Prediction of Spatiotemporal Distributions of Transient Urban Populations with Statistics Gathered by Cell Phones

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Abstract: There is a growing demand for data that facilitate highly accurate understanding of the spatiotemporal distribution of both moving and static occupants in urban areas. Currently, a large amount of population data are available, however none of the data provide an accurate understanding of the numbers and departure/arrival locations of moving people using detailed units of space and time. In this paper, after evaluating the advantages and disadvantages of existing population statistics, including Mobile Spatial Statistics, Konzatsu-tokei®, and Person Trip survey data, we propose a method based on maximum likelihood method is investigated for using their strengths to best advantage and compensating for weaknesses. The proposed method is then validated by comparing with another flow data, which featured spatiotemporal data including departure/arrival locations, and demonstrate that the present procedure provides accurate estimates for population flows. This study makes it possible to analyse urban regions from new and never-before employed points of view by identifying the number of transient occupants and their travel directions at any time on high level of detail.

1 INTRODUCTION

1.1 Research Background

There has recently been growing interest in the observation and analysis of people's movements on a large map scale, with the goals of mitigating crowding and avoiding risks at large-scale public events, identifying appropriate initial responses, and guiding evacuation during the aftermath of major earthquakes, and for area marketing in the commercial and travel industries. Since distribution of population in the largest conurbations fluctuates rapidly with the advance of public transportation systems, the conventionally used "static" data such as previously gathered population statistics are of only limited value in analyses. This has resulted in a need for a technological method to map dynamic population distributions on a large map scale at any desired time. Namely, we need a method which enables us to identify the number of transient occupants and their travel directions at any time, on large map scales for the analyses on human activities in urban areas from new and never-before employed points of view.

1.2 Existing Research and Population Statistics

A variety of statistical analyses of population have been created and are available for use by parties observing the behavior of static and transient populations in urban areas. Table 1 shows examples of data that have been useful for wide areas.

The first of these is the set of regional grid-cell statistics based on the long-established national census of Japan. It includes the population, number of households, levels of schooling, and much other information. Only a few national censuses around the world offer such a rich store of demographic information. However, it is conducted at 5-year intervals and based on residential location, so it is a static population distribution.

Person Trip survey data (PT data) focus on people's spatial motions. PT data are based on responses to questionnaire surveys and provide much

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Table 1: Characteristics of population statistics.

Dataset		Content	Object of survey	Area [Spatial unit]	Survey interval	Frequency	Available information	Related research
Complete survey [Information at a point in time]	Census data	Residents in an area	Persons living in the following area	All Japan area [250m grid] (Minimum)		Every 5 years	Age, gender,residence, number of family member	Hidaka et al. (2016)
Sample survey [Information on one day]	Person Trip Suvey	Travel behavior in cities	Persons aged 5+ living in the following area (sample rate: about 2~3%)	Metropolitan area [zone]	Every minutes on weekdays	Every 10 years	Age, gender, residence, position and time of departure/arrival, purpose of trip, etc.	Osaragi (2009, 2012, 2015, 2016) Sekimoto et al. (2011) Nakamura et al. (2013)
Spatial distribution of people who have mobilephone [Information on any day]	Mobile Spatial Statistics (MSS) (Distribution)	Spatial distribution of people	Persons aged 15~79 who have mobile phone using the cellular phone network (NTT Docomo) (sample rate: about 40%)	All Japan area [250m grid] (Minimum)	Every 1 hour	Everyday	Age, gender, residence (prefecture or municipality or oaza)	Seike et al. (2011, 2015a,b) Osaragi & Kudo (2019) Arimura et al. (2016)
Spatial distribution of moving people who have mobilephone [Information on any day]	Konzatsu-tokei®	Moving people between grids	Persons who have mobile phone using the specific application and the cellular phone network (NTT Docomo) (sample rate: about 0.5%)	All Japan area [250m grid] (Minimum)	Every 5 minutes	Everyday	Residence, occupation (Larger than oaza)	Kamada (2017)
	Mobile Spatial Statistics (Flow)	Origin and Destination of moving people	Persons aged 15~79 who have mobile phone using the cellular phone network (NTT Docomo) (sample rate: about 40%)	All Japan area [250m grid] (Minimum)	Every 1 hour	Everyday	Age, gender, residence (prefecture or municipality or oaza)	Ishii et al. (2017)
	Agoop	Origin and Destination of moving people	Persons who have mobile phone using the specific application	All Japan area [point]	Every 1 hour (according to carrier)	Everyday	Direction and velocity of move	Matsubara (2017)

information, including the sex, age classification, purpose of movement/stay, means of transportation, departure/arrival locations and times, etc. Osaragi et al. (2009, 2012, 2015) has used the PT data and building geographic information system (GIS) data to construct a model for estimating how many people are statically occupying a given spatial unit of a city at any given time, and in models for estimating the spatiotemporal distribution of transient city occupants (railroad and automobile users).

Another proposed approach is to estimate PT data for weekends and holidays by using a time use survey (Osaragi, 2016). Numerous studies exploiting PT data have been published in the civil and transportation planning fields. For example, researchers have used spatiotemporal interpolation to examine problems in spatial units (Sekimoto et al., 2011) and have combined observed data of differing types to reevaluate trips as an approach to the problem of low sampling fraction (Nakamura et al., 2013). Another study combined the national census with time use surveys to construct daily mobility and activity data (Hidaka et al., 2016). These studies were all attempts to compensate for the shortcomings of PT data and provide useful background for this study, which has the same theme. However, the PT data were taken at 10-year intervals, so they do not help in overcoming the lack of fresh data.

In counterpoint to the above methods, recent studies have employed location data from cell phone records to create and provide spatiotemporal data for people's locations. For example, Mobile Spatial Statistics (MSS) from mobile phones provide regional populations in grid-cell units at any desired time, which are provided by NTT DoCoMo Inc. Mobile terminals connect to the base stations in a certain time interval in order to maintain the mechanism that allows mobile terminals to be paged at any time and any place. Location data is estimated using the locations of coverage area of base stations (the grid-cell) (Okajia et al., 2013). These are population statistical data, the number of cell phones using the cellular network, and incorporate the penetration ratio among cell phones operated by DoCoMo (rate of DoCoMo users to the total number of mobile phone users). The spatial information (each user's location) is presented as the grid-cell, which is generally about 500 m by 500 m grid. MSS is a registered trademark by NTT DoCoMo. Seike et al. (2011) validated the reliability of MSS (distribution) and showed that it is also possible to use these statistics for transportation and urban planning. Osaragi and Kudo (2019) proposed a method for estimating the purpose of the buildings people stopped in and their reasons for staying there by combining MSS (distribution) with PT data. The same studies have also been carried out in foreign countries (Deville et al., 2014; Ratti et al., 2006). However, MSS (distribution) do not make it possible to distinguish between persons who are moving and those who are static. Arimura et al. (2016) have published an extremely interesting estimate of the population inflows into buildings, but were not able to identify their movement directions.

New data regarding the numbers of transient city occupants and their trajectories have been compiled and offered in response to the increasing need for these data. Konzatsu-tokei® (KT) are the locations of the cell phones, provided under the consent of the user by an application provided by NTT DoCoMo. These are provided as overall data, with statistical information added. The location data are transmitted every 5 minutes along with Global Positioning System (GPS) data (latitude and longitude), and any information that would identify the user is excluded. This application is a part of the DoCoMo map and navigation service (map application and current location guide). Since those data were taken from an application loaded just by certain users, however, the sampling fraction was low, and the accuracy is unstable in regions with low population densities (Kamada, 2017). Additionally, MSS (flow) data are based on the departure/arrival location information obtained from cell phones, just as MSS (distribution) data are. MSS (flow) are provided by NTT DoCoMo Inc. These are population statistical data, the number of cell phones using the cellular network, and incorporate the penetration ratio among cell phones by DoCoMo. These data are the total numbers of travelers who departed from one location and moved to another. Phone users who have not moved (that is, static occupants) are not included in these data. These provide a greater sampling fraction and higher accuracy than KT, but since they are taken at 60-minute intervals, it is difficult to construct trajectories for people who move quickly. These data are also obscured by the process of anonymization (Ishii et al., 2017).

Agoop data (point-type floating population data) are location information from users whose cell phones are equipped with a special application. These data are provided without reference to the user's cell phone carrier, but again, the sampling fraction is low (Matsubara, 2017). Turning overseas, however, Calabrese et al. (2011) has proposed a method for tabulating departure/arrival location data which can accommodate daily and seasonal fluctuations, while Iqbal et al. (2014) has proposed a method for creating departure/arrival location data by combining the transmission histories of cell phones with actual data from sampling surveys. Nevertheless, these approaches do not generate data on a large map scale, and it would be impractical to use them when carrying out actual surveys in a large city due to the cost involved.

Thus, each of the existing datasets for transient and static individuals has its own advantages and disadvantages from the viewpoints of time units, spatial units, sampling fraction, etc., and each imposes a variety of limitations on research objects and methods. This study investigates a method for creating a spatiotemporal data structure of transient city occupants by providing their numbers and their directions of travel. The data were integrated while employing the useful aspects of each of the population statistics types such as arbitrary time units, large-map-scale units, and high sampling fraction, and compensating for their defects.

2 DATA INTEGRATION METHOD

2.1 Overview of Integration Method

The integration process is summarized in Fig. 1. The main variants are shown below:

$_a n_i^t$, $_a P_i^t$: Number of people and population fraction occupying grid-cell i

$_b n_i^t$, $_b P_i^t$: Number of people and population fraction exiting grid-cell i

$_c n_i^t$, $_c P_i^t$: Number of people and population fraction entering grid-cell i

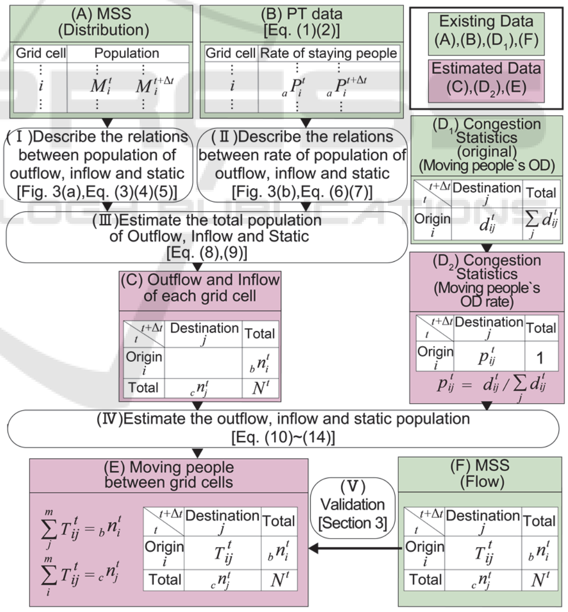


Figure 1: Integration of multiple demographic datasets.

This report employs MSS (distribution) data, which consists of detailed records featuring high sampling fractions and precise temporal and spatial units, as the basic information expressing the spatiotemporal population distribution. However, population M_i^t (Fig. 1(A)) occupying cell i at time t, which is obtained from the MSS (distribution), fails to distinguish between transient and static occupants.

Therefore, we attempted to make this distinction by defining the fraction of static occupants (static occupant fraction ${}_aP_i^t$, Fig. 1(B)) obtained from the PT data using the following method. M_i^t, obtained from the MSS (distribution), was imposed as a constrain and a maximum likelihood algorithm was written to hold the sum of the number of static, entering, and exiting occupants to M_i^t. This provided estimates for ${}_an_i^t$, the number of static occupants, ${}_bn_i^t$, the number of exiting occupants, and ${}_cn_i^t$, the number of entering occupants (Fig. 1(C)).

Next, data for spatial motions were compiled from KT, which contains detailed spatiotemporal information about departure/arrival locations and times. The fraction of population motions between cells i and j during time span t to t+Δt is denoted p_{ij}^t (Fig. 1(D)).

Last, the maximum likelihood estimator T_{ij}^t for the number of individuals moving between grid-cells i and j is found via the inter-grid-cell motion fraction p_{ij}^t, using the number of individuals leaving grid-cell i, ${}_bn_i^t$, and the number of individuals entering grid-cell i, ${}_cn_i^t$, in the criterion (Fig. 1(E)).

2.2 Method for Estimating Fractions of Static and Transient Occupants

It is quite common for the population (static and transient numbers) of any given region to fluctuate widely from year to year, due to redevelopment and other factors. In contrast, individual movement patterns, whether these people are static or transient, vary most dramatically with clock time and day of the week (Osaragi, 2012). For this reason, one would expect the fractions represented by static and transient occupants to be relatively stable from year to year. Therefore, in this study, PT data was used to estimate these fractions, as it is the only dataset that allows distinguishing between static and transient occupants.

First, based on the consideration that the numbers of static and transient occupants could be proportional to the floor area of a building, depending on the building's use classification (Osaragi, 2012), the static and transient occupants indicated by the PT data were distributed proportionately among all of the buildings. In other words, the information about spatial motion incorporated in the PT data was used to identify ${}_{uv}S_{kl}^t$, the number of people passing between buildings of use classifications u and v, located in small zones k and l, during time span t to t+Δt. It was assumed that the transient occupants moved at a constant speed over the shortest route on a transient irregular network (TIN) between the centers of gravity of their starting and destination zones; the times t and t+Δt in the occupied small zones k and l were identified (Fig. 2). The proportions of floor areas of the buildings in grid-cells i and j in zones k and l, ${}_uA_i/{}_uA_k$ and ${}_vA_j/{}_vA_l$, were found using the GIS data for the buildings, and the number of transient individuals between grid-cells i and j during time span t to t+Δt, s_{ij}^t, was calculated using the equation below. The reader's attention is directed to s_{ii}^t, which designates individuals moving within grid-cell i:

$$s_{ij}^t = \sum_u \sum_v \sum_k \sum_l \left(\frac{{}_uR_i}{{}_uR_k} \times \frac{{}_vR_j}{{}_vR_l} \times {}_{uv}S_{kl}^t \right) \tag{1}$$

Last, the number of transient occupants s_{ij}^t and the number of static occupants s_i^t in grid-cell i (who did not move at all) were used to find the static occupant fraction ${}_aP_i^t$ in grid-cell i during time span t to t+Δt.

$${}_aP_i^t = \frac{s_i^t}{s_i^t + \sum_j s_{ij}^t} \tag{2}$$

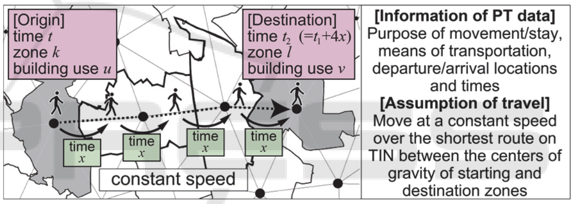


Figure 2: Estimation of traveling route between OD zones.

2.3 Method for Estimating Grid-cell Inflows and Outflows

For the populations M_i^t and $M_i^{t+\Delta t}$ in grid-cell i obtained from the MSS (distribution), relational expressions Eqs. (3)-(5) below provide estimates of the number of people not moving within grid-cell i (number of static occupants) ${}_an_i^t$, the number of people leaving the zone ${}_bn_i^t$, and the number of people entering the zone ${}_cn_i^t$ during time span t to t+Δt (Fig. 1(I), Fig. 3(a)).

$$M_i^{t+\Delta t} = M_i^t - {}_bn_i^t + {}_cn_i^t \tag{3}$$

$${}_an_i^t + {}_bn_i^t = M_i^t \tag{4}$$

$${}_an_i^t + {}_cn_i^t = M_i^{t+\Delta t} \tag{5}$$

Suppose motions in grid-cell i during time span t to t+Δt are summarized as the following four cases (Fig. 3(b)).

(i) The individual remains in grid-cell i during time span t to t+Δt.

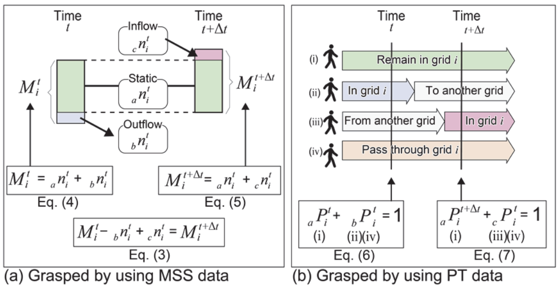


Figure 3: Relationships between moving people and static people.

(ii) The individual moves out of grid-cell i to another grid-cell.

(iii) The individual moves from another grid-cell into grid-cell i.

(iv) The individual passes through (into and out of) grid-cell i during time span t to $t+\Delta t$.

Then static occupants correspond to (i), exiting occupants can be (ii) or (iv), and entering occupants can be (iii) or (iv). The following expression describes the relationships between the static occupant fraction ${}_aP_i^t$ and the population fraction exiting grid-cell i ${}_bP_i^t$, and between the static occupant fraction ${}_aP_i^{t+\Delta t}$ and the population fraction entering grid-cell i ${}_cP_i^t$ (Fig. 1(II)): The details are described in Appendix (A).

$$ {}_a P_i^t + {}_b P_i^t = 1 \tag{6} $$

$$ {}_a P_i^{t+\Delta t} + {}_c P_i^t = 1 \tag{7} $$

When the populations M_i^t and $M_i^{t+\Delta t}$ and the static occupant fractions ${}_aP_i^t$ and ${}_aP_i^{t+\Delta t}$ are known, the following equations for the maximum likelihood estimator for the number of static occupants satisfying the criteria (Eqs. (3)-(5), Eqs. (6) and (7)) can be derived:

$$ {}_a n_i^t = \frac{\left(M_i^t + M_i^{t+\Delta t}\right) - \sqrt{\left(M_i^t + M_i^{t+\Delta t}\right)^2 - 4PM_i^t M_i^{t+\Delta t}}}{2P} \tag{8} $$

$$ P = \frac{{}_a P_i^t + {}_a P_i^{t+\Delta t} - 1}{{}_a P_i^t \; {}_a P_i^{t+\Delta t}} \tag{9} $$

Once the number of static occupants ${}_an_i^t$ in grid-cell i during time span t to $t+\Delta t$ has been found, the number of people exiting grid-cell i ${}_bn_i^t$ and the number of people entering grid-cell i ${}_cn_i^t$ can be calculated (Fig. 1(III)).

2.4 Method for Calculating Number of Transient Occupants

The numbers of people leaving (${}_bn_i^t$) and entering (${}_cn_i^t$) are used in criteria for the hourly calculations of population distribution. Additionally, the inter-grid-cell motion fractions p_{ij}^t between grid-cells i and j during time span t to $t+\Delta t$ can be calculated from KT. These are used to calculate the maximum likelihood estimator for individuals moving between grid-cells i and j during time span t to $t+\Delta t$.

Between the numbers of people leaving and entering and the number of individuals moving between grid-cells T_{ij}^t, we establish Eqs. (10) and (11) (Fig. 1(E)). (Note that m denotes the number of grid-cells.)

$$ {}_b n_i^t = \sum_j^m T_{ij}^t \tag{10} $$

$$ {}_c n_j^t = \sum_i^m T_{ij}^t \tag{11} $$

The number of individuals moving between grid-cells T_{ij}^t is calculated as follows, employing the inter-grid-cell motion fractions p_{ij}^t obtained from the KT under the above the maximum likelihood estimators providing the highest values for the occurrence probabilities. The details are described in Appendix (B).

$$ T_{ij}^t = p_{ij}^t \times A_i^t \times B_j^t \tag{12} $$

$$ A_i^t = \frac{{}_b n_i^t}{\sum_j^m p_{ij}^t B_j^t} \tag{13} $$

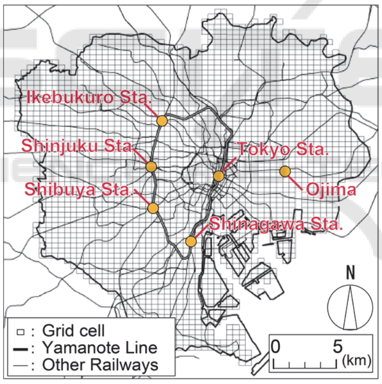
$$ B_j^t = \frac{{}_c n_j^t}{\sum_i^m p_{ij}^t A_i^t} \tag{14} $$

Variables A_i^t and B_j^t are mutually dependent, but arbitrary starting values are chosen for a converging calculation, and this will provide the unique value for the number of individuals moving between grid-cells T_{ij}^t.

3 CALCULATION AND VALIDATION OF NUMBER OF TRANSIENT CITY OCCUPANTS EMPLOYING ACTUAL DATA

3.1 Study Region and Data

The region used for analysis was the Tokyo 23-ward area (Fig. 4), divided into a grid-cell of spatial units 500 m by 500 m grid. Data from MSS (distribution) on a weekday and a weekend day in October were used. The location of each individual was estimated from the PT data at 60-minute intervals, and the PT data from the weekend day was assessed using time use survey results (Osaragi, 2016). Since the sampling rates for KT are low, datasets from multiple days were combined. Days when anomalies occurred due to natural causes and when there were large public events were excluded, leaving approximately half a year, and data from this set were extracted to create one day's worth each of weekday and weekend data.



Dataset	Date (weekday)	Date (weekend)
MSS (Distribution)	Tuesday, Oct. 20, 2015	Sunday, Oct. 18, 2015
PT data	A weekday in Oct. of 2008 (Excluding Mon. and Fri.)	A weekend in Oct. of 2008 (Estimated by Osaragi, 2016)
Konzatsu-tokei®	223 weekdays from Apr. 1, 2015 to Mar. 31, 2016	87 weekends from Apr. 1, 2015 to Mar. 31, 2016
MSS (Flow) (for validation)	Tuesday, Oct 20, 2015	

Area: 2500 grids (about 500 m by 500 m) in Tokyo ward
Time: 3:00~26:00

Figure 4: Study area and data used in this paper.

3.2 Pre-processing of Data for Integration of Time Intervals

Data were generally extracted from MSS (distribution) at 60-minute intervals, but from KT, they were extracted at 5-minute intervals. The following process was performed in order to integrate those intervals.

First, the grid-cell i population $M_i^{t+\Delta t}$ and static occupant fraction ${}_aP_i^{t+\Delta t}$ at time $t+\Delta t$ (Δt=1, 2, …, 60) were estimated by linear interpolation using the following equations (t+60 means 60 minutes after time t):

$$M_i^{t+\Delta t} = M_i^t + \frac{\Delta t}{60}\left(M_i^{t+60} - M_i^t\right) \qquad (15)$$

$${}_aP_i^{t+\Delta t} = {}_aP_i^t + \frac{\Delta t}{60}\left({}_aP_i^{t+60} - {}_aP_i^t\right) \qquad (16)$$

The numbers of people moving between grid-cells i and j at 5-minute intervals in KT, d_{ij}^t, were obtained by calculations with the data taken at 60-minute intervals. The 5-minute means were evaluated using the inter-grid-cell motion fraction p_{ij}^t (Δt=5 minutes) in the following equation:

$$p_{ij}^t = d_{ij}^t / \sum_j d_{ij}^t \qquad (17)$$

If it is assumed that the inter-grid-cell motion fraction during any arbitrary time span Δt is the simple Markov type, then the motion fraction matrix $\boldsymbol{P}^t$, whose elements are the inter-grid-cell motion fraction p_{ij}^t, can be obtained by multiplying the motion fraction matrix by $\Delta t/5$ (Fig. 5).

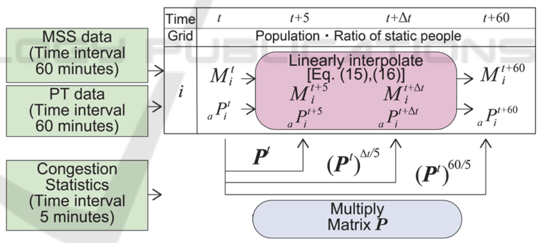


Figure 5: Unifying time interval of datasets.

3.3 Validation of Accuracy of Estimates

No data exist that clearly show the numbers of transient city occupants in fine temporal or spatial units, but comparing results with the MSS (flow), which actually do offer rather fine detail, allows the accuracy of the proposed procedure to be validated. First, since trips in the MSS (flow) are anonymized when there are few travelers, it is inappropriate to compare the numbers of people per se. Instead, the ratios between the numbers of people exiting ${}_bn_i^t$ and entering ${}_cn_i^t$ (Δt=60 minutes) are compared. Here, the spatial grid-cell unit was widened to 1 km in order to minimize the influence of anonymization.

During the 08:00-09:00 hour, when numerous people are commuting to work or school (Fig. 6(a)), the outflows are people leaving residential areas in all possible directions, so the above ratios are not high. In general, since the proportion of numerical errors are relatively large for small values, the result shows low correlation. On the other hand, examining the people who are entering grid-cells (Fig. 6(b)), the reader can see that this approach provided particularly accurate predictions of the tendencies for high numbers of commuter inflow at grid-cells in the vicinity of large train stations. Turning to the 17:00-18:00 hour, when many are returning home (Fig. 6(c), (d)), both inflows and outflows are seen to be accurately predicted.

However, a close examination of Fig. 6 also reveals some overestimates in all estimates for outflow/inflow in the morning/evening. One of the reasons for this was the data based on departure/arrival locations in the MSS (flow) information. This is because the numbers of individuals were counted only at the departure and the arrival locations. In other words, since the people passing through a grid-cell during a 5-minute period were not counted in MSS (flow), the actual population was undercounted by that amount. In this procedure, in contrast, the much more accurate MSS (distributions) were employed in criteria for calculating the number of people passing through a grid-cell. This highlights the potential of this procedure to provide highly accurate calculations.

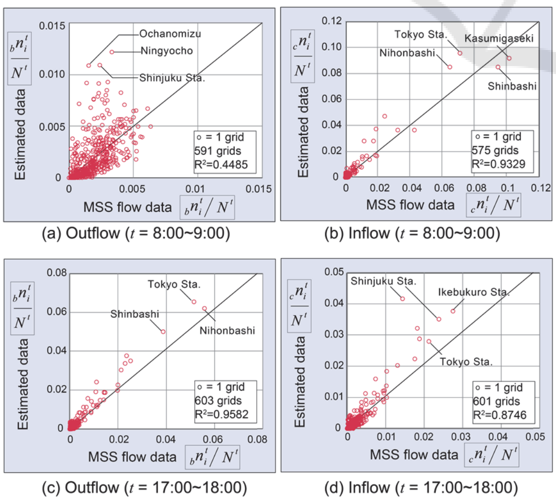


Figure 6: Validation by using MSS flow data.

4 ANALYSIS OF SPATIAL MOTION DISTANCES TRAVELLED BY TRANSIENT CITY OCCUPANTS

4.1 Spatial Distributions of Inter-grid-Cell Crossing Numbers per Unit Time

This procedure enables prediction of static, transient, and incoming populations at any desired time interval (Fig. 7(c)), parameters which are not available from the existing data from MSS (distributions) (Fig. 7(a)). For example, there is little difference in the spatial distributions of static, transient, or incoming populations during the 5 minutes from 08:00 to 08:05, and we can see high concentrations near the large train stations. Over the 60 minutes between 08:00 and 09:00, however, the static populations become quite widely distributed. The reader can see that exiting populations show high numbers near Shinjuku Station, which is a commonly used stop for transfers between lines, while there are large inflows around the main stations of lines connecting to the Yamanote Line. Thus, this procedure allows close examination not only of the total population but also separate examinations of the differences between the static, outflowing, and inflowing populations, and these examinations can take place over any desired time units.

Now, let us turn to some observations about the distributions of inflows and outflows on a special grid-cell in order to clarify some characteristics of the Tokyo population. Focusing first on the grid-cell surrounding Shinagawa Station, the average numbers of people exiting and entering the station at 5-minute intervals between 08:00 and 09:00 obtained from KT are shown in Fig. 7(b). Many of the exiting people leave in the direction of Tokyo Station, and many of the incoming people are from Kanagawa Prefecture. This combination can easily be read as early-morning commuting to work. Since the sampling fraction in KT is low, however, it is difficult to make an accurate estimate of the number of people. Additionally, estimates can only be made about locations with large transient populations.

Examining the predictions of the proposed procedure for outflow from and inflow to Shinagawa Station (Fig. 7(d)), we found they were similar to the results from KT during the 5 minutes of 08:00-08:05 (Fig. 7(d)(1),(2)), but the reader can see that during the 60 minutes of 08:00-09:00, inflow originated from a wide region and was not limited to that from

Kanagawa Prefecture (Fig. 7(d)(3),(4)). As this example demonstrates, this procedure is capable of indicating the numbers of exiting and incoming people and their trajectory directions over a variety of time spans. Therefore, it can be used for a variety of analyses that require data about static and transient people in the city.

4.2 Analysis of Region based on Temporal Fluctuations of Inflow and Outflow

Next, we attempted to identify the characteristics of a region by the variation with time of exiting and incoming individuals. Figure 8 shows how the numbers of people exiting ${}_bn_i^t$ and entering ${}_cn_i^t$ 6 regions (grid-cells) varied with time (Δt=60 minutes). Here, the location on the graph found from the outflow ${}_bn_i^t$ and the inflow ${}_cn_i^t$ was graphed and is here called the "pole"; the surface area D_i of the closed region generated by observing the translation of the pole as the clock time was calculated as follows:

$$D_i = \sum_t \frac{1}{2}\left({}_bn_i^{t+\Delta t} - {}_bn_i^t\right)\left({}_cn_i^{t+\Delta t} + {}_cn_i^t\right) \qquad (18)$$

The value of D_i in this calculation was positive when the pole shifted in the clockwise direction and negative when it shifted counterclockwise.
D_i took a positive value in the densely built commercial and office areas around Tokyo Station, Shinagawa Station, and others, as the rotation of the pole was generally clockwise. Many people commuted to these areas in the morning, while there was little outflow or inflow during the day. They resembled each other in that greater numbers of people began to leave for home in the late afternoon (Fig. 8(a),(b)), but the reader can see that Tokyo Station saw greater numbers of people from 09:00 to 18:00. Shinjuku Station (a commercial and office district, as well as a station hosting many transfers between lines) showed the same tendencies in the morning, but saw greater numbers of people exiting and entering during the day and in the late afternoon; due to this, the closed district had a larger area (Fig. 8(c)).

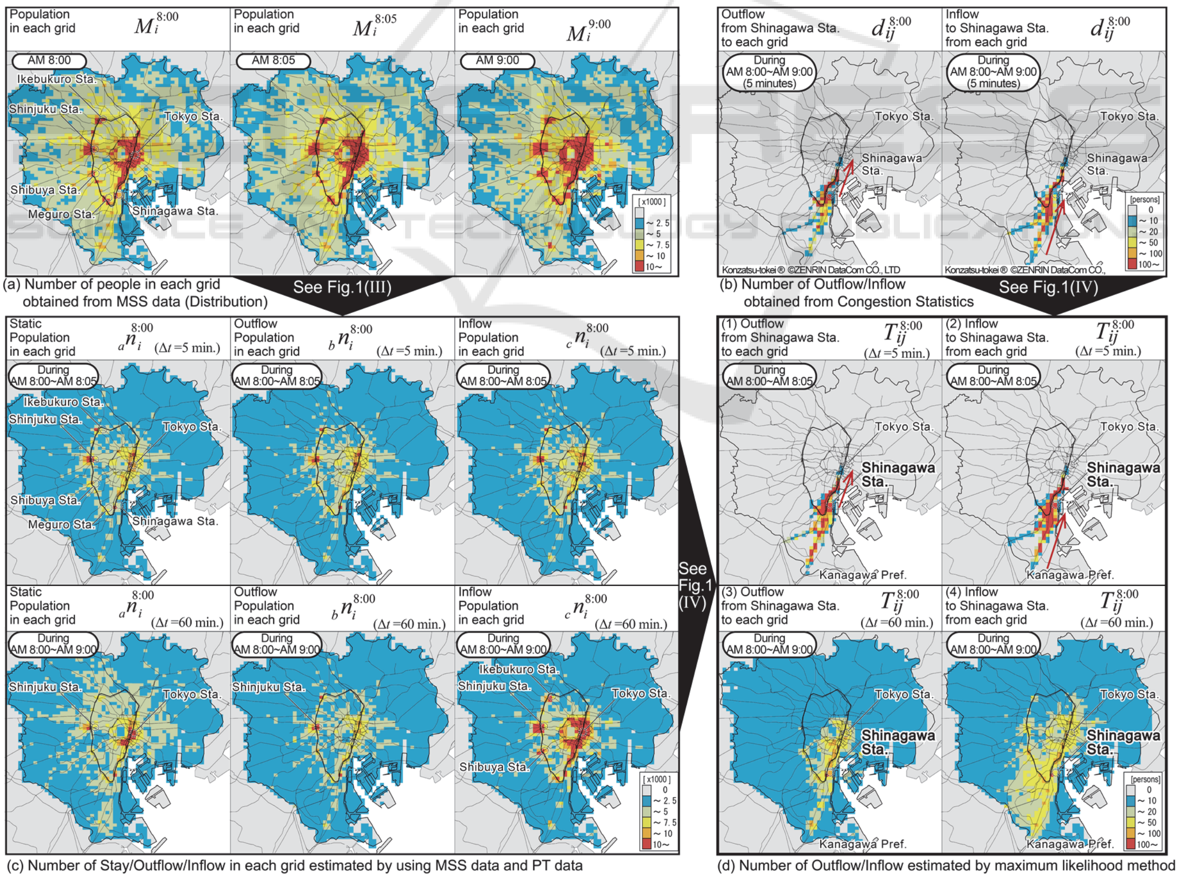


Figure 7: Spatial distribution of Static/Outflow/Inflow population grasped by using MSS data, Konzatsu-tokei® (KT) and estimated results.

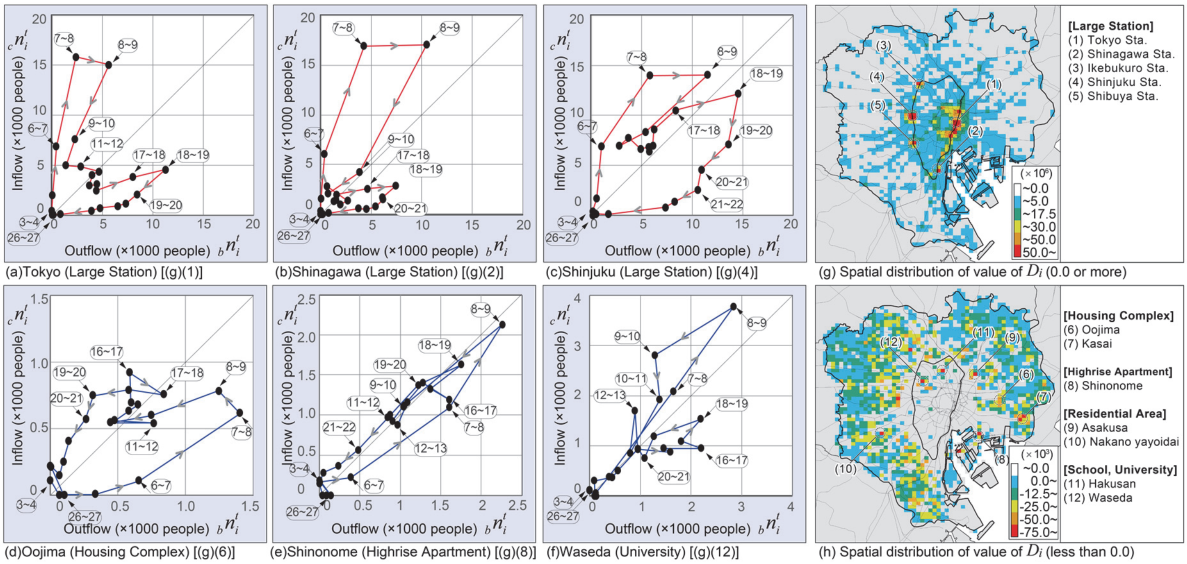


Figure 8: Temporal change in the relation between outflow population and inflow population and Spatial distribution of value of *Di*.

In Oojima (an area with large-scale housing), however, exiting people were in the overwhelming majority in the morning and inflow increased from the late afternoon on, resulting in a D_i with a large negative value (Fig. 8(d)). The same pattern was found in Shinonome (an area with high-rise condominiums), but because the numbers of people exiting and entering the region changed similarly, the closed region was longer but thinner than in Oojima (Fig. 8(e)). Thus, the poles in such regions with large residential areas tend to rotate in a counterclockwise direction, resulting in negative D_i.

Figures 8(g) and (h) show the spatial distributions and the areas D_i of the closed regions when the same calculations were performed at other locations (grid-cells). Grid-cells with positive values crowd the areas adjacent to the rail routes. This was particularly true along routes connecting to the main stations of the Yamanote Line, where the positive values were high. On the other hand, grid-cells with strongly negative values had many groups of high-rise condominiums, large-scale residential neighborhoods, universities, and the like. These areas saw gradually increasing inflows of population from the morning into the daytime (Fig. 8(f)).

4.3 Directions of Travel on Weekdays and on Weekends

Next, we make some observations about the directions of travel of the users of Shinjuku Station between 09:00 and 10:00 on weekday and weekend

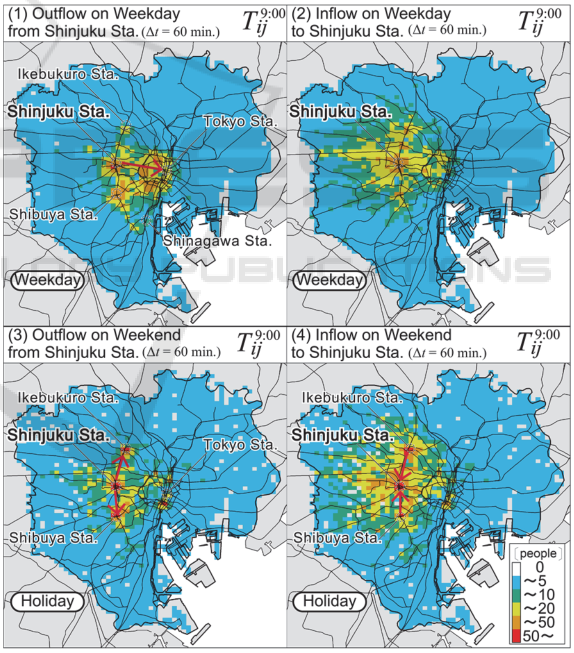


Figure 9: Spatial distribution of the estimated moving population from/to Shinjuku Sta. between 9:00 and 10:00 on weekday and weekend.

exiting the grid-cell on weekday mornings indicate that many proceed in the direction of Tokyo Station (Fig. 9(1)). On weekend mornings, in contrast, most outflows are in the directions of other stations including Shibuya and Ikebukuro, which are densely built commercial areas (Fig. 9(3)). Thus, we see that weekend mornings showed a higher diversity of directions of travel than weekday mornings. Further examination of the spatial distributions of inflow to Shinjuku Station revealed that the same grid-cells furnished most of the inflows on both weekdays and weekends, but there were higher inflows from Shibuya Station and Ikebukuro Station on weekends (Fig. 9(4)).

5 SUMMARY AND CONCLUSIONS

This study has proposed a method for estimating the spatiotemporal distribution of static and transient populations of urban areas by using population statistics created from the location information for users of cell phones. The advantages and disadvantages of the various population statistics available were evaluated and methods were investigated for integrating the data while using their strengths to best advantage and compensating for weaknesses. MSS (distribution), with its high numbers of samples and high accuracy, was employed in a criterion for population distribution data consisting of summed numbers of transient and static individuals.

Additionally, KT, with their low sampling rate but detailed information about individuals' motions, were used for generating the inter-grid-cell motion fraction data. These were applied to a method constructed to evaluate the maximum likelihood estimator for calculating the numbers of people exiting or entering a given grid-cell. These were then compared with the MSS (flow), which featured spatiotemporal data including departure/arrival locations to verify that the present procedure provides accurate estimates for these population flows.

Next, we attempted analysis of regions by calculating the numbers of transient occupants and their directions of motion, per unit of time, in several regions. This was found to provide a quantitative grasp of the characteristics of transient urban occupants, which had been difficult to identify previously. For example, differences between weekdays and weekends in the characteristics of motion were noted, and large differences between otherwise similar areas with commercial and office concentrations in occupants' travel directions were identified.

The procedure proposed in this study makes it possible to identify the number of transient occupants and their travel directions at any time, on large map scales, by using the constructed spatiotemporal data for both static and transient urban occupants, and to obtain and use these basic data to analyze urban regions from new and never-before employed points of view.

In further research, we would like to undertake a comparison of our proposed approach with relevant studies conducted in other countries addressing the same topic of people's movements. Also, using our proposed method, we would like to construct a model to evaluate the influence of large-scale public events or natural disaster on people's movements, which assists mitigating crowding and avoiding risks, identifying appropriate initial responses, and guiding evacuation.

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APPENDIX

Appendix A: Maximum Likelihood Estimator for the Number of Static Occupants

When the known numbers of people in grid-cell i during time t are M_i^t and $M_i^{t+\Delta t}$ and the known static occupant fractions are ${}_aP_i^t$ and ${}_aP_i^{t+\Delta t}$, then the number of static occupants ${}_an_i^t$ (Eqs. (3)-(5)) can be calculated using the static occupant fraction (Eqs. (6) and (7)) as a method for maximizing the statistic V_i by using the maximum likelihood algorithm:

$$\begin{aligned} V_i^t &= \left\{ {}_{M_i^t}C_{{}_an_i^t} \left({}_aP_i^t\right)^{\left({}_an_i^t\right)} \left({}_bP_i^t\right)^{\left({}_bn_i^t\right)} \right\} \\ &\quad \times \left\{ {}_{M_i^{t+\Delta t}}C_{{}_an_i^t} \left({}_aP_i^{t+\Delta t}\right)^{\left({}_an_i^t\right)} \left({}_cP_i^t\right)^{\left({}_cn_i^t\right)} \right\} \\ &= \left\{ \frac{M_i^t\,!}{\left({}_an_i^t\right)!\left({}_bn_i^t\right)!} \left({}_aP_i^t\right)^{\left({}_an_i^t\right)} \left({}_bP_i^t\right)^{\left({}_bn_i^t\right)} \right\} \\ &\quad \times \left\{ \frac{M_i^{t+\Delta t}\,!}{\left({}_an_i^t\right)!\left({}_cn_i^t\right)!} \left({}_aP_i^{t+\Delta t}\right)^{\left({}_an_i^t\right)} \left({}_cP_i^t\right)^{\left({}_cn_i^t\right)} \right\} \end{aligned} \tag{A1}$$

Taking the logarithm of both sides, we obtain

$$\begin{aligned} \ln V_i^t &= \left(\ln M_i^t\,! - \ln {}_an_i^t\,! - \ln {}_bn_i^t\,!\right) \\ &\quad + {}_an_i^t \ln {}_aP_i^t + {}_bn_i^t \ln {}_bP_i^t \\ &\quad + \left(\ln M_i^{t+\Delta t}\,! - \ln {}_an_i^t\,! - \ln {}_cn_i^t\,!\right) \\ &\quad + {}_an_i^t \ln {}_aP_i^{t+\Delta t} + {}_cn_i^t \ln {}_cP_i^t \end{aligned} \tag{A2}$$

Then, from Stirling's equation, we find

$$\ln N! = N \ln N - N \tag{A3}$$

Substituting this into Eqs. (4)-(7), we obtain the following:

$$\ln V_i^t = \left\{ M_i^t \ln M_i^t \left(1 - {}_aP_i^t\right) + M_i^{t+\Delta t} \ln M_i^{t+\Delta t} \left(1 - {}_aP_i^t\right)\right\} - M_i^t \ln\left(M_i^t - {}_an_i^t\right) - M_i^{t+\Delta t} \ln\left(M_i^{t+\Delta t} - {}_an_i^t\right) + {}_an_i^t \ln\left\{\frac{\left(M_i^t - {}_an_i^t\right)\left(M_i^{t+\Delta t} - {}_an_i^t\right)}{\left({}_an_i^t\right)^2}\right\}\left\{\frac{\left({}_aP_i^t\right)\left({}_aP_i^{t+\Delta t}\right)}{\left(1-{}_aP_i^t\right)\left(1-{}_aP_i^{t+\Delta t}\right)}\right\} \quad \text{(A4)}$$

The value of ${}_an_i^t$ maximizing V_i^t occurs when

$$\frac{\partial \ln V_i^t}{\partial {}_an_i^t} = \ln\left\{\frac{\left(M_i^t - {}_an_i^t\right)\left(M_i^{t+\Delta t} - {}_an_i^t\right)}{\left({}_an_i^t\right)^2}\frac{\left({}_aP_i^t\right)\left({}_aP_i^{t+\Delta t}\right)}{\left(1-{}_aP_i^t\right)\left(1-{}_aP_i^{t+\Delta t}\right)}\right\} = 0 \quad \text{(A5)}$$

Thus, the number of static occupants ${}_an_i^t$ is expressed by

$${}_an_i^t = \frac{\left(M_i^t + M_i^{t+\Delta t}\right) - \sqrt{\left(M_i^t + M_i^{t+\Delta t}\right)^2 - 4PM_i^t M_i^{t+\Delta t}}}{2P} \quad (8)$$

where,

$$P = \frac{{}_aP_i^t + {}_aP_i^{t+\Delta t} - 1}{{}_aP_i^t \; {}_aP_i^{t+\Delta t}} \quad (9)$$

Appendix B: The Number of Individuals Moving between Grid-cells

The maximum likelihood algorithm is applied using the inter-grid-cell motion fraction p_{ij}^t, which was obtained from Konzatsu-tokei® (KT) using the numbers of people exiting ${}_bn_i^t$ and entering ${}_cn_i^t$ during the time span t to $t+\Delta t$ in criterias. The number of individuals moving between grid-cells i and j T_{ij}^t can be calculated by maximizing the following statistic W^t:

$$W^t = \prod_i^m \prod_j^{m-1}\left[{}_{{}_bn_i^t}C_{T_{ij}^t} \times \left(p_{ij}^t\right)^{T_{ij}^t}\right] \times \prod_i^m\left[{}_{{}_bn_i^t}C_{T_{im}^t} \times \left(1 - \sum_j^{m-1} p_{ij}^t\right)^{T_{im}^t}\right] = \frac{\prod_i^m {}_bn_i^t!}{\prod_i^m\prod_j^m T_{ij}^t!} \times \prod_i^m\prod_j^{m-1}\left[\left(p_{ij}^t\right)^{T_{ij}^t}\right] \times \prod_i^m\left[\left(1-\sum_j^{m-1}p_{ij}^t\right)^{T_{im}^t}\right] \quad \text{(A6)}$$

Taking the logarithm of both sides, we obtain

$$\ln W^t = \sum_i^m \ln {}_bn_i^t! - \sum_i^m\sum_j^m \ln T_{ij}^t! + \sum_i^m\sum_j^{m-1} T_{ij}^t \ln p_{ij}^t + \sum_i^m T_{im}^t \ln\left(1 - \sum_j^{m-1} p_{ij}^t\right) \quad \text{(A7)}$$

From Stirling's equation, we obtain

$$\ln W^t = \sum_i^m {}_bn_i^t \ln {}_bn_i^t + \sum_i^m\sum_j^m T_{ij}^t \ln\frac{p_{ij}^t}{T_{ij}^t} + \sum_i^m T_{im}^t \ln\frac{1-\sum_j^{m-1} p_{ij}^t}{T_{im}^t} \quad \text{(A8)}$$

Formulating the Lagrange function L under the criteria (10) and (11), we obtain

$$L = \ln W^t + \lambda_i^t\left({}_bn_i^t - \sum_j^m T_{ij}^t\right) + \gamma_j^t\left({}_cn_j^t - \sum_i^m T_{ij}^t\right) \quad \text{(A9)}$$

It reduces to the problem of finding the parameters λ_i^t and γ_j^t, which maxim the value of L.

$$\frac{\partial L}{\partial T_{ij}^t} = \left(\ln\frac{p_{ij}^t}{T_{ij}^t} - 1\right) + \left(-\lambda_i^t\right) + \left(-\gamma_j^t\right) = 0 \quad \text{(A10)}$$

Thus, the number of individuals moving between grid-cells i and j T_{ij}^t can be calculated with Eqs. (12)-(14).

$$T_{ij}^t = p_{ij}^t \times A_i^t \times B_j^t \quad (12)$$

where,

$$A_i^t = \exp\left[-\lambda_i^t - \frac{1}{2}\right] \quad \text{(A11)}$$

$$B_j^t = \exp\left[-\gamma_j^t - \frac{1}{2}\right] \quad \text{(A12)}$$

Summing the values for i and j in T_{ij}^t, we obtain the following:

$$A_i^t = \frac{{}_bn_i^t}{\sum_j^m p_{ij}^t B_j^t} \quad (13)$$

$$B_j^t = \frac{{}_cn_j^t}{\sum_i^m p_{ij}^t A_i^t} \quad (14)$$

The variants A_i^t and B_j^t are mutually dependent but can be calculated by guessing at initial values and performing a converging calculation. However, in order to confer consistency on the data, a single exterior zone was assumed and the flows into and out of the region of interest were absorbed into single flows involving that zone.