JP22H01664.

References:

[1] C. Feliciani, K. Shimura, and K. Nishinari, "Introduction to Crowd Management: Managing Crowds in the Digital Era: Theory and Practice," Springer, 2021. https://doi.org/10.1007/978-3-030-90012-0

[2] G. Sidiropoulos, C. Kiourt, and L. Moussiades, "Crowd simulation for crisis management: The outcomes of the last decade," Machine Learning with Applications, Vol.2, Article No.100009, 2020. https://doi.org/10.1016/j.mlwa.2020.100009

[3] A. Simonov, A. Lebin, B. Shcherbak, A. Zagarskikh, and A. Karsakov, "Multi-agent crowd simulation on large areas with utility-based behavior models: Sochi Olympic Park Station use case," Procedia Computer Science, Vol.136, pp. 453-462, 2018. https://doi.org/10.1016/j.procs.2018.08.266

[4] V. A. Sindagi and V. M. Patel, "A survey of recent advances in CNN-based single image crowd counting and density estimation," Pattern Recognition Letters, Vol.107, pp. 3-16, 2018. https://doi.org/10.1016/j.patrec.2017.07.007

[5] A. Lesani, E. Nateghinia, and L. F. Miranda-Moreno, "Development and evaluation of a real-time pedestrian counting system for high-volume conditions based on 2D LiDAR," Transportation Research Part C: Emerging Technologies, Vol.114, pp. 20-35, 2020. https://doi.org/10.1016/j.trc.2020.01.018

[6] M. Grieves, "Origins of the digital twin concept," Florida Institute of Technology, 2016.

[7] K. M. Alam and A. El Saddik, "C2PS: A digital twin architecture reference model for the cloud-based cyber-physical systems," IEEE Access, Vol.5, pp. 2050-2062, 2017. https://doi.org/10.1109/ACCESS.2017.2657006

[8] Ministry of Land, Infrastructure, Transport and Tourism, "Project PLATEAU" (in Japanese). https://www.mlit.go.jp/plateau [Accessed September 10, 2023]

[9] Tokyo Metropolitan Government, "Tokyo Digital Twin Project" (in Japanese). https://info.tokyo-digitaltwin.metro.tokyo.lg.jp [Accessed September 10, 2023]

[10] IoTwins. https://www.iotwins.eu [Accessed September 10, 2022]

[11] I. Meta et al., "The Camp Nou Stadium as a testbed for city physiology: A modular framework for urban digital twins," Complexity, Vol.2021, Article No.9731180, 2021. https://doi.org/10.1155/2021/9731180

[12] Z. Lin, J. Feng, Z. Lu, Y. Li, and D. Jin, "DeepSTN+: Context-aware spatial-temporal neural network for crowd flow prediction in metropolis," Proc. of the AAAI Conf. on Artificial Intelligence, Vol.33, No.1, pp. 1020-1027, 2019. https://doi.org/10.1609/aaai.v33i01.33011020

[13] M. Fu et al., "Fast crowd density estimation with convolutional neural networks," Engineering Applications of Artificial Intelligence, Vol.43, pp. 81-88, 2015. https://doi.org/10.1016/j.engappai.2015.04.006

[14] K. Nagao, D. Yanagisawa, and K. Nishinari, "Estimation of crowd density applying wavelet transform and machine learning," Physica A: Statistical Mechanics and its Applications, Vol.510, pp. 145-163, 2018. https://doi.org/10.1016/j.physa.2018.06.078

[15] V. Karbovskii et al., "Ensemble learning for large-scale crowd flow prediction," Engineering Applications of Artificial Intelligence, Vol.106, Article No.104469, 2021. https://doi.org/10.1016/j.engappai.2021.104469

[16] D. Sharma, A. P. Bhondekar, A. K. Shukla, and C. Ghanshyam, "A review on technological advancements in crowd management," J. of Ambient Intelligence and Humanized Computing, Vol.9, No.3, pp. 485-495, 2016. https://doi.org/10.1007/s12652-016-0432-x

[17] L. A. Toledo Diaz, I. R. Rivas, K. Rodriguez, and I. Rudomin, "Crowd data visualization and simulation," Procedia Computer Science, Vol.139, pp. 622-629, 2018. https://doi.org/10.1016/j.procs.2018.10.201

[18] Thunderhead Engineering, "Pathfinder Technical Reference," 2017. https://www.thunderheadeng.com/files/com/pathfinder/tech_ref.pdf [Accessed September 10, 2023]

[19] W. van Toll et al., "Comparing navigation meshes: Theoretical analysis and practical metrics," Computers & Graphics, Vol.91, pp. 52-82, 2020. https://doi.org/10.1016/j.cag.2020.06.006

[20] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," IEEE Trans. on Systems Science and Cybernetics. Vol.4, No.2, pp. 100-107, 1968. https://doi.org/10.1109/TSSC.1968.300136

[21] G. Johnson, "Smoothing a navigation mesh path," S. Rabin (Ed.), "AI Game Programming Wisdom 3," pp. 129-139, Charles River Media, 2006.

[22] Japan Science and Technology Agency (JST) Project Website (in Japanese). http://webpark5056.sakura.ne.jp/crowdmanagement [Accessed September 10, 2023]

[23] J. J. Fruin, "Pedestrian planning and design," Metropolitan Association of Urban Designers and Environmental Planners, 1971.

[24] J. E. Nash and J. V. Sutcliffe, "River flow forecasting through conceptual models Part I – A discussion of principles," J. of Hydrology, Vol.10, No.3, pp. 282-290, 1970. https://doi.org/10.1016/0022-1694(70)90255-6

[25] A. Portz and A. Seyfried, "Analyzing stop-and-go waves by experiment and modeling," R. D. Peacock, E. D. Kuligowski, and J. D. Averill (Eds.), "Pedestrian and Evacuation Dynamics," pp. 577-586, Springer, 2011. https://doi.org/10.48550/arXiv.1003.5446

Name:
Kensuke Yasufuku

ORCID:
0000-0003-0525-7326

Affiliation:
Associate Professor, Cybermedia Center, Osaka University

Address:
5-1 Mihogaoka, Ibaraki, Osaka 567-0047, Japan

Brief Career:
2007- Assistant Professor, Cybermedia Center, Osaka University
2015- Associate Professor, Cybermedia Center, Osaka University

Selected Publications:
• "Noticeability of illuminated route signs for tsunami evacuation," Fire Saf. J., Vol.91, pp. 926-936, 2017.
https://doi.org/10.1016/j.firesaf.2017.04.038

Academic Societies & Scientific Organizations:
• Architectural Institute of Japan (AIJ)
• Japan Society for Graphic Science (JSGS)

Name:
Akira Takahashi

ORCID:
0000-0002-8376-4027

Affiliation:
Specially Appointed Assistant Professor (full time), Cybermedia Center, Osaka University

Address:
5-1 Mihogaoka, Ibaraki, Osaka 567-0047, Japan

Brief Career:
2013- Kyoto Center for Community Collaboration
2016- School of Policy Studies, Kwansei Gakuin University
2020- Cybermedia Center, Osaka University

Selected Publications:
• "Evaluation of evacuation guidance plan for large-scale underground mall at the time of flooding using the simulation," J. Archit. Plan., Vol.86, No.786, pp. 2104-2114, 2021 (in Japanese).
https://doi.org/10.3130/aija.86.2104

Academic Societies & Scientific Organizations:
• Architectural Institute of Japan (AIJ)
• Japan Society for Graphic Science (JSGS)