Crowd Flow Prediction from Mobile Traces Through Time Series PoI Stay Counts

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***Abstract*—Predicting crowd flow is crucial for decision-making to mitigate various risks. For instance, in social problems such as traffic congestion and over-tourism, countermeasures can be taken by predicting crowd flows in advance. Typically, people visit multiple Points of Interest (PoI) for various purposes. Previous work has proposed methods to incorporate the behavioral characteristics of people in different areas, such as dining areas or office areas, into machine learning models. However, they have not considered the specific behavioral characteristics associated with each PoI, such as when restaurants or train stations experience peak periods. Recently, there has been an increase in the ability to handle large amounts of location information, leading to a growth in the volume of individual trace data. In this study, we propose a crowd flow prediction method that aggregates large-scale individual trace data of movements between PoIs and considers the behavioral characteristics associated with each PoI. We define this information as time series PoI stay counts generated from trace data collected from mobile phones. Using this, we developed a machine learning model to predict the number of people in an area (mesh) over the next several minutes to hours. This prediction is based on the number of people staying at each PoI (category) in neighboring areas (meshes). We applied this approach to densely populated areas in central Tokyo, where congestion is a significant concern, and conducted validation. The results showed that the method utilizing time series PoI stay counts improved prediction accuracy by up to 50% compared to methods that did not use it. Additionally, the Mean Absolute Percentage Error (MAPE) for predicting the number of people staying 1 hour later was only 2.57%.**

***Index Terms*—Cloud flow prediction, population data, PoI congestion**

I. Introduction

Predicting human behavior has become one of the most important keys to solving social problems in recent years. The Covid-19 in 2020 spread rapidly throughout the world and became a social problem. Since avoiding human contact is effective in preventing the spread of infection, it was necessary to know in advance where congestion is expected and to plan activities accordingly. In urban areas and sightseeing spots, traffic congestion or overtourism is caused by the large number of people gathering. In such problems, we can take countermeasures in advance by predicting human behavior. Thus, predicting human behavior has become an important means of solving contemporary social problems.

Existing work focuses on predicting crowd flow and transition probabilities in specific areas based on datasets such as the number of people, taxi pick-up/drop-off, and ride-sharing [1]–[14]. These studies have seen significant advancements by utilizing machine learning techniques to reduce prediction errors and incorporating information related to human behavior as features. Particularly, data representing locations known as Points of Interest (PoI), such as Tokyo Tower and Senso-ji Temple, have been reported to be effective [15], [16]. For instance, if there are several restaurants or bars serving as Points of Interest (PoI) in the area, it can be classified as a dining area. This would enable consideration of the fact that many people gather in that area during dinner time. Various methods have been proposed to integrate the characteristics of an area based on the number and type of each PoI and incorporate them into machine learning as features.

However, existing work only reflect the characteristics of an area and do not consider behavioral characteristics of people at each PoI, such as the level of crowding in restaurants or stations. Additionally, aggregated data on the number of people and taxi data in specific areas do not capture the individual purposes behind each person's actions. In recent years, with the proliferation of applications capable of handling location information, it has become possible to manage vast amounts of individual trace data. Therefore, we believe that by successfully aggregating individual trace data, it is possible to extract the characteristics of people's behavior for each PoI, such as how many people stayed at each PoI, thereby reducing the predicting error.

Furthermore, individual trace data, being time-series data, allows for the consideration of temporal congestion levels at each PoI, which was not possible previously. For instance, intuitively, one can imagine that a cafe is crowded at 3 p.m. and emptier at 9 p.m. However, when predicting crowds in large-scale areas, such as cities, such temporal congestion at each PoI was not considered. While there are studies predicting crowd flow by placing sensors to measure congestion levels in limited areas like stadiums or stations, achieving this on a large scale (city-wide) has been challenging. By aggregating individual trace data, it becomes possible to represent congestion levels at each PoI at different times, thus enabling the consideration of temporal congestion levels.

In this study, we utilize a large amount of individual trace data, which has not been previously addressed, and aggregate it to generate information on the number of people staying at each PoI at different times. We define this as time series PoI stay counts and use it to develop a prediction model for crowd flow. The prediction model was experimentally evaluated to determine whether it can reduce prediction errors compared to aggregated data typically used in existing crowd prediction methods. As a result, the method utilizing time series PoI stay counts was confirmed to improve predictive accuracy compared to the method not utilizing them, demonstrating its effectiveness.

II. Related Work

There are two types of studies related to crowd movement: one is to estimate the crowd density for a specific location, and the other is to predict the crowd flow for the whole city. In addition, studies focusing on PoI, which represents the characteristics of an area, are described, and these existing studies are summarized.

A. Crowd Density

In the estimation of crowd density, there are two approaches: one is the image processing approach using a camera, and the other is the measurement approach by using Bluetooth of mobile phones and sensors [17]–[20]. Recently, a method to measure the crowd density from the angular velocity of a tablet has been proposed [21]. This approach, based on the installation of images, sensors, etc., is an estimation of a specific location and is not suitable for the estimation of the entire city, which is the target of this research.

B. Crowd flow

Many deep learning and machine learning methods have been proposed in crowd flow prediction [1]–[11]. In deep learning and machine learning methods, two types of features are used for prediction: spatial and temporal features. Spatial features are geographical features, such as road information in the target area, while temporal features are time-dependent regularities of human behavior. These features contribute greatly to the prediction model. These studies predict future flows from past flows by using data on the inflow and outflow of people into and out of an area. However, the movement of people will be affected by the characteristics of the area. Zeng et al. showed that the movement of people and the PoI are highly related [22]. Therefore, we focus on the PoI, which indicates the characteristic of the city.

C. Crowd prediction by using PoI

In crowd prediction, some proposals have been made using PoI [12]–[14], [16]. Wang et al. proposed a method that can predict the inflow and outflow of people in an area using the number and category of PoI [12]. They also discussed the motivations that cause people to move and the mobility of people for each cause. Focusing on the relationship between human activities and PoI information, Jiang et al. proposed a prediction method that combines CNN and LSTM with human trajectory data and PoI data as input [16]. By dividing the prediction area into meshes and creating a single image of the number and distribution of PoI for each divided mesh, the characteristics of each mesh are incorporated in the CNN. By doing so, They developed a predicting model that effectively incorporates the characteristics of each area and human trajectory data.

However, these existing methods have two problems. One is the datasets. In urban areas, there are various means of transportation and a wide variety of flows. For this reason, we believe that a method utilizing human mobility datasets, rather than just traffic data, would be effective. Additionally, aggregated data on the amount of inflow and outflow into an area does not capture the purpose of each individual's activities. The second issue concerns the behavioral characteristics of people at each PoI. While the characteristics of each area can be incorporated, the specifics of how many people are staying at each PoI and at what time are not accounted for. We hypothesize that integrating the characteristics of each PoI, rather than each area, will result in a further reduction in prediction error.

III. Definition of Time Series PoI Stay Counts

In this section, we define time series PoI stay counts. In this study, we generate crowd behavior information by aggregating trace data indicating when each individual stayed at which PoI. This information includes the purpose of each individual's actions and captures the movement of people between PoIs over time. We define this information as time series PoI stay counts in this study. This time series PoI stay counts must meet the following two requirements:

- The number of people "staying" at PoI
- Identifiable categories indicating the purpose of actions

In this section, we will discuss these two requirements in detail.

A. The number of people staying at PoI

time series PoI stay counts contains the individual's purpose of action, reflecting the movement of people between PoIs over time. In order to include such information, the primary requirement is information on people's stay in PoI. People have a purpose for staying at a location, and upon finding their next destination, they move there. Thus, the location of stay represents the purpose of individuals' actions. On the other hand, while in transit, passing through a PoI does not reflect the purpose of action. For example, considering a "restaurant" as a PoI, during a stay, it can be assumed that people are dining and will move to another location after an hour. However, while in transit, passing through a restaurant implies no indication of the next destination. Thus, stay information reflects the purpose of individuals' actions, whereas in transit, the purpose of action is not reflected.

The next requirement involves information about the number of people. By observing changes in the volume of people staying at a PoI, we can capture the movement of people between PoIs over time. For instance, reconsidering the "restaurant" example, if there were 10 people at the restaurant at 7 p.m. and this number decreased to 5 by 8 p.m., it can be anticipated that 5 people have finished dining and moved on. Therefore, it can be intuitively expected that there would be an increase in the number of people at the station for their return home. Thus, changes in the volume of people staying at a PoI represent the movement between PoIs.

B. Categories of PoI with identifiable purposes of actions

It is necessary to categorize the PoI into categories where the purpose of actions is identifiable. If PoI categories are too fragmented, the data will be sparse and cannot be incorporated into the model. On the other hand, if the categories are too integrated, the purpose of the action becomes unclear. For example, if the category is restaurant, the purpose of the action is known as a place to eat, but if the category is food, the purpose of the action is not known because it is not known whether the place is a restaurant or a supermarket. Therefore, it is necessary to categorize the categories appropriately so that the purpose of action can be understood.

IV. Making Time Series PoI Stay Counts

In this section, we describe the method of making time series PoI stay counts from mobile GPS trajectory data. The making step consists of four processes: stay determination, PoI identification, data formatting, and aggregation, in order to meet the requirements. In this study, we use trajectory data purchased from Agoop, Inc [23]. as mobile GPS trajectory data, and PoI data from Agoop for PoI identification.

A. Dataset

The trajectory data is obtained through the GPS functionality of smartphones, tablet devices, etc., with the consent of the user, by incorporating Agoop's SDK into applications provided by Agoop and its partner applications. The data to be used includes Daily ID, GPS data (latitude, longitude), date, GPS accuracy, prefecture code, and municipality code. Daily ID is a unique ID assigned to each user, with a new ID assigned to each user every day at midnight. Therefore, by connecting the same Daily ID within the same day, it is possible to understand the user's movement trajectory.

The PoI data comprises 456,450 entries covering locations within Tokyo. This dataset includes listing names, major industry classifications, sub-industry classifications, sub-category names, prefecture codes, latitude, and longitude information. In this study, we utilized the sub-industry classifications and major industry classifications, which are categorized to reflect the purpose of actions. There are 195 categories in the sub-industry classification and 17 categories in the major industry classification. We define these two classifications in this study as the "PoI Small" (Table I) and "PoI Large"(Table II) respectively.

TABLE I
PoI Small (excerpt)

Bicycle/parking	Railways/stations/Parking
Clothing (retail)	Catering/home delivery
Rental cars	Department stores/supermarkets
Electrical (wholesale) Retail	Office and equipment

TABLE II
PoI Large

Wholesale	Sports/Hobbies/Entertainment/Leisure
Restaurant	Medical/Medicine/Insurance
Publishing/Printing	Transportation/Warehouse
Construction	Manufacturing/Processing
Other Services	Schools/Hobby classes/Libraries
Government/Organizations/Welfare	
Automobiles/Motorcycles/Bicycles/Driving	
Travel/Tourism/Hot springs/Hotels	
Real Estate/Rental/Exhibition space	
Finance/Insurance/Securities	
Agriculture/Forestry/Fisheries	
Electricity/Gas/Telecom./Broadcasting/Newspapers	

B. Process

1) Stay determination: In this study, a simple algorithm was applied to determine stay because of the need to process a large amount of data for 130,000 people. If the distance between two consecutive trajectory data points (at least one minute apart) was 100 m or more, the data was defined as "move" and if the distance between two trajectory points was less than 100 m, the data was defined as "stay". The distance was calculated using the *Hubeny* formula. The threshold value of 100 m was chosen because the error radius of the data used was 40 m (80 m in diameter). In some studies, the threshold for stay is roughly 100m [24], [25].

2) PoI identification: For data identified as "stay," both PoI Small and PoI Large were assigned using the PoI dataset. From the PoI candidates within the mesh to which the trajectory data belongs, the distance between the PoI's latitude and longitude information and the latitude and longitude information obtained from the trajectory data was calculated using the *Hubeny* formula. The PoI information with the closest distance was then utilized. Additionally, for data identified as "move," the PoI category "move" was assigned.

3) Data formatting: The sampling rate is non-uniform because the time interval of the collected data varies depending on the OS and application status of the smartphone. Therefore, the data was supplemented at 10-minute intervals by referring to the previous and following values to achieve a uniform sampling rate.

4) Aggregation: The generated data consists of User ID, Time (in 10-minute intervals), Mesh ID, and PoI category (PoI Large, PoI Small). These data are aggregated per 1km mesh, resulting in the generation of time series PoI stay counts. This time series PoI stay counts includes data for Mesh ID, Time (in 10-minute intervals), PoI category, and the number of people. We show the time series PoI stay counts in Table III.

V. Crowd flow prediction model

We developed a crowd flow prediction model using the generated time series PoI stay counts. Supervised learning was performed using as input time series PoI stay counts up to the present for the mesh to be predicted and the nine surrounding

TABLE III
TIME SERIES POI STAY COUNTS

Mesh ID	Time	PoI category	Counts
Mesh A	9:00	Restaurant	13
Mesh A	9:10	Restaurant	14
Mesh B	9:50	Schools	45

meshes adjacent to the mesh, with the correct answer label as the number of future people of the mesh to be predicted.

Considering that including too many meshes as input may introduce irrelevant information and not necessarily decrease prediction errors, we focused on selecting meshes strongly related to the target mesh. Therefore, in this study, we used the target mesh along with its surrounding meshes as inputs.

Since the objective of this study was to validate the reduction of prediction errors using time series PoI stay counts as a feature, we opted for modeling techniques that could straightforwardly discern the contribution of this feature. Therefore, we utilized three basic regression analysis methods: Random Forest, XGBoost, and LightGBM. These models are simple to use and widely applicable across various tasks. Additionally, they can be trained with small datasets and tend to reflect feature importance in the results, unlike deep learning approaches. The parameters were set using the default values of the Python machine learning library, Scikit-learn [26].

Furthermore, to consider the temporal aspects, we incorporated lag features. These features not only include the current data but also incorporate past data as input, thereby increasing the dimensionality of the features. As a result, the features for a certain time include information from past time series PoI stay counts.

VI. PROBLEM DEFINITION

In this study, we aim to predict crowd flow using time series PoI stay counts and verify if it reduces prediction errors. We set up the following problem and conduct experiments to evaluate it.

Problem Statement: Predicts the number of people in the target mesh in the future based on the number of people in each mesh in the past in the target area divided into meshes.

A. Experimental Method

To verify the effectiveness of time series PoI stay counts, experiments were conducted from two perspectives: (1) a comparison between time series PoI stay counts and aggregated data, and (2) the impact of lag features.

1) Comparison between time series PoI stay counts and Aggregated Data: In previous studies, predictions were made using aggregated data such as the number of people staying in a specific area and inflow and outflow of people. In this experiment, to confirm the effectiveness of time series PoI stay counts, we compared aggregated data, represented by "Head count(Number of people)" with time series PoI stay counts categorized by PoI Large and PoI Small. The "Stay/Move" created by the stay determination was also used. The number of people staying after 10 minutes, 1 hour, and 3 hours was predicted.

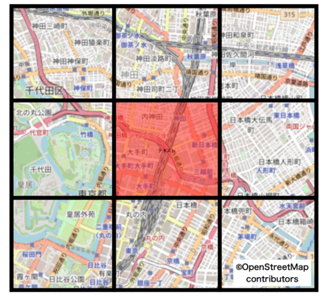

Fig. 1. Tokyo station

2) Lag Features: Considering the temporal aspect of human behavior is crucial as behaviors evolve over time. We explored the effectiveness of lag features in reducing prediction errors by incorporating historical information as features. The inputs remained consistent with those mentioned earlier: "Head count" ,"PoI Large," "PoI Small," "Stay/Move." The number of people staying after 10 minutes, 1 hour, and 3 hours was predicted. We conducted experiments to examine three different levels of past information: "10 minutes prior," "up to 30 minutes prior (10 minutes prior, 20 minutes prior, 30 minutes prior)," and "up to 60 minutes prior (10 minutes prior, 20 minutes prior, 30 minutes prior, 40 minutes prior, 50 minutes prior, 60 minutes prior)."

B. Experimental Settings

The target mesh for prediction was set in Chiyoda-ward, Tokyo. The target area is shown in Fig. 1. This area is centered around Tokyo Station, making it a high-traffic location where sufficient data can be obtained. The experiment period was set from July 1, 2020, to July 31, 2020, excluding holidays and public holidays, from 8:00 to 23:00. This period is after the lifting of the state of emergency and marks the beginning of increased mobility.

C. Evaluation Method

In this experiment, common metrics for regression analysis, namely Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), were used for evaluation. These metrics were calculated based on the predicted number of people staying in the target mesh and the actual number of people staying in the mesh, providing two indicators for evaluation.

VII. RESULT

The results of the validation of the effectiveness of time series PoI stay counts and the prediction results using lag features are shown.

A. Effectiveness of Time Series PoI Stay Counts

The experimental results are presented in Table IV. Evaluating the effectiveness of time series PoI stay counts, in the prediction for three hours later, compared to Head count, RMSE decreased by approximately 50% for PoI Small, and MAPE decreased by up to 11% compared to Head count.

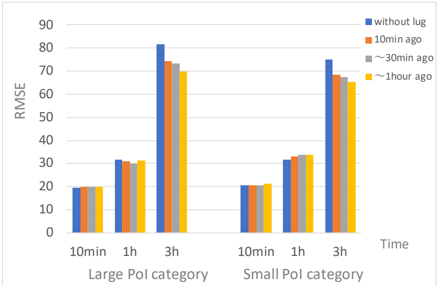

Fig. 2. Results of the differences with and without lag features

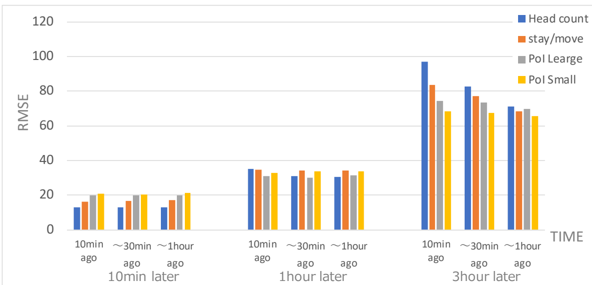

Fig. 3. Results of the difference between inputs

Comparing Head count with time series PoI stay counts, significant reduction in prediction errors was observed for one hour and three hours later, while no decrease in prediction error was observed for ten minutes later. Comparing PoI Small and PoI Large, it was found that the prediction error decreased more for PoI Small with a larger number of categories three hours later. The number of categories was found to influence the prediction of crowd flow, with a greater number of categories leading to a decrease in prediction error. Moreover, in the other two prediction models (Random Forest and XGBoost), the utilization of time series PoI stay counts led to a reduction in prediction errors, affirming their effectiveness.

B. Consideration of Time Series with Lag Features

The results for lag features are shown in Fig. 2. This graph show the cases where lag features were included and excluded as inputs. For the prediction three hours later, including lag features resulted in a decrease in prediction error. This indicates the effectiveness of time series features. Furthermore, the comparison of lag features for "Head count", "PoI Large", "PoI small", "Stay/Move" is depicted in Fig. 3. In the prediction for three hours later, PoI Small exhibited the smallest error. A one-hour lag showed lower error compared to a 10-minute lag, suggesting that lag features are effective in predicting crowd flow.

VIII. Discussion

The experiment results revealed that using time series PoI stay counts resulted in a reduction of prediction errors compared to predictions based solely on Head count. It also became evident that the number of categories in PoI classification affects predictions. While there was no significant difference in

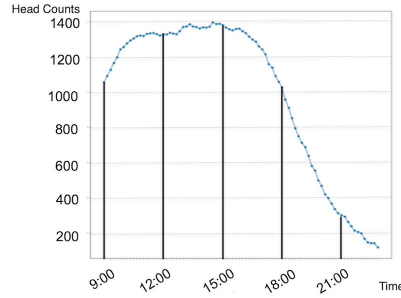

Fig. 4. Transition of Stay Counts for Target Mesh, 2020/07/01

predictions between 10 minutes and 1 hour ahead, a significant difference was observed for data 3 hours later. This suggests that the behavior patterns of people within the target area, which includes many stations and department stores, play a role in prediction difficulty. It's presumed that within the target area, people tend to stay within a mesh for longer periods after 10 minutes or 1 hour, while the likelihood of movement increases after 3 hours, thereby demonstrating the effectiveness of time series PoI stay counts. Additionally, considering the ease of prediction, the transition in the number of people within the predicted mesh per hour is shown in Figure 4. As the graph shows, the change in the number of people per hour is minor, but substantial over a span of 3 hours. Therefore, predicting 3 hours ahead is more challenging than 1 hour ahead. With the increased information provided by time series PoI stay counts compared to merely the number of people, the prediction errors could be reduced. Regarding lag features, the addition of such features reduced prediction errors for data 3 hours ahead. This implies that, similar to the previous observation, while past information may not be effective for 10 minutes or 1 hour predictions due to the low variability in staying patterns, it becomes beneficial for 3-hour predictions due to significant changes in the number of people staying.

IX. Conclusions

In this paper, we proposed a crowd flow prediction method using time series PoI stay counts with the aim of supporting behavior planning for crowd avoidance. The evaluation results showed that using time series PoI stay counts led to a maximum 50% reduction in RMSE for predicting the number of people in the target mesh 3 hours ahead compared to predictions based solely on Head count. Additionally, we demonstrated that the method could estimate the number of people 1 hour ahead with a MAPE of 2.57%. The method we proposed, which utilizes time series PoI stay counts, is simple yet powerful. It can easily be combined with existing deep learning methods, enabling the achievement of higher accuracy in crowd flow prediction.

For future work, we are planning the comparison with existing approaches, which could not be validated in this study, and the model utilizing time series PoI stay counts. Additionally, reflecting effective features in predictions and considering the temporal nature of time series PoI stay counts

TABLE IV
RUSULT OF PREDICTION(LIGHTGBM)

	Head count		Stay/Move		PoI Large		PoI Small	
Prediction time	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
10 min later	13.62	1.36	14.26	1.39	16.50	1.62	17.90	1.79
1 hour later	55.70	4.52	33.07	2.93	29.78	2.57	29.52	2.65
3 hour later	128.96	16.13	84.55	8.01	71.11	6.43	64.08	5.66

are crucial. The proposed method in this study does not fully consider the temporal aspects of PoI Stay information since it utilizes time series PoI stay counts captured at a specific moment of movement. Thus, factors such as the transition patterns between PoIs and the duration of PoI stays are not fully incorporated. To address this, analyzing individual trajectories and clustering them can help extract transition probabilities between PoIs, thereby revealing crowd behavior patterns between PoIs. Furthermore, although our proposed model used 9 meshes as input for predicting behavior, it's possible that individuals may travel to farther locations or that inflows from meshes beyond the 9 considered may occur within 3 hours. Therefore, expanding the input mesh range and considering the relationships between meshes could lead to further reduction of prediction errors.

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