A method for city-wide PoI-level congestion prediction via assimilation of actual and simulation-based PoI congestion data

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Abstract*—Regulating human flow is essential to reducing congestion in areas where people gather. A digital twin that realistically simulates human flow helps for this purpose. To realize a realistic human flow simulation mechanism, it is essential to take into account people's attributes. However, existing simulation methods use only location-specific information to predict people's behavior, thus do not reflect the routines that appear in people's actual lives. In this paper, we propose a human flow simulation using synthetic population data that help extract the attributes of people living in a target area. In the proposed method, we simulate the movement of people with each attribute like office workers, students, etc. every 15 minutes using the synthetic population data and the hourly transition probability matrix between PoIs (Points of Interest) by computing the transition probability matrix from hourly PoI-level congestion (people count) in the target area using people trajectory data included in the point-type fluid population data commercially available and applying a Markov chain to the congestion. The proposed simulation mechanism is based on the data assimilation of the actual PoI congestion vector (how many people were staying in each PoI) obtained from the point-type fluid population data and the virtual PoI congestion vector generated from the prediction of people's movement using the attribute information in the synthetic population data at regular time intervals. The data are assimilated at regular intervals to obtain highly accurate PoI-level congestion forecasts. The results of the mobility simulation for office workers showed that the maximum cosine similarity with the actual PoI congestion was 0.96 after 12 hours even when the actual PoI congestion vector is known only for a part of the area (one mesh).

***Index Terms*—Human flow simulation, synthetic population data, PoI congestion, digital twin**

I. Introduction

In recent years, tourist destinations in Japan have been overflowing with tourists from both Japan and abroad, and over-tourism has been cited as a serious problem. In addition to sightseeing spots, crowding occurs in various areas due to unbalanced human flows. Changing people's behavior from crowded places to less-crowded places is necessary to solve congestion. In order to get people to change their behavior, it is too late to do so after congestion has occurred, and it is necessary to guide people appropriately in anticipation of congestion.

In order to properly regulate the flow of people, it is necessary to predict the future flow of people and the congestion at each location. Therefore, it is necessary to develop a technology for sensing information on the number of people visiting and staying at each point of interest (PoI) and a technology for predicting the number of people in the future based on the current number of people staying at each PoI. Matsuda et al. [1] proposed a system that uses BLE to sense the number of people staying at each PoI, such as public transportation facilities and restaurants. Yamada et al. [2] predicted the number of people staying at each location from GPS trajectory data by performing four processes: outlier removal, mesh identification, stay detection and PoI identification, and data formatting. These forecasts are based on location-specific information such as congestion and GPS, and do not reflect the routines of actual people's lives because all people are treated identically.

Addressing this problem, in this paper, we propose a novel simulation mechanism to accurately predict the future congestion of all PoIs using people flow simulation with their attribute information and data assimilation with the actual PoI-level congestion data. As attribute information, we use synthetic population data that can provide information on the pseudo-residence and occupation of people living in the target area created by Murata et al. [3] based on the results of the census.

This simulation mechanism is based on the data assimilation of the actual PoI congestion vector (how many people were staying in each PoI) obtained by using the point-type fluid population data (commercially available) generated from the location information obtained by the smartphone application and the virtual PoI congestion vector generated from the prediction of people's movement based on the attribute information of the synthetic population data at regular time intervals. The data are assimilated at regular time intervals to obtain highly accurate PoI-level congestion forecasts. More specifically, the proposed assimilation mechanism consists of the following five steps. In Step 1, the movement of people is considered as a stochastic transition between PoIs, and a Markov chain that predicts the next PoI from the current PoI is applied to obtain the probability of movement between PoIs and the transition probability matrix at each time point. In Step 2, a virtual PoI congestion vector at the beginning of the simulation is calculated by simulating the predicted movement of people generated from synthetic population data. In step 3, the transition probability matrix is repeatedly applied to each person in the virtual PoI congestion vector at time t, and the virtual PoI congestion at the next time period $t+1$ is calculated in n ways. This is repeated until time $t+k$. In step 4, among the n^k virtual PoI congestion vectors at time $t+k$, select m vectors that are closest to the actual PoI congestion vector at the same time. Finally, in step 5, steps 2 through 4 are applied repeatedly to each of the m PoI congestion vectors. In this study, the unit time is 15 minutes, $k = 4$, $n = 10$, and $m = 3$, respectively.

The proposed method was applied to simulate the movement of people in Chofu City, Tokyo, from 6:00 a.m. to 6:00 p.m. The results showed that the maximum Cosine similarity between the predicted and actual PoI congestion vectors was 0.961. Therefore, we believe that the method of extracting the Top3 vectors every 15 minutes using different PoI transition probabilities for each attribute is an effective method for predicting the movement of people. Even when the actual PoI congestion vector is known only for a part of the area (one mesh), a cosine similarity of 0.96 is obtained between the prediction and the actual PoI congestion vector.

II. Related work

A. Estimation of urban congestion

There are several approaches for estimating crowd congestion in urban areas, including image processing approaches using cameras and measurement approaches using Bluetooth and sensors on smartphones [4]–[8]. In addition, a method to measure crowd density based on information from inertial sensors mounted on tablets has been proposed in recent years [9]. These approaches are suitable for estimating the flow of people in a specific narrow area where devices are installed. Still, it is not suitable for predicting the behavior of crowds in the entire city, which is the target of this study, because the flow of people in areas where cameras are not installed cannot be estimated.

In addition, there are approaches using WiFi access points and BLE for estimating congestion in public transportation facilities such as buses and trains, public facilities, restaurants, and other indoor locations [1], [10]–[12]. However, these methods are also effective within a limited area, such as a train or restaurant, but difficult to obtain information over a large area.

B. Crowd Congestion Prediction

In the field of crowd behavior prediction, similar to congestion estimation, prediction methods using sensors have been proposed. However, these methods are not suitable for predicting the behavior of crowds in the entire city, which is the target of this study. Crowd behavior is determined by various factors. Many deep learning and machine learning methods have been proposed to capture these factors [13]. Deep learning and machine learning methods use two types of features for prediction: spatial and temporal. Zang et al. proposed a method called Double-Encoder, which models the correlation between spatial and temporal features and daily movements [13]. This method focuses on the fact that each region has the same daily flow due to the regular living patterns of its citizens and that several regions share similar flow patterns and are correlated with each other. They constructed two encoders to capture the spatio-temporal dependence and correlation of daily flows, respectively, built the model, and conducted extensive experiments using two real-world datasets. As a result, the proposed model showed significant advantages over existing methods for predicting inflows and outflows. These studies predict future crowd behavior based on past behavioral information. However, human movements are influenced by the characteristics of a city, so past behavior alone is not enough.

C. Behavior prediction using PoI

In crowd forecasting, a forecasting method using information on PoIs (Points of Interest), which correspond to locations closely related to human behavior, has been proposed as a spatial feature. Wang et al. propose a method for predicting population outflow/inflow in a region using only the number and categories of PoI and also consider the motives that cause people to move and the number of people moving for each cause [14]. Jiang et al. focus on the relationship between human behavior and PoI information and propose a prediction method that combines CNN and LSTM using human trajectory data and urban PoI data as inputs [15]. The forecast area is divided into meshes, and the PoI information for each mesh is used as input data for spatial features using CNN convolution. Targeting cities with limited data, they use transfer learning, in which learning in one city is transferred to another city so that a more powerful model can be built by using data from other cities. Their method outperforms the baseline method, especially when training data is limited.

D. Research on Digital Twin

Digital twin refers to a technology to reproduce various data collected from the real world on a computer and was first proposed by NASA [16]. The digital twin in the industrial field can be used for simulation and operation to make predictions and tests from learning models before actual production, etc., and has been proposed for remote monitoring and streamlining of factory operations [17]. In recent years, the technology has been used in urban digital twin projects around the world, such as the digital prototype of the city of Herrenberg in Germany [18], the digital twin project of the Tokyo Metropolitan Government, and the digital twin construction of the city of Singapore [19]. Much of the current urban digital twin research is simulation-based for disaster simulation and urban planning [20], [21]. The digital twin in these studies does not necessarily require the use of real-time data but rather the estimation of daylight conditions using 3D digital twin data or the estimation of disaster conditions. Therefore, how to utilize data such as real-world congestion data for human flow simulation and how to reflect such data in the digital twin is not considered, as is the case in this study.

E. Positioning of this research

In existing research, much research has been conducted on predicting behavior in limited areas with a narrow scope for congestion estimation and people flow simulation and on building learning models to improve the accuracy of such predictions. In most cases, only past information on people's behavior and congestion data are used to predict the behavior of crowds, and future behavior prediction based on this information has been the norm. In this case, behavior forecasting does not take into account the attribute status of people. Therefore, the simulation does not reflect the routines of daily activities of many adults and students, such as going to work or school in the morning and returning home in the evening or at night, which are observed for each attribute.

In this study, we address the estimation of future PoI congestion that can consider local circumstances and social conditions. We have performed simulations considering attribute information under the assumption that the actual PoI-level congestion for the entire target area is known. However, it is not realistic to know the actual PoI-level congestion for the entire area of interest. Therefore, in this study, we try to realize a more versatile human flow simulation mechanism and tackle the problem of forecasting when only PoI-level congestion only in a part of the target area is known as a new problem.

III. Problem description

This section provides an overview of the human flow simulation mechanism using PoI transition probabilities and synthetic population data. The objective is to predict future congestion conditions of all PoIs from a realistic human flow simulation mechanism.

A. Assumptions

We put the following three assumptions required to devise a realistic human flow simulation method.

1) Knowing the past congestion of all PoIs
2) Knowing the current congestion status of some PoIs
3) Knowing the attributes of people in the target area

B. Obtaining real congestion data

We suppose that the following technologies are available to obtain past and current congestion at all PoIs.

1) Congestion sensing at PoIs: We suppose to use existing congestion sensing systems that acquire real-time PoI congestion vector in transit vehicles, public facilities, and restaurants such as BLECE [1] which is an inexpensive congestion sensing system using Bluetooth Low Energy (BLE).

2) Congestion calculation using PoI congestion vector: To obtain the number of people staying at each PoI, we can use the method developed by Yamada et al. [2]. This method is used to create data on the number of people staying at each PoI by searching for the PoI nearest to the location information of the staying PoI when dividing the GPS trajectory data of each person in the "Point-type Current Population Data" provided by Agoop Inc. into moving segments and staying segments. In this study, this data is used as real congestion data.

C. Acquisition of each person's attribute information

Synthetic population data [3] is used to obtain attribute information on people in the target area. The synthetic population data is the data compiled by using national statistics, prefectural statistics, municipal statistics, town and street statistics, and basic unit district statistics from the national census conducted every five years. By using this data, it is possible to obtain information on the attributes of people living in the target area.

D. Problem to be solved by proposed method

In this study, we aim to construct a more realistic human flow simulation method that combines data obtained from a congestion sensing system and PoI congestion vector with attribute information obtained from synthetic population data, in order to understand future congestion in all PoIs, and to predict future congestion levels more accurately. The goal is to minimize the difference between the predicted future congestion and the actual congestion in each PoI of the target area as much as possible. We propose a method consisting of the following three steps.

1) Using historical real PoI-level congestion data, determine the transition probability matrix between PoIs.
2) Simulating peoples' movements by their attributes extracted from the synthetic population data.
3) Assimilating actual congestion data and simulated congestion data.

IV. Simulation method of human flow movement considering attribute information

In this section, we propose a method for predicting future PoI congestion in a target area by applying the three approaches described in the previous chapter. In this paper, we assume Chofu City, Tokyo, Japan as the target area. Tabel I shows information for Chofu City. The tertiary mesh here is one of the regional meshes that divide the area into meshes of approximately the same size based on latitude and longitude for statistical use, and the size of a mesh is 1000m $\times$ 1000m. We used this tertiary mesh as information on the location of a person at a certain point in time, and the location of the person at a certain time was used as the location of the person.

A. Definition of Attribute Information

In applying the proposed approach, we categorized the people living in Chofu City into three types of attributes based on synthetic population data: "office worker," "student," and

TABLE I
CHOFU CITY

population	242,917 persons
area	21.53 km^2
GridCode3	37

"other" who stay at home. The definitions of all attributes are shown in Table II.

TABLE II
DEFINITION OF ATTRIBUTE INFORMATION

worker	Number of people	88,000
	classification	Use of "Age" and "Occupation" information
	movement	Movement based on inter-PoI transition probabilities
student	Number of people	55,000
	classification	Use of "age" and demographic information
	movement	moved to a school location in the city
Other	Number of people	63,000
	classification	Use "age" and "household" information
	movement	Stay at the location

B. Calculation of PoI-to-PoI transition probability matrix

Markov chains are generally used in the problem of predicting the next destination in the trajectory of a person's movement. Assuming that a person's movement is a stochastic transition between PoIs, we applied a Markov chain to predict the next PoI. Here, the probability of moving between PoIs and the transition probability matrix are obtained by applying a Markov chain to real congestion data for all past PoIs.

We generate the probability matrix $M_{t,t+\Delta}$ from the congestion at time t and at time $t+\Delta$, the pair of two times at a PoI. Denoting P_t as the vector of real congestion for all PoIs at time t, this matrix $M_{t,t+\Delta}$ can be expressed as a Markov chain of the following formula.

$$P_{t+\Delta} = P_t \cdot M_{t,t+\Delta} \tag{1}$$

We obtain the congestion information (number of people staying at each time) at each PoI, called *real PoI congestion vector* hreafter, by generating a trajectory of each person's behavior based on the PoI congestion vector. Then, at 0, 15, 30, and 45 minutes of every hour, a judgment is made as to whether the person is moving or staying, and if the judgment is that the person is staying, the number of people staying at each location at each time is calculated by assigning PoI information to that location.

The PoI information given here is based on the addition of "Move," "Home," and "Uncategorized" to the major industry category of Agoop Corporation's PoI data for Tokyo, and the details are shown in Table III.

C. Overview of Simulation Mechanisms

The transition probability matrices obtained in Sect. IV-B are used to simulate the movement of 88,000 workers in Chofu City from 6:00 a.m. to 6:00 p.m. The steps of the simulation are as follows.

TABLE III
LARGE CATEGORIES OF POI

Traffic, Transportation, Warehousing
Automobiles, Motorcycles, Bicycles, Driving
restaurant
Sales, wholesale
Sports, Hobbies, Leisure
Medical, Pharmaceutical, Health Care
Government, Organization, Welfare
Travel, Sightseeing, hot springs, Ryokan, Hotels
Schools, Libraries
Finance, insurance, securities
Manufacturing, processing
Construction, Engineering
Real Estate, Leasing, Exhibition Space
Agriculture, Fisheries, Mining
Electricity, gas, telecommunications, broadcasting, newspapers
Publishing, Printing
Other Services
Unclassified
Move
Home

Step 1 Calculate a *virtual PoI congestion vector* at the start of the simulation.

Step 2 For each person in the virtual PoI congestion vector at time t, the transition probability matrix is applied iteratively to compute the n possible virtual PoI congestion at the next time period $t+1$, and the process is repeated until time $t+k$.

Step 3 Among the n^k virtual PoI congestion vectors at time $t+k$, select m vectors closest to the actual PoI congestion vector.

Step 4 Repeat steps 2 to 4.

Figure 1 shows an overview of this simulation. First, assuming that most workers are at home in the morning, we set 6:00 a.m. as the starting time of the simulation, so we obtained information on the residences of all people based on the town and street information in the synthetic population data and assigned "Home" as PoI congestion vector according to the assignment rule described above. Each person has information that combines location information and PoI information (e.g., 111111111-Home) and is placed at the initial location with reference to this location information. Then, PoI-to-PoI transition probabilities were applied to all of the initial locations, one by one, to obtain the new PoI congestion vector for each person after 15 minutes. This new PoI information is the new position of each person 15 minutes after moving from the initial position. The transition probabilities are applied to each person one by one in order to produce variations in where people move to for each simulation. The transition probability matrix between PoIs is used as the basis for determining whether or not each person moves and where they move. Ten movement patterns are created every 15 minutes for one placement ($n = 10$). This is repeated four times to create 10,000 movement patterns in one hour ($k = 4$). Compare this result with the actual PoI congestion vector and extract the

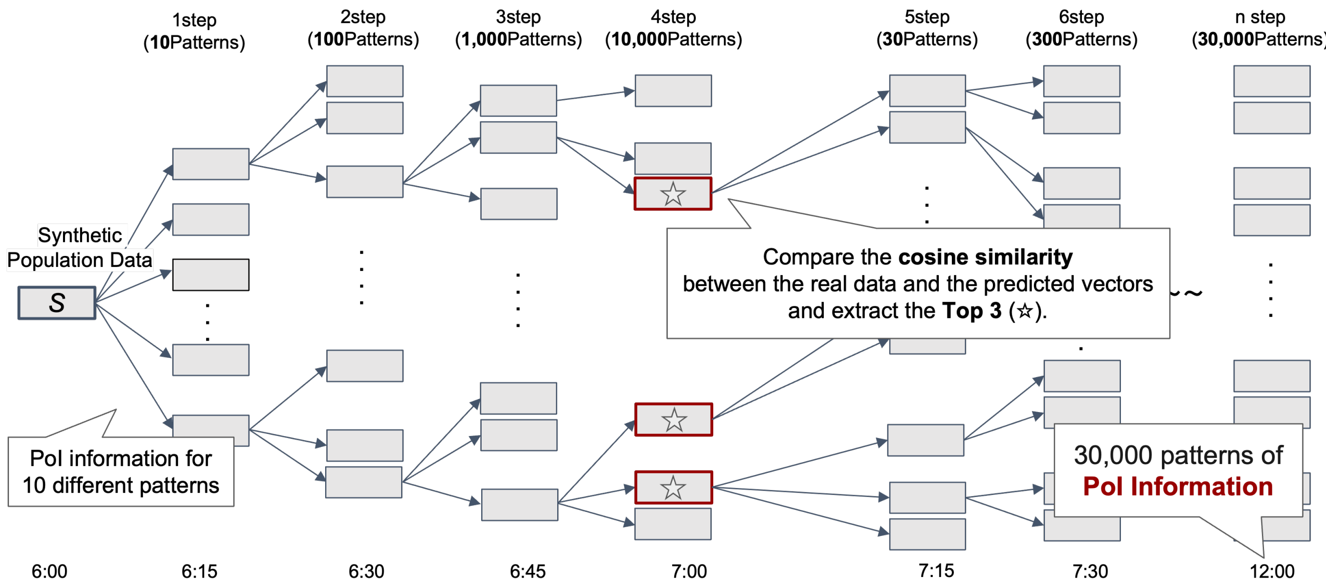

Fig. 1. Overview of Simulation

three with the highest cosine similarity ($m = 3$). Using these initial values of people and their movement transitions, the proposed method simulates their movements every 15 minutes from 6:00, set as the start time, to 18:00, set as the end time.

D. Hourly Cosine Similarity Comparison Method

For every k time unit (e.g., 60 minutes when $k = 4$), cosine similarity is calculated between the real PoI congestion vector obtained in Sect. IV-B and 10,000 different patterns of the virtual PoI congestion vectors obtained from the simulation in Sect. IV-C. Here, each vector is in the form of location information plus PoI information and contains 740 elements. Then, the three virtual PoI congestion vectors with the highest similarities are selected and used as the base for the next one-hour simulation (see Fig. 1).

V. Results of Experimental Evaluation of Movement Simulation

A. Experiment 1: Congestion prediction in the case when PoI congestion vector for all meshes is known

1) Outline of Experiment: Experiment 1 was conducted to check the accuracy of the proposed method's travel simulation under the condition that real-time congestion data (PoI congestion vector) for all meshes in the target area (Chofu City) are known. Two comparison methods, the local search and the bottom selection method, were used to determine the effectiveness of the proposed method. Each evaluation method is as follows.

Local Search Method: In this method, the initial positions of all people are set the same as in the proposed method. For the first transition (first 15 minutes), 10,000 simulations were performed, generating 10,000 different virtual PoI congestion vectors. After that, instead of applying transition probabilities to each person one by one as in the proposed method, transition probabilities were applied directly to each of 10,000 PoI congestion vectors every 15 minutes, thus updating 10,000 vectors until 18:00 every 15 minutes.

Bottom Selection Method: Contrary to the proposed method, this method selects m virtual PoI congestion vectors with the lowest cosine similarities ($m = 3$ is used in this experiment). This method is used to give a rough lower limit of the cosine similarity.

2) Results of experiments: The results of the cosine similarity for each method at different times of the day are shown in Table reftable:res. starting at 6:00, the cosine similarity gradually increased, reaching a maximum of 0.961 at 18:00.

In the local search method, similarly to the proposed method, there was a gradual improvement in the cosine similarity until 18:00, and the maximum cosine similarity at 18:00 was 0.919. The proposed method outperforms the local search method at all times until 18:00. In the case of the bottom selection method, the cosine similarity decreases with time, reaching 0.804 at 18:00. These results indicate that the proposed method is more effective than the local search and that the proposed method may decrease the cosine similarity to 0.804 in the worst case.

3) Discussion: We calculated the mean absolute percent error (MAPE) per mesh between the predicted PoI congestion vector and the actual. The results of the top and worst five meshes are shown in Table V and Table VI, respectively. All meshes in Chofu City are shown in Figure 2.

The meshes with large MAPE in Table VI are characterized by the fact that there are actual samples in the Point-type Current Population Data (by Agoop Inc.) in those meshes due to the fact that they border with other cities and have forests. On the other hand, the meshes with low MAPE

TABLE IV
COSINE SIMILARITY FOR EACH TIME PERIOD

		6:00-7:00	7:00-8:00	8:00-9:00	9:00-10:00	10:00-11:00	11:00-12:00	12:00-13:00	13:00-14:00	14:00-15:00	15:00-16:00	16:00-17:00	17:00-18:00
Proposed Method	Top 3	0.920	0.948	0.966	0.965	0.976	0.985	0.983	0.984	0.976	0.965	0.959	0.961
		0.920	0.947	0.966	0.965	0.976	0.985	0.981	0.981	0.964	0.961	0.939	0.945
		0.920	0.947	0.966	0.964	0.975	0.985	0.979	0.981	0.974	0.961	0.941	0.940
Local Search	average	0.893	0.908	0.914	0.920	0.929	0.924	0.934	0.930	0.915	0.923	0.916	0.894
	Top	0.921	0.947	0.957	0.962	0.969	0.971	0.975	0.966	0.954	0.941	0.926	0.919
Bottom	Bottom 3	0.920	0.941	0.937	0.937	0.894	0.849	0.841	0.842	0.834	0.831	0.826	0.821
		0.920	0.941	0.937	0.937	0.894	0.848	0.847	0.837	0.832	0.832	0.816	0.819
		0.920	0.941	0.936	0.936	0.893	0.847	0.844	0.832	0.830	0.827	0.816	0.804

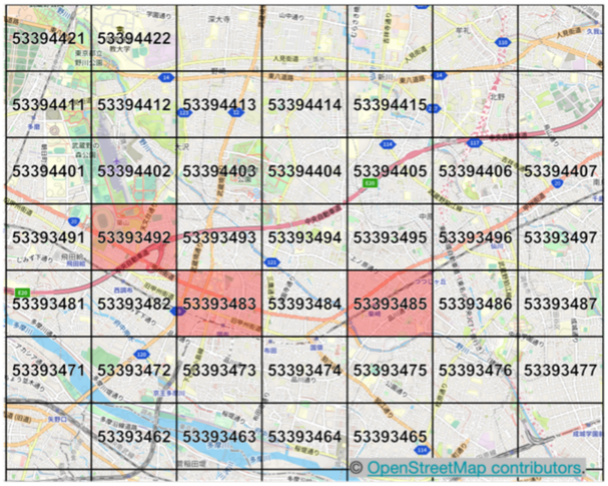

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Fig. 2. Chofu City Mesh ID

(high prediction accuracy) in Table V are characterized by the presence of a large number of actual samples and the presence of popular places where many people gather, such as stations, shopping centers, and residential areas.

TABLE V
MAPE FOR TOP 5 MESHES

meshID	%
53393487	0.1
53393494	0.5
11111111	1.5
53393485	1.5
53393483	1.8

TABLE VI
MAPE FOR WORST 5 MESHES

meshID	%
53393471	30.2
53394405	28.9
53394412	27.4
53394465	27.1
53394407	23.5

The results of Experiment 1 as a whole show that it is possible to predict people's movements based on synthetic population data that includes information on people's attributes and places of residence. The proposed method selects the top three cosine similarity vectors every hour, and people's movements are explored from those three vectors. When 10,000 random movement patterns are calculated (Local Search Method), the maximum cosine similarity value becomes 0.919, while the proposed method achieves 0.961, which is 0.04 higher than the Local Search Method. Therefore, we consider the proposed method to have some merits.

Furthermore, the large MAPE difference between meshes indicates that the proposed method may be able to make predictions even when the congestion vector for only a specific mesh is available.

B. Experiment 2: Congestion prediction when only some meshes' PoI congestion vector is known.

1) Outline of Experiment: Experiment 2 was conducted to see how well the proposed method can predict the PoI-level congestion when only some meshes' real PoI congestion vectors are available. Specifically, we selected three characteristic meshes in Chofu City and conducted simulations when one of the meshes' information was known and when two of the meshes' information was known.

The three meshes selected this time are 53393483, 53393485, and 53393492 (Figure 2), and a description of each mesh is shown in Table VII. The meshes will be denoted as $M_{downtown}$, $M_{housing}$, and $M_{stadium}$, respectively.

TABLE VII
OVERVIEW OF SELECTED MESH IDS

	mesh	explanation
$M_{downtown}$	53393483	Urban area with Chofu Station, which has the highest number of passengers in Chofu City, and shopping centers.
$M_{housing}$	53393485	Residential area with two stations, Shibasaki and Tsutsujigaoka, in the same mesh.
$M_{stadium}$	53393492	The Ajinomoto Stadium occupies 1/4 of the mesh, and there are several other sports facilities such as sports grounds.

In addition to this, simulations were also performed for the case where two meshes $M_{downtown}$ and $M_{housing}$ are known.

2) Results of Experiment:

Case1: One mesh's congestion information is known: The results of each simulation, when only one PoI congestion vector of the three selected meshes is known, are shown in Table VIII. The maximum cosine similarity when only $M_{downtown}$'s congestion information is known is 0.943 at 18:00, which is only 0.02 less than 0.961 at 18:00 when congestion

TABLE VIII

COSINE SIMILARITY FOR CASES KNOWING ONLY A SPECIFIC MESH

	6:00-7:00	7:00-8:00	8:00-9:00	9:00-10:00	10:00-11:00	11:00-12:00	12:00-13:00	13:00-14:00	14:00-15:00	15:00-16:00	16:00-17:00	17:00-18:00
$M_{downtown}$	0.921	0.923	0.942	0.946	0.951	0.959	0.953	0.957	0.941	0.927	0.946	0.943
$M_{housing}$	0.984	0.972	0.993	0.963	0.968	0.965	0.951	0.952	0.961	0.967	0.954	0.949
$M_{stadium}$	0.792	0.890	0.806	0.863	0.803	0.792	0.872	0.871	0.864	0.860	0.858	0.852
2 meshes	0.920	0.955	0.959	0.977	0.974	0.974	0.975	0.981	0.969	0.958	0.949	0.954
All	0.920	0.948	0.966	0.965	0.976	0.985	0.983	0.984	0.976	0.965	0.959	0.961

information from all meshes is used. When only $M_{housing}$'s congestion information is known, the maximum cosine similarity is 0.949 at 18:00, which is only 0.01 lower than the value at 18:00 when the information of all meshes is known. Compared to the previous $M_{downtown}$, the difference between the simulation results and the actual congestion prediction results is large at the beginning of the simulation, but the prediction accuracy gradually improves after 8:00. Next, when only $M_{stadium}$'s congestion information is known, the maximum cosine similarity is 0.852 at 18:00, which is 0.11 lower than that of all meshes case at 18:00. The result was significantly lower than that of the two meshes ($M_{downtown}$ and $M_{housing}$).

Case2: Two meshes' congestion information is known: Next, we describe the simulation results when the congestion vector for two meshes is known. For this simulation, we selected $M_{downtown}$ and $M_{housing}$, which gave the best simulation results when one mesh ID was known. We performed simulations using only the congestion information of these two meshes. The results are shown in Table VIII, with a cosine similarity of 0.954 at 18:00. This result is higher than that obtained individually for each mesh ID, $M_{downtown}$ and $M_{housing}$.

Next, the simulation results are plotted on a scatter plot at two-hour intervals, as shown in Figures 3 to 8. At 8:00, two hours after the start of the simulation, the divergence between the simulation results and the actual data was the largest, but it began to converge with the passage of time.

3) Discussion: The results of Experiment 2 show that real-time congestion data (PoI congestion vector) can be used to predict future PoI-level congestion by simulation, even with a limited number of mesh IDs in the target area. The high prediction accuracy of $M_{downtown}$ and $M_{housing}$, which have many samples and PoIs, indicates that future congestion prediction is possible even with only some data if real-time congestion data (PoI congestion vector) is known for key locations where people gather, such as residential areas and the center of an area.

The prediction accuracy using real-time congestion data from two meshes was higher than that using only one mesh, and the difference in maximum cosine similarity was only 0.01 compared to when all meshes' real-time congestion data was known, suggesting that it is possible to predict the future congestion with sufficiently high accuracy using only some data.

VI. CONCLUSION

In this paper, we proposed a realistic human flow simulation mechanism using transition probabilities between PoIs and synthetic population data for Chofu City, Tokyo, Japan. Using real-world residential information from the synthetic population data as the initial people's locations in the simulation and applying transition probabilities every 15 minutes obtained from the actual PoI congestion vector (calculated with Point-type Current Population Data provided by Agoop Inc.), we found that the proposed method could achieve the maximum cosine similarity at 18:00, 12 hours later of approximately 0.961, indicating that it is possible to predict people movement with high accuracy. In addition, when the congestion information is known only for one or two meshes, the simulation results were good enough.

The data used in this study is biased toward some categories of PoI where people are staying, such as "Home" and "Move," and the accuracy of the simulation may not always be accurately reflected in the simulation results. In the future, we aim to build a more accurate simulation mechanism by adopting a smaller mesh size.

We are currently simulating up to 30,000 movement patterns for a one-hour simulation, but we aim to build a more versatile simulation mechanism by learning and scoring the model. We also aim to build a realistic simulation of human flow and estimate future congestion in all PoIs, which will serve as a basis for creating a digital twin of human flow.

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REFERENCES

[1] Y. Matsuda, K. Ueda, E. Taya, H. Suwa, and K. Yasumoto, "Blece: Ble-based crowdedness estimation method for restaurants and public facilities," in *The 14th International Conference on Mobile Computing and Ubiquitous Networking (ICMU '23)*, 2023, pp. 1–6. [Online]. Available: https://doi.org/10.23919/ICMU58504.2023.10412158

[2] O. Yamada, Y. Matsuda, H. suwa, and K. Yasumoto, "Investigation of mesh congestion prediction using time-series congestion information by PoI," in *The 29th IPSJ DPS Workshop*, 2021 (in Japanese), pp. 41–49.

[3] T. Murata and T. Harada, "Synthetic method for population of a prefecture using statistics of local governments," in *2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, 2018, pp. 1175–1180.

[4] H. Song, X. Liu, X. Zhang, and J. Hu, "Real-time monitoring for crowd counting using video surveillance and gis," in *2012 2nd International Conference on Remote Sensing, Environment and Transportation Engineering*, 2012, pp. 1–4.

[5] M. Fu, P. Xu, X. Li, Q. Liu, M. Ye, and C. Zhu, "Fast crowd density estimation with convolutional neural networks," *Engineering Applications of Artificial Intelligence*, vol. 43, pp. 81–88, 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0952197615000871

[6] Y. Yuan, C. Qiu, W. Xi, and J. Zhao, "Crowd density estimation using wireless sensor networks," in *2011 Seventh International Conference on Mobile Ad-hoc and Sensor Networks*, 2011, pp. 138–145.

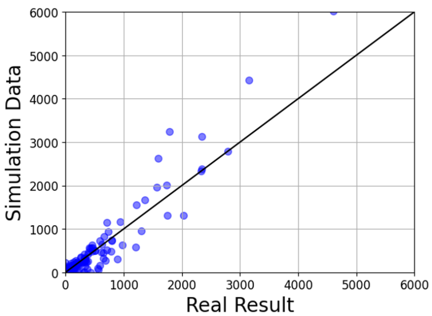

Fig. 3. 8:00 a.m.

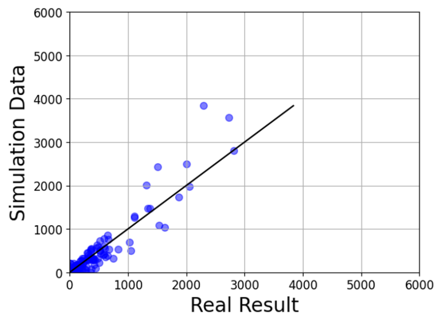

Fig. 4. 10:00 a.m.

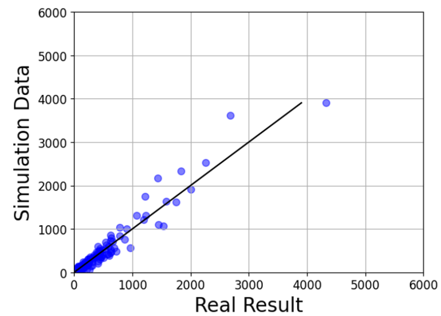

Fig. 5. 12:00 p.m.

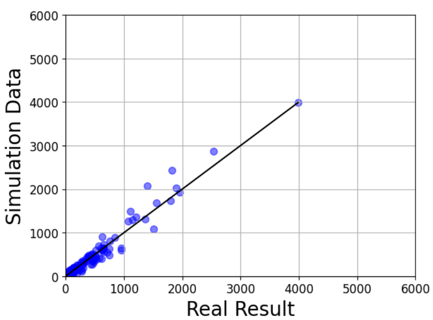

Fig. 6. 2:00 p.m.

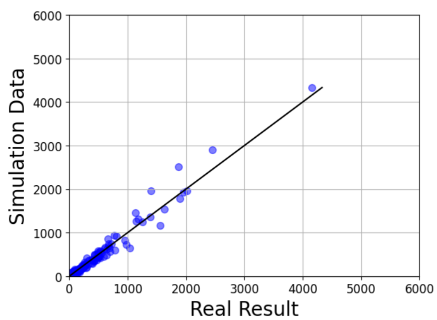

Fig. 7. 4:00 p.m.

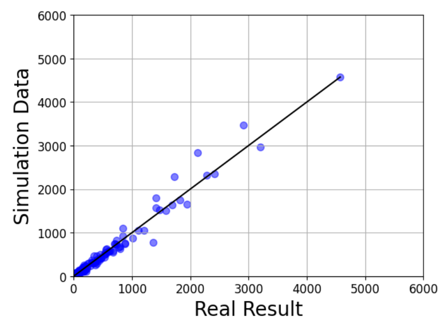

Fig. 8. 6:00 p.m.

[7] J. Weppner and P. Lukowicz, "Bluetooth based collaborative crowd density estimation with mobile phones," in *2013 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 2013, pp. 193–200.

[8] L. Schauer, M. Werner, and P. Marcus, "Estimating Crowd Densities and Pedestrian Flows Using Wi-Fi and Bluetooth," in *11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, ser. MOBIQUITOUS '14, 2014, pp. 171–177. [Online]. Available: https://doi.org/10.4108/icst.mobiquitous.2014.257870

[9] 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, 06 2018.

[10] M. Handte, S. Foell, S. Wagner, G. Kortuem, and P. J. Marrón, "An internet-of-things enabled connected navigation system for urban bus riders," vol. 3, no. 5, 2016, pp. 735–744.

[11] Y. Kanamitsu, E. Taya, K. Tachibana, Y. Nakamura, Y. Matsuda, H. Suwa, and K. Yasumoto, "Estimating Congestion in a Fixed-Route Bus by Using BLE Signals," *Sensors*, vol. 22, no. 3, pp. 1–15, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/3/881

[12] E. Taya, Y. Kanamitsu, K. Tachibana, Y. Nakamura, Y. Matsuda, H. Suwa, and K. Yasumoto, "Estimating Congestion in Train Cars by Using BLE Signals," in *The 2nd Workshop on Data-Driven and Intelligent Cyber-Physical Systems for Smart Cities (DI-CPS '22)*, 2022, pp. 1–7.

[13] T. Zang, Y. Zhu, Y. Xu, and J. Yu, "Jointly modeling spatio–temporal dependencies and daily flow correlations for crowd flow prediction," *ACM Trans. Knowl. Discov. Data*, vol. 15, no. 4, mar 2021. [Online]. Available: https://doi.org/10.1145/3439346

[14] M. Wang, S. Yang, Y. Sun, and J. Gao, "Human mobility prediction from region functions with taxi trajectories," *PLOS ONE*, vol. 12, no. 11, pp. 1–23, 11 2017. [Online]. Available: https://doi.org/10.1371/journal.pone.0188735

[15] R. Jiang, X. Song, Z. Fan, T. Xia, Z. Wang, Q. Chen, Z. Cai, and R. Shibasaki, "Transfer urban human mobility via poi embedding over multiple cities," *ACM/IMS Trans. Data Sci.*, vol. 2, no. 1, jan 2021. [Online]. Available: https://doi.org/10.1145/3416914

[16] E. Glaessgen and D. Stargel, "The digital twin paradigm for future nasa and u.s. air force vehicles," in *53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference*. [Online]. Available: https://arc.aiaa.org/doi/abs/10.2514/6.2012-1818

[17] F. Tao, J. Cheng, Q. Qi, M. Zhang, H. Zhang, and F. Sui, "Digital twin-driven product design, manufacturing and service with big data," *The International Journal of Advanced Manufacturing Technology*, vol. 94, no. 9, pp. 3563–3576, Feb 2018. [Online]. Available: https://doi.org/10.1007/s00170-017-0233-1

[18] Herrenberg, "Herrenberg project," https://www.herrenberg.de/MpS?project_id=37.

[19] G. of Singapore, "Virtual Singapore," 2022, https://www.nrf.gov.sg/programmes/virtual-singapore.

[20] S. Shirowzhan, W. Tan, and S. M. E. Sepasgozar, "Digital twin and cybergis for improving connectivity and measuring the impact of infrastructure construction planning in smart cities," *ISPRS International Journal of Geo-Information*, vol. 9, no. 4, 2020. [Online]. Available: https://www.mdpi.com/2220-9964/9/4/240

[21] C. Fan, Y. Jiang, and A. Mostafavi, "Social sensing in disaster city digital twin: Integrated textual–visual–geo framework for situational awareness during built environment disruptions," *Journal of Management in Engineering*, vol. 36, no. 3, p. 04020002, 2020. [Online]. Available: https://ascelibrary.org/doi/abs/10.1061/%28ASCE%29ME.1943-5479.0000745