Spatiotemporal Distribution of Automobile Users: Estimation Method and Applications to Disaster Mitigation Planning

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ABSTRACT

When discussing human casualties from a severe earthquake with regard to urban disaster mitigation planning, it is important to clarify the characteristics of the spatiotemporal distribution of people. In this paper, we construct a model that estimates the spatiotemporal distribution of automobile users using data from the Person Trip Survey and the Road Traffic Census. We use this model to estimate the spatiotemporal distribution of automobile users in Tokyo and demonstrate several ways to apply this data to urban disaster mitigation planning.

Keywords

spatiotemporal distribution, automobile user, person trip survey, road network, Tokyo.

INTRODUCTION

Related works

In disaster mitigation planning, it is essential to have information about the spatiotemporal distribution of transient occupants in a city (Freire and Aubrecht, 2012). The limited available data in this regard has forced previous studies to assume static population distributions. However, the transient occupants and passengers in a large metropolitan area change dynamically, which suggests large potential variations in the number of individuals affected by an earthquake.

A number of studies, particularly in the traffic engineering and planning fields, have attempted to estimate automobile traffic volumes from various viewpoints (Kato, 1988; Chen et al., 1999; Lo and Tung 2003; Lama et al., 2003; Clark and Watling, 2005; Billings, 2006; Toplak, 2010). Typical reports have addressed the cost of road links (that is, segments of road between intersections) or attempted to model variations in flow for different times of day (Widhalm et al., 2012; Fujita et al., 1988). Such studies have generally attempted to predict traffic volumes (that is, the number of automobiles). On the other hand, there are many research papers discussing transportation demand and modeling during evacuation scenarios. Choe (2002) is one of disaster preparedness studies to analyze the demands of evacuation traffic. Pel et al. (2010) indicated the importance to include traveler information and compliance behavior in evacuation modeling. Also, they reviewed travel behavior modelling in traffic simulation models for evacuations, with focusing on how travelers' decisions are predicted through simulation regarding the choice to evacuate, departure time choice, destination choice, and route choice (Pel et al., 2011).

In the event of a major earthquake, vehicle occupant individuals may be obliged to abandon these forms of transportation and flee from the affected areas on foot. While most healthy adults can be expected to exercise judgment and act independently, the youngest and oldest passengers may need extra care and protection during an evacuation. As emergency planning develops, previous number-based plans must be expanded to take account of the various populations expected to use automobiles. While such numbers may be comparatively small, it is worth assembling some basic data in order to analyze the types of individuals who are most likely to be present and to require aid.

When determining routes for emergency vehicles after an earthquake, it is important to anticipate the barriers to road blockage caused by building collapses and fires, road surface subsidence, soil liquefaction, and other factors (Sekizawa and Yoshihara, 1997). These barriers can also impede people who are attempting to walk home or elsewhere (Tambara et al., 2004). Automobiles driven into the city may become obstacles to evacuation in an emergency. In addition, the number of automobile users who return home or elsewhere on foot should also be examined.

Using Person Trip Survey (PT) data, which is described in more detail later on, Osaragi and Hoshino (2012) proposed a model that describes the spatiotemporal distributions of people inside and outside buildings and in other establishments. Osaragi (2009) also constructed a model for estimating spatiotemporal distributions of railway users to augment the data on automobile users; this model offered detailed information on individual classifications such as sex, age, and profession. The present paper focuses on automobile users, who make up an important subset of passengers, and attempts to provide a spatiotemporal distribution of this population.

Person trip survey (PT) data and goal of research

Some of the information provided in the PT data is listed in Table 1. The PT data can be used to determine the automobile users' position and time information for the departure/arrival.

Item	Contents
Regions subject to survey	Tokyo, Kanagawa, Saitama, Chiba and Southern Ibaragi Prefectures
Survey time and day	24 hours on weekdays, excluding Monday–Friday in October–December of 1998
Object of survey	Persons aged 5+ living in the above region
Sampling	Random sampling based on census data (1,235,883 persons selected from 32,896,705 persons)
Valid data	883,044 samples (mean weighting coefficient is approximately 37.3)
Content of data	Personal attributes, position and time of departure/ arrival, purpose of trip, etc.
Purpose of trip	Purpose of each trip (18 purposes : e.g., commuting, business, shopping, eating)
Means of trip	Means of unlinked trip (5 means: on foot, bicycle, car, bus, train, ship, airplane)

Note: We have confirmed “change of the mean traffic volumes for 12 hours” and “change of the mean travel speed” in Tokyo Metropolitan, using the Road Traffic Census (1980 - 2010). There exists no large change from 1998 to 2010. Hence, the authors think the PT data (1998) are still applicable.

Table 1. Outline of Person Trip Survey (PT) data

Figure 1 shows the study area, the Tokyo metropolitan area, and boundaries of zones which are the spatial unit for aggregating the PT data are observed. Figure 2 shows basic information about automobile users found in the PT data. Although the number of people using cars in Tokyo during ordinary commuting hours is smaller than those using trains, subways, walking, or bicycles, it still represents approximately 2.5 million people, which means it cannot be ignored. The fraction is higher during the daytime, reaching approximately 1.0 million, which is equal to the number of pedestrians or passengers using other means of transportation. Women and the elderly account for higher fractions as well: roughly 40 percent and 10 percent, respectively. Thus, the types of passengers using automobiles vary greatly throughout the day. The proportions of passengers commuting between home and work or school is approximately 80 percent at 8:00 a.m. and 90 percent after 8:00 p.m., while those traveling for personal or work reasons account for about 30 percent during the daytime.

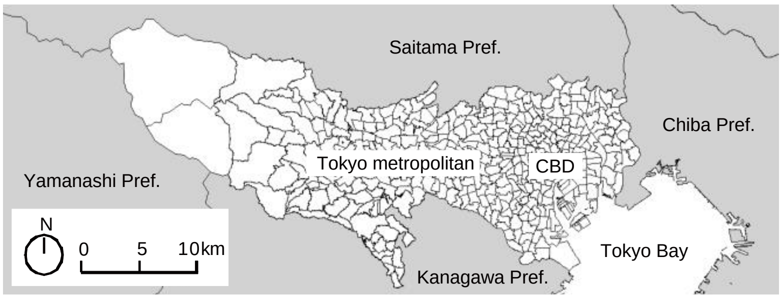


Figure 1. Study area and boundaries of zones

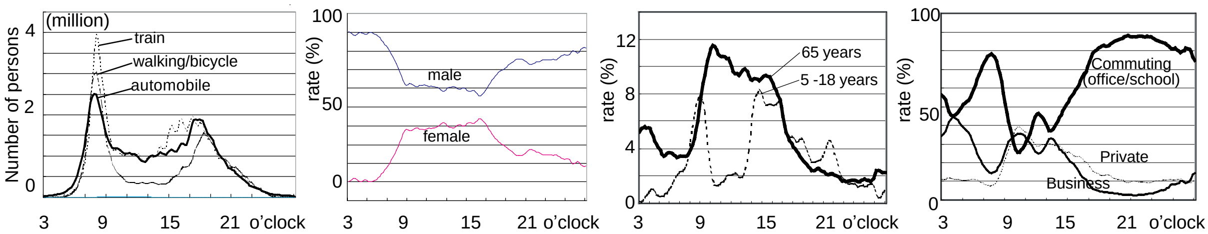


Figure 2. Basic information about automobile users taken from the PT data

As the above examples show, the PT data contains very fruitful information. However, we are unable to obtain the spatiotemporal distribution (trajectories) of automobile users because the PT data can only provide information about the position (zones shown in Figure 1) and time of departure/arrival. Therefore, we need a method of estimating routes on which automobile users move and for predicting their spatiotemporal distribution over the road networks with their detailed personal attributes, such as sex, age, and profession.

The remainder of this article is structured as follows. Section 2 presents a basic framework and estimation methods for predicting the spatiotemporal distribution of automobile users. Section 3 validates the models using the actual data and some key technical implementation details of the proposed methods. In Section 4, we demonstrate applications of the estimated spatiotemporal database of automobile users to disaster mitigation planning in the Tokyo metropolitan area. The paper ends with a summary and some conclusions.

PREDICTION OF SPATIOTEMPORAL DISTRIBUTION OF AUTOMOBILE USERS

Outline of prediction method

Figure 3 shows an outline of the prediction method. The details are described in the following sections. The aim of this procedure was to predict the trajectories of users of private automobiles/cars and public bus, including drivers and passengers, and to estimate their spatiotemporal distribution on road network spaces (trajectories), under the condition that their starting points (origin) and arriving points (destination) were given. The following steps correspond to the numbers in Figure 3.

(1) First, extract the information on the position and time of the origin/destination for individual trips from the PT data.

(2) Assume that the initial value of each road link speed (that is, the automobile speed on each road segment) is constant and equal to the legal speed, and estimate the fastest route from the origin to the destination for each trip (see the next section for details).

(3) Count the number of automobiles at the observation points (768 points) of the Road Traffic Census (2005) and calculate the estimation error.

(4) Adjust the road link speed to reduce the estimation error (see the next section for details).

(5) Use the adjusted road link speed to estimate the fastest route from origin to destination for each trip.

(6) Count the number of automobiles at the observation points (768 points) and calculate the estimation error.

(7) If the estimation error exceeds the limits of tolerance, return to step (4) and iterate the calculation until the estimation error converged toward tolerance level.

(8) If the estimation error is within the limits of tolerance, simulate the movement of every individual automobile user, including non-drivers, by using the adjusted road link speed. Using the departure time from origin and the arrival time to destination taken from the PT data, we can estimate the exact position and time of each automobile user on the road networks. We calculated the exact position and time of each automobile user at every 10-minute interval.

(9) Aggregate the spatiotemporal data of all automobile users and obtain their spatiotemporal distribution for every 10 minutes. This process also aggregates the purpose of trips and the personal attributes.

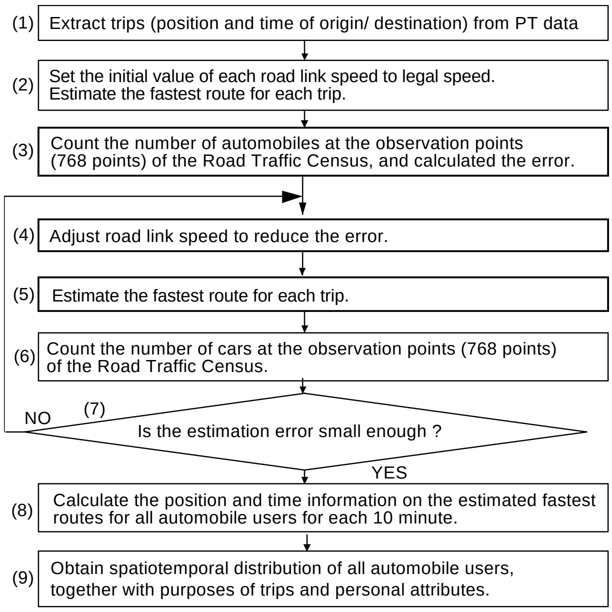


Figure 3. Estimation method for spatiotemporal distribution of automobile users

Methods for predicting transit routes and counting traffic volume

Calculating the routes for all automobiles required considerable processing time; therefore, 10 percent of drivers were selected at random to carry out the calculation. The route of each automobile was predicted as follows:

(1) The positions of origin/destination in the PT data were given as zones that include approximately 10 traditional Japanese address units (chō, chōme). If the centroids of the zones were used for the specific positions of origin/destination, only a few roads around the centroids would be congested. In order to reduce this unrealistic congestion, the road intersections in each zone were selected at random and employed as the positions of origin and destination.

(2) We assumed that the driver would select the route from the origin to the destination to minimize the time of transit (the fastest path bases). As noted above, vehicle speeds for each road (road link speed) varied according to the time period of the day. In this analysis, we divided the 24-hour day into 10 time periods (based on the authors' experience) during which we assumed differing travel speeds (Figure 4) in order to incorporate a dynamic simulation of congested traffic conditions in Tokyo. The higher the number of time periods, the more accurate the estimated model would be. However, the calculation time of iteration was proportional to the number of time periods.

(3) Vehicle speeds for each road (road link speed) varied according to the direction of travel (toward or away

from downtown Tokyo). The road network data was composed of two networks, which were the same network data except for the direction in which automobile can move (Figure. 5). Networks 1 and 2 are the same network data, with only the movement directions being different. An automobile can move between networks 1 and 2 on intersections without travel time.

(4) Utilizing data for all of the roads (effective width ≥ 3.0 m) in the road networks in the study area to calculate long drives would require an immense amount of calculation time. Therefore, the roads examined for use in long trips were limited to the main thoroughfares (effective width ≥ 5.5 m). More specifically, the road network data was classified by the straight-line distance between the starting and destination points and by the density of intersections in the starting and destination zones (Figure 6). Our pre-processing on the actual data showed that calculation time can be reduced by selecting road network data according to the distance between origin and destination and the density of intersections. Trial and error analysis showed that we could achieve effective calculation if we selected route-finding methods (i) and (ii), based on the relationship between the OD distance and the density of intersections shown in Figure 6.

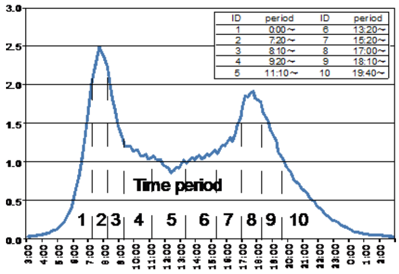


Figure 4. Setting of time periods

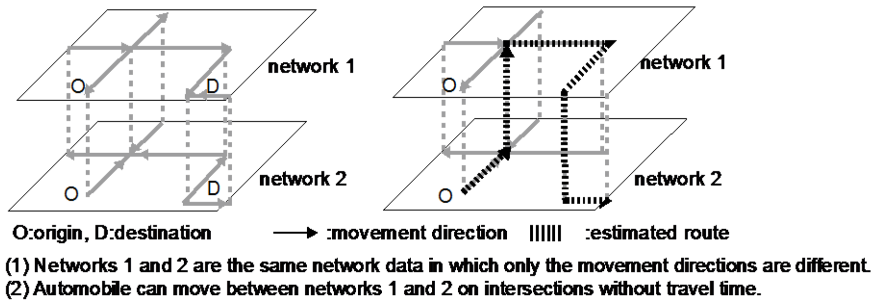


Figure 5. Road network and direction of travel

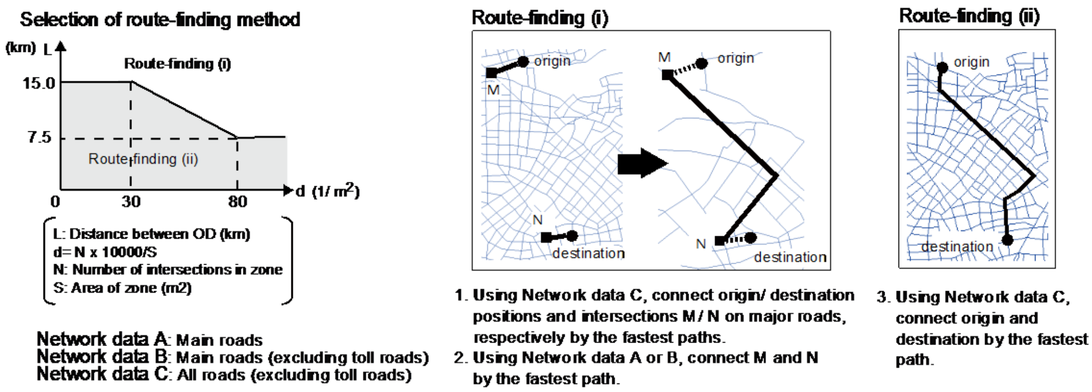


Figure 6. Route finding methods to reduce calculation time

Method for adjusting traffic speed on road links

Figure 7 shows the method for adjusting the speed of road links. The observed data employed in this method was obtained from the Road Traffic Census, which provides 24-hour weekday volumes of automobiles (the total number of automobiles in a 24-hour weekday period, for lanes toward and away from central Tokyo) and peak one-hour traffic volume (the number of automobiles at peak hour for each lane). The more precise data, as 15-minute interval data, are necessary to the model's calibration. This is the limitation to be solved in the future.

Using the method shown in Figure 7, we adjusted the road link speed for different time periods of the day and different directions (lanes) to reduce the difference between the estimated numbers of automobiles and the observed numbers.

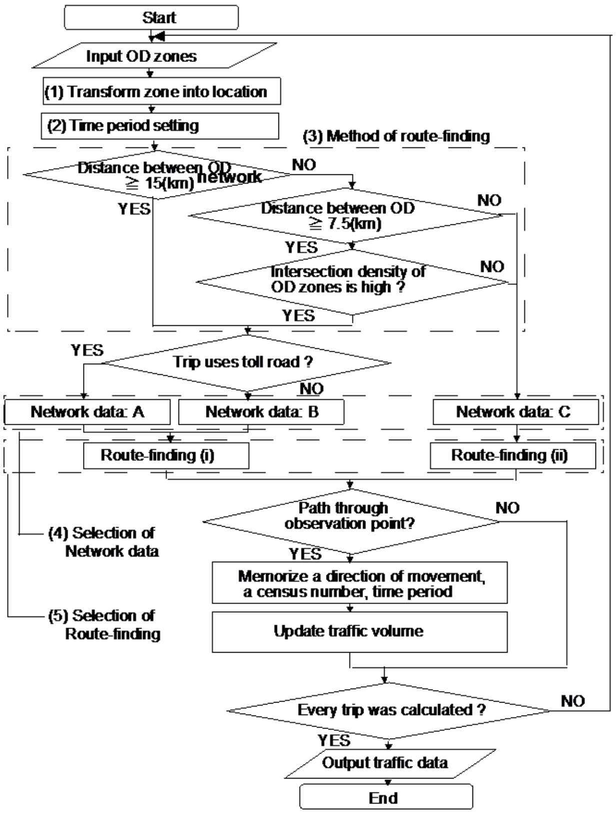


Figure 7. Method for adjusting speed of road link

(1) The speed v during all time periods t in travel direction j on small roads (3.0 m < effective width < 5.5 m) was assumed to be constant, since any observation data was collected for small roads and it is not possible to vary the speed of such roads.

$$v^t_{ijk} = 20\ (km/h), \qquad (1)$$

where i designated the road link and k designated the iteration number for speed.

(2) When the total number of automobiles in a 24-hour period was greater than the observed number from the Road Traffic Census, the average speed was reduced for road link i; when the estimated number was lower, the average speed was increased.

$$\bar{v}_{ik+1} = \bar{v}_{ik} + b_k \frac{S_i^* - \hat{S}_i}{\hat{S}_i} \quad for\ \hat{S}_i > S_i^*, \qquad (2)$$

$$\bar{v}_{ik+1} = \bar{v}_{ik} + b_k \frac{S_i^* - \hat{S}_i}{S_i^*} \quad for\ \hat{S}_i \le S_i^*, \qquad (3)$$

where S_i represented the total number of automobiles in a 24-hour period (S_i^* was the observed number), v was the road link speed, and b_k was a positive constant value set by verifying the accuracy of the estimated number of automobiles. In this process, the speed of each road link of each time period was not updated; only the average speed was estimated to be higher or lower.

(3) The following equation was used to change the speed on the given road link when the estimated number of automobiles during a 60-minute period was lower than the observed number during the peak hour (60-min).

$$v^t_{ijk+1} = v^t_{ijk} + \left(\bar{v}_{ik+1} - \bar{v}_{ik}\right). \tag{4}$$

The following equation was used to reduce the speed of the road link when the estimated number of automobiles was greater than the observed number,

$$v^t_{ijk+1} = v^t_{ijk} + c_{k+1} \frac{s_{ij}^{t*\max} - \hat{s}^t_{ijk}}{\hat{s}^t_{ijk}}, \tag{5}$$

where s^t_{ij} indicates the number of automobiles for the time periods. Therefore, the following relation held:

$$S_i = \sum_j \sum_t s^t_{ij}, \tag{6}$$

$s^{t\,*}_{ij}\max$ was the observed maximum number of automobiles on road link i during an hour either toward or away from downtown Tokyo. c_k was a positive constant value set by verifying the accuracy of the estimated number of automobiles. Since the exact time of the peak period was unknown, we changed the speed of each road link of each time period by using the information of the above average speed updated by Equations 2 or 3.

The upper and lower limits were imposed in order to ensure that the predicted speed did not have an excessively high or a negative value,

$$1 \leq v^t_{ijk} \leq 80\ (km/h). \tag{7}$$

In other words, the speed of each road link of each time period was always changed dynamically in each iteration process.

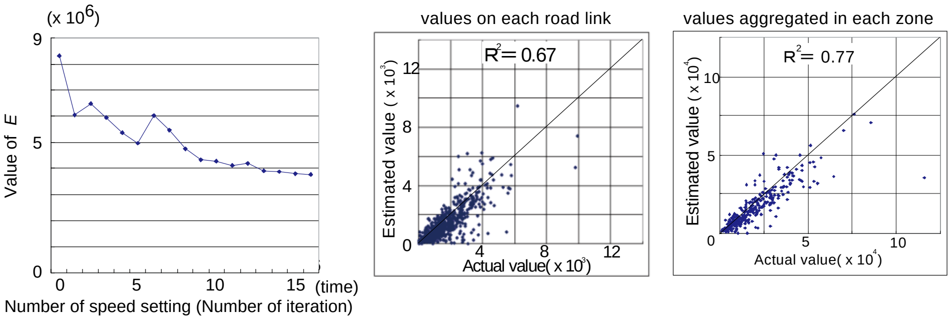
VALIDATION OF PROPOSED METHODS

Accuracy of predictions for daily traffic volume

The simulation model of automobiles was encoded with Microsoft Visual Basic (Ver.6.0) using the application programming interface (API) of GIS software called Spatial Information System (SIS, Ver. 7.0).

Figure 8 (left) shows the behavior of the sum of absolute errors in the total number of automobiles during a 24-hour period at the observation points (768 points) in the links of main thoroughfares. The errors gradually diminished as the speed was adjusted. However, the automobiles' routes were affected by the speeds in the neighboring roads, which made it difficult to obtain complete convergence of the calculation. Due to limitations on the calculation time, speed adjustments were stopped after 16 iterations.

Figure 8 (center) demonstrates the accuracy of the predictions on each main road links after 16 iterations. Each dot indicates the total number of automobiles during a 24-hour period at the observation points (768 points). Figure 8 (right) shows the same results of the sum of all the main road links included in the same zone. The figure shows that the prediction accuracy of each zone was sufficient, while that of each road link was relatively low.



$E = \sum_{i=1}^{768} \left| S_i^* - \hat{S}_i \right|$ E : sum of absolute errors S_i^* : observed number of automobiles $\hat{S}_i$: estimated numberof automobiles

Figure 8. Behavior of sum of absolute errors in iteration and accuracy of predictions

Accuracy of predictions for time period

Figure 9 shows the accuracy of the estimated number of automobiles for each time period. Figure 9(a) shows the fraction of road links whose estimated numbers for the peak hour in each period exceeded the actually observed numbers for the same time period, while Figure 9(b) shows the mean number of vehicles represented by this overestimate on the road links in question. Overestimates occurred for a relatively large fraction (35 percent) during the morning rush. Because the calculations were applied only to the main thoroughfares for long-distance trips, the volumes in smaller roads have been underestimated. In other words, many vehicles use smaller roads during the morning and evening rush hours in an attempt to avoid traffic jams. When using the estimates provided by this model, it will be necessary to note the concentration of traffic into the smaller roads in the districts most prone to congestion. Nonetheless, the road links showing overestimates of automobiles accounted for fewer than 25 percent of the total during the off-peak periods, which predicts small overestimates of only several hundred vehicles.

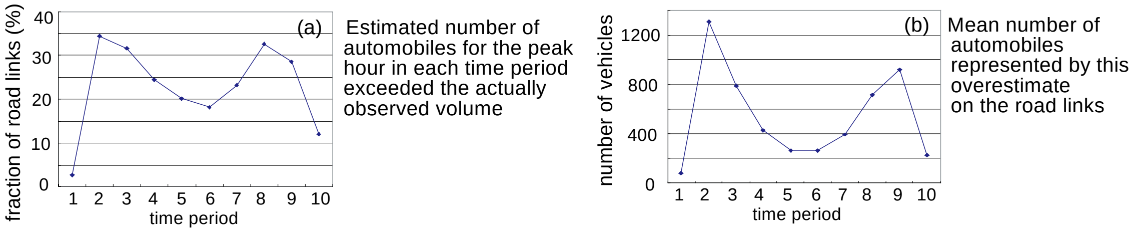


Figure 9. Accuracy of traffic volume for each time period

APPLICATION OF ESTIMATED SPATIOTEMPORAL DATABASE OF AUTOMOBILE USERS

Spatiotemporal distribution of automobile users

The proposed model provides spatiotemporal information on all automobile users, including non-drivers. Figure 10 presents the spatiotemporal distribution of the automobile user density (the number of users per 100 linear m of road) for each road link. The density of automobile users is exceptionally high in downtown Tokyo during commuting hours; between 7:00 and 9:00 a.m., many roads show more than 40 automobile users per 100 m. Densities also become particularly high on the main suburban throughways.

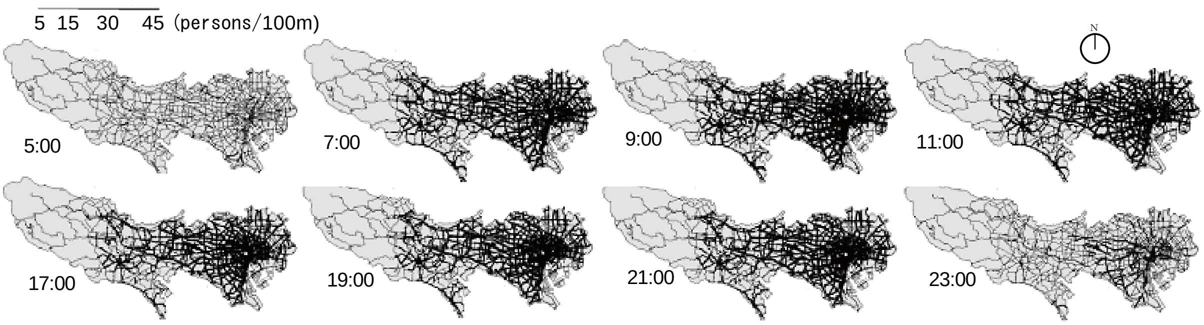


Figure 10. Spatiotemporal distribution of automobile user density for main road links

Figure 11 shows the spatiotemporal distribution of elderly automobile users (65 years or older). The gross zone density (the number of users in the zone divided by the zone area) is shown in order to enhance visualization of the spatiotemporal distribution of automobile users. The number of elderly people, who would have a comparatively high need for assistance during an emergency, is relatively small, shows no tendency to be concentrated in downtown Tokyo, and is evenly distributed throughout the day.

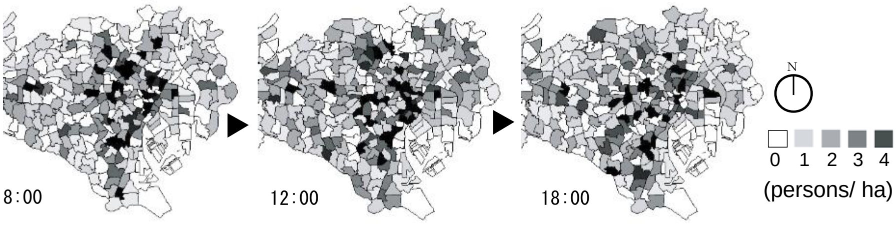


Figure 11. Spatiotemporal distribution of elderly automobile users

Figure 12 presents the results of a re-calculation for automobile users in each zone, based on their use purposes. High densities of automobile users commuted to work or school in the mornings and evenings; some zones showed gross densities of 10–15 people per hectare, which corresponds to approximately 30 persons/100 m of road.

Car travel becomes difficult after a serious earthquake due to fires and collapsed buildings and blockage of roads. Consequently, automobile users will be forced to move on foot. The above results provide basic estimates of the type and number of individuals that could be affected in such circumstances.

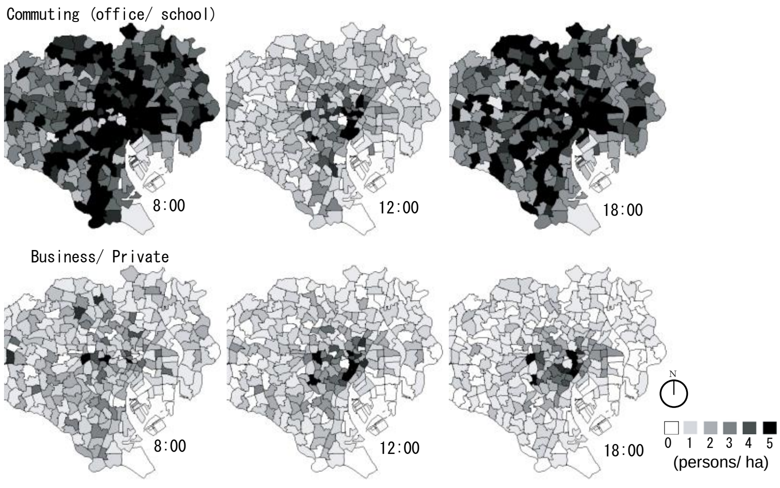


Figure 12. Spatiotemporal distribution of automobile users in each zone based on their purposes

Basic information for disaster mitigation planning

Figure 13 shows the spatiotemporal distribution of automobile users who travel straight-line distances of more than 20 km from home (that is, distances that would be difficult to travel on foot). The automobile users who face these long distances are scattered widely among the outlying parts of Tokyo, as well as in the center.

If roads are blocked and all trains and subways are stopped in the aftermath of a serious earthquake, automobile users will be forced to abandon their automobiles and walk. Spatiotemporal distributions of automobile users have never been analyzed, unlike surveys of transient occupants in and around establishments. Therefore, no plans have estimated the number of individuals who may have difficulty returning home or elsewhere or require special assistance during emergencies. The estimates in this model can be used as basic data to examine those needs.

Figure 13. Spatiotemporal distribution of automobile users traveling more than 20 km from home

Next, we attempted to analyze the possibility of road congestion in the jurisdictions of main fire stations and sub-stations. However, because no information was available for fire station jurisdictions, we assumed that the nearest station or sub-station to any given location was in charge of fire-fighting at that location. The map was then divided into provisional areas that were assumed to be under the jurisdiction of the stations and sub-stations (provisional jurisdictions) for this investigation.

Figure 14 shows the spatiotemporal distribution of the rate of road area occupied by automobiles in the jurisdictions (road occupied fractions). In the Great East Japan Earthquake of 2011, traffic jams disturbed the activity of the emergency vehicles such as fire engines and ambulances. The rate of road area occupied by automobiles is one index with which to describe the level of the obstacles. This rate was approximately 10 percent during the day, but exceeded 40 percent during the morning and evening rush hours in some districts. This tendency was stronger in the outlying regions than in central Tokyo. Intuitively, we expected to see the highest road occupied fractions in the city center, in view of the congestion in that area. However, the fact that the main thoroughfares in central Tokyo are quite wide, while roads are much narrower in the surrounding municipalities, exacerbated their occupied fractions.

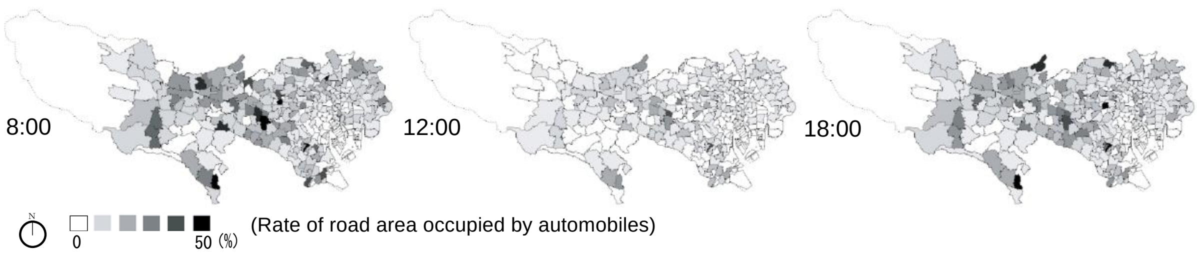


Figure 14. Spatiotemporal distribution of rate of road area occupied by automobiles

The seismic safety survey data (Bureau of Urban Development Tokyo Metropolitan Government) was examined from the viewpoint of the road occupied fractions. The data was furnished in traditional Japanese address units (chō, chōme) and expressed three types of danger (fire, difficulty of evacuation, building collapse) in an aggregate danger score of 1–5, where higher values represented greater danger (Figure 15). The mean value of the aggregate danger score was compiled for each provisional jurisdiction as described above (multiplied by the weighted area represented by the addresses). This value, as well as the road occupied fraction value for automobiles, were found and graphed together in Figure 16. The figure is divided into four areas based on high or low (greater or less than 2.5) aggregate danger scores and high or low road occupied fractions (greater or less than 20 percent). Group II had high occupied fractions but low danger scores, while Group III had high danger scores but low occupied fractions. Group IV had high tallies for both parameters, indicating a risk that automobiles would block the movement of emergency vehicles (Figure 17).

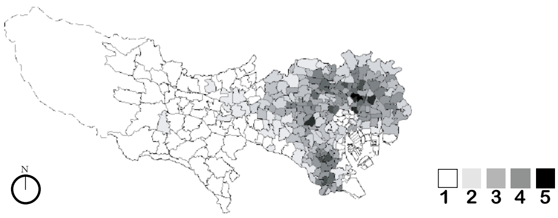


Figure 15. Mean value of aggregate danger score

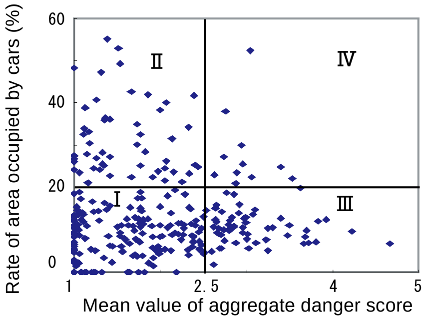


Figure 16. Mean value of aggregate danger score and road occupied fraction value

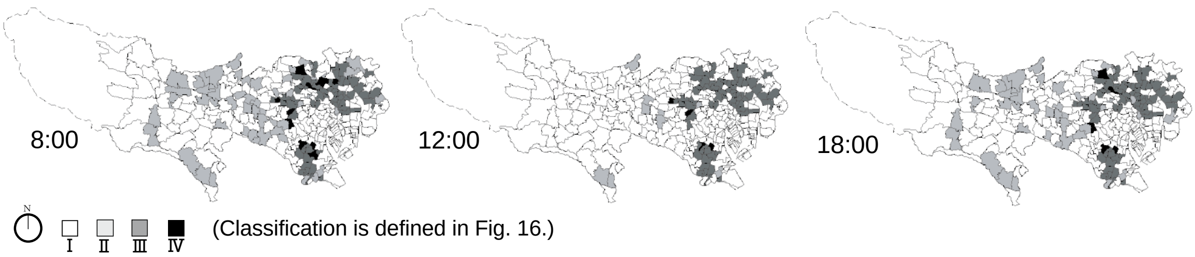


Figure 17. Spatiotemporal distribution of risk based on danger scores and road occupied fractions

SUMMARY AND CONCLUSIONS

This paper has presented a method for estimating the spatiotemporal distribution of the population of automobile users (a population that varies widely depending on the time of day and location) using PT data and data from the Road Traffic Census. Instead of an equilibrium traffic assignment model (Smith, 1993; Huanga and Lamb, 1993; Terry et al., 1993; Smith and Demetsky, 1997; Lo and Szeto, 2002; Yoshida and Harada, 2002; Szeto and Lo, 2004), we developed a non-stochastic model to assign the PT data (driver movements) to approximate real traffic volume observed in the Road Traffic Census. The distribution rule was used to predict the spatiotemporal distribution of all automobile users, including non-drivers as well as drivers. The model was constructed to simulate the spatial movements of automobile users on a GIS map, in terms of when (time), where (location), and how many (number) of each type of individual (sex, age, affiliations and purposes of movement) used automobiles for transportation.

The long processing time for calibrating the model made it necessary to have other effective estimation method for unknown parameters, and also to encode the model with other fast programming languages. However, this model will enable us to estimate this distribution while classifying drivers and obtain reasons for driving, distance from home, and other detailed information. The model can be applied to obtain basic data for disaster planners to estimate the numbers of individuals who will be forced to walk home or who will face difficulties returning home, and to determine the best responses to the needs of evacuees following a disaster.

The importance of this study lies in providing a fundamental database for quick emergency response and recovery. Congested road networks impede people from arriving at medical centers or conducting emergency activities, such as firefighting. Furthermore, in the case of a secondary earthquake, road network congestion could lead to further loss of life. Hence, in the future research, we need to discuss automobile flows under such extreme scenarios in order to establish emergency and evacuation planning, by using the fundamental database constructed in this study. The model proposed here can be used to assess not only the potential number of stranded automobiles users, but also their detailed attributes. Such information would undoubtedly prove helpful in actual planning for immediate post-disaster mitigation. Future research could also model a mixed flow of automobiles and pedestrians chaotically attempting to use the same urban infrastructure (Osaragi, 2013).

The primary aim of this study was to propose a method of constructing the fundamental data needed for spatial analysis of automobiles for detailed disaster mitigation planning; therefore, this paper only presents some rather basic examples of how the model can be used. Future studies could present more spatial analyses with a variety of data to examine variations of the transient occupants of establishments and railway passengers with time of day, weekdays vs. weekends (Osaragi and Shimada, 2009), and other information.

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