Journal of Transport Geography 34 (2014) 274–281

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Network-based spatial interpolation of commuting trajectories: application of a university commuting management project in Kyoto, Japan

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ARTICLE INFO

Keywords:
Interpolation
Network
Student commuting
Public transportation
Geographic Information System (GIS)
Japan

ABSTRACT

This study presents an application of network-based spatial interpolation of student commuting trajectories from a series of origin–destination trip datasets. In particular, we incorporated multimodal public transportation networks, including bus networks, to estimate the student commuting routes. The student samples for this study were collected from an online travel diary survey conducted by Ritsumeikan University in Kyoto, Japan. The ArcGIS Network Analyst was used to construct spatial network datasets and reconstruct trajectories from the origin–destination trip dataset. In addition, line densities of estimated trajectories were calculated and displayed on maps for geovisualization. These maps helped us understand the precise locations of congestion and spatial patterns of student commuting, unlike linear representations of people's movements that connect origins and destinations. Our study also showed that estimated trajectories can simulate quantitative impacts on travel time by promoting walking or the use of public transportation.

1. Introduction

This study presents an application of network-based spatial interpolation of student commuting trajectories from a series of origin–destination trip datasets. In particular, we incorporated multimodal public transportation networks, including bus networks, to estimate the student commuting routes.

This application is motivated by the student commuting management project conducted by Ritsumeikan University (RU) in Kyoto, Japan, called "Improving Accessibility to Kinugasa Campus, Ritsumeikan University." The project is a part of the "Slow Life Project," supported by the local government (Kyoto City, 2012). According to a student travel survey for RU students (Table 1), the percentage of "walk only" and "railway & walk" commuters was 11.9% and "bicycle only" and "railway & bicycle" commuters was 44.3%. The "bus only" (including a short walk to a bus stop) and "railway & bus" percentage was 35.8%. This result indicates that almost half the students use a bicycle to commute.[1] The estimated number of bicycle commuters is more than 7900 students (among approximately 18,000 RU students), which easily exceeds the road capacity and causes severe congestion around the campus every morning. Therefore, the abovementioned project aims to provide efficient bus services for the campus to alleviate the congestion and reduce the excessive number of bicycle commuters. Similar problems on bicycle commuting have been commonly reported in other universities in large cities, Japan (e.g. Matsumoto, 2006; Okamura, 2010) and thus need to be resolved.

It should be noted that bicycle commuting is regarded as an active mode of commuting, which contributes to reducing CO_2 emissions and promoting health both in international and Japanese contexts (Muromachi, 2008; Oja et al., 1998; Shannon et al., 2006). However, excessive bicycle use may increase the risk of traffic accidents between bicycle commuters and cars or pedestrians on narrow streets that do not have a separate bicycle path[2]. In fact,

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[1] The proportion of motorbike commuters was approximately 5% in total (Table 1). Their travel routes are similar to those of bicycle commuters. We thus analyzed both bicycle and motorbike commuters together in the later sections.

[2] According to a government report (Committee of Thinking New Bicycle Transport Environment, 2007), the total length of bicycle lanes installed in Japan is 2,530km, which is less than 1% of all roads.

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http://dx.doi.org/10.1016/j.jtrangeo.2013.09.006

Table 1
Travel modes to the Kinugasa Campus, Ritsumeikan University. *Source*: student travel survey.

Travel mode	Students (n)		Proportion (%)
Walk only	76		7.2
Bicycle only	372		35.1
Motorbike only	51		4.8
Bus	94		8.9
Railway and bus	285	26.9	41.5
Railway and walk	50	4.7	
Railway and bicycle	98	9.2	
Railway and motorbike	7	0.7	
Other modes	27		2.5
Total	1060		100.0

45 Samples who did not answer travel mode or did not commute to the campus are removed.

according to ITARDA (2013), in Japan, the proportion of the death during cycling comprised 15.7% of the total death caused by traffic accidents, which is higher than other countries such as Germany (10.0%), and Sweden (6.6%). In particular, bicycle accidents with pedestrians and between bicycles have grown by 134% and 111% respectively from 2001 to 2012 (National Police Agency, 2013) while the total volume of traffic accidents constantly decreased. The number of bicycle related accidents concentrate during rush hour congestions (8–10am and 16–18 pm) and people involved in the accidents are mainly young people in 10s and early 20s (ITARDA, 2011).

Although many Japanese cities have attempted to provide more bicycle parking spaces and expand the width of streets to install separate bicycle paths (Cabinet Office, 2011), such solutions cannot be easily implemented in old built-up areas containing several narrow streets. In the case of RU which is located in high density residential areas in a historical city, the space–time concentration of bicycle commuters around the campus—particularly in the morning—increases the risk of traffic accidents in neighborhoods. Thus, controlling such space–time concentration of bicycle use by promoting walking or public transportation use as modes of commuting is a reasonable target of transportation planning in this context.

RU identified two issues regarding student commuting (Ritsumeikan University, 2011). The first relates to the congestion of bicycles around the campus each morning during a semester. RU provides parking spaces for more than 7,000 bicycles and employs approximately 40 traffic guards to control traffic around the campus. As a result, some students who previously commuted by public transportation or on foot began using bicycles to travel from railway stations or, if they lived in close proximity, from their homes. The RU report stated that the more parking spaces RU provides, the more students use bicycles for commuting. Thus, providing more bicycle parking space will confound congestions around the campus.

The second issue involves congestion and long queues of RU students waiting for buses to RU at bus stops at the nearby railway stations.[3] Based on the RU survey conducted from January 6–12, 2009, a maximum of approximately 40–80 students stood in a queue for a bus in the morning (7:45–8:45 a.m.). Because buses become full at main bus stops, students waiting at other stops along the route cannot board them. Moreover, the crowded buses are uncomfortable and stressful for students. Such a situation eventually reduced the use of bus services and caused some students to shift from public transportation to bicycles to avoid tardiness.

[3] Students and staff of Kinugasa Campus, Ritsumeikan University are not permitted to commute by car owing to inadequate car parking capacity within the campus. Moreover, if commuting by car is permitted, congestion and illegal parking would disturb residents around the campus (Ogawa, 2006).

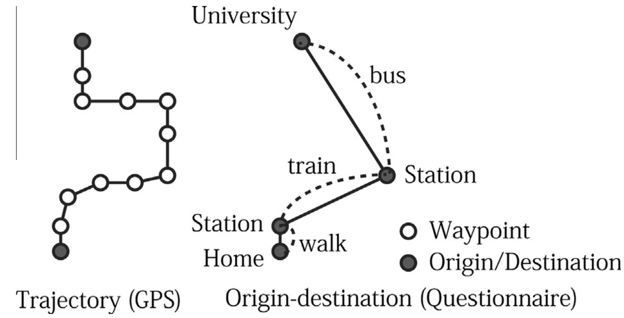

Fig. 1. Representations of trip data.

In the student commuting management project, RU experimented by providing better bus services to induce bicycle commuters to use public transportation or walk. As noted, this project did not intend to promote less active form of commuting (car commuting is not allowed by RU). It aimed to ease congestions and traffic accidents by controlling intensive use of bicycles. At the initial stage of the project, it was necessary to understand how students traveled to the RU campus as well as the geographical characteristics of routes and traffic congestion. Therefore, this study proposes a network-based spatial interpolation based on a multimodal public transportation network and a geovisualization method by line density to capture student commuting patterns, which facilitates a better understanding of traffic congestion and the impact of the student commuting management project.

This article consists of (1) modeling multiple public transportation networks because of their important role in student commuting, (2) estimating trajectories from origin–destination trip datasets by spatially incorporating them on the basis of public transportation networks, and (3) demonstrating the utility of estimated trajectories for geovisualization and post-intervention simulations for promoting public transportation and walking.

2. Data models and representations of people's movements in the GIS environment

In a GIS environment, there are two data models of people's movements. First, the origin–destination of trips in a day or week is surveyed using a written travel diary or an online questionnaire. The second model involves collecting recent georeferenced trajectory data using GPS receivers or Wi-Fi positioning system. Fig. 1 presents a typical data structure of two datasets. Origin–destination data include only start and end points of a trip, while georeferenced trajectory data register waypoints throughout a journey. As discussed below, both data collection methods have merits and demerits related to geovisualization.

Georeferenced trajectory data are appropriate to trace individual movements and analyze traffic congestion because they are gathered by GPS receivers and usually record xy coordinates during a trip at intervals of ten seconds or shorter. While georeferenced trajectories are easier to collect because of the pervasiveness of GPS receivers and GPS-equipped mobile devices, data collection for a large sample remains expensive and time consuming. For example, the samples for travel surveys in many cities easily exceed 1000 individuals. In addition, when using GPS data, we must estimate travel modes, speed, and the purposes of traveling.[4] Since it is difficult to receive GPS signals in areas that contain high-rise buildings (Duncan et al., 2013) or that are

[4] Regarding travel modes, the UCSD PALMS Project proposes a method to infer travel modes by using GPS in combination with accelerometers. (URL: http://ucsd-palms-project.wikispaces.com/).

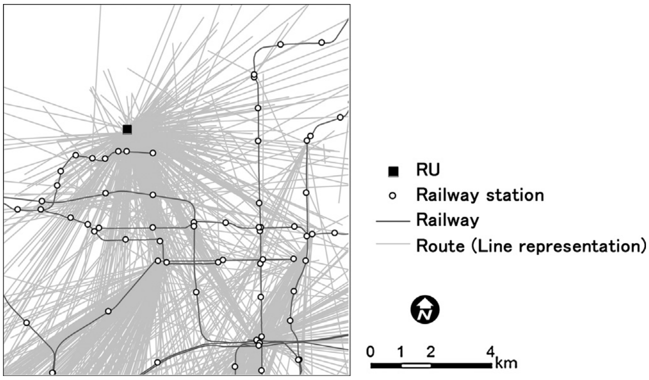

Fig. 2. Student commuting to Kinugasa campus, Ritsumeikan University. Connecting student homes (dot) and the campus (square) with a straight line. *Source*: student travel survey.

underground, data cleaning for such positional errors is necessary. In addition, data management and processing requires converting GPS data into a usable form before analysis due to the large volume of data recorded by GPS receivers. Furthermore, privacy protection must be considered when collecting detailed georeferenced trajectory data (Pedreschi et al., 2008).

On the other hand, origin–destination trip datasets are collected from a large sample using a written travel diary or an online survey. However, because these are not trajectory data, linearly connecting an origin and destination does not reflect actual routes or paths chosen by people. Drawing many straight lines renders a disorganized representation that does not present visible spatial patterns which reveal particular characteristics of routes (Fig. 2). Furthermore, these straight lines cannot be directly used for further analysis such as calculating travel distance and time or identifying routes and congestion. Therefore, two types of methods have been proposed to effectively represent an origin–destination trip dataset.

The first method uses an origin–destination trip dataset without using external datasets. Population migrations of regional scales are often mapped using straight or smooth curved lines with arrows. Since the pioneering work of Tobler's flow mapper (Tobler, 2004), many methods and software have been developed (e.g., Flowmap by Breukelman et al., 2009; Visual Analytics by Andrienko et al., 2008; Guo, 2009). The recently developed JFlowMap, by Boyandin et al. (2010) presents trip data with arrows by using advanced functionalities such as changing color, transparency, as well as line width and edge bundles. Furthermore, instead of using lines, they propose "Flowstrate," a method combining non-cartographic displays with maps, which visualizes temporal changes in flow volumes using a chart-like heat map. The OD Map, proposed by Wood et al. (2009), draws origin–destination matrices by destination that are allocated within a grid cell of each origin on a map with a nested structure of origin–destination maps. Although such representations of origin–destination trip datasets are suitable for visualizing spatial interactions at the municipality level or a higher geographic scale, they do not provide precise locations of traffic congestion caused by people's interactions because of insufficient route information.

The second method uses external datasets to interpolate a route between an origin and destination. This method produces a plausible route between these two points by using a wide range of geographic information about roads, railway networks, and related facilities such as railway stations, bus stops, and schools. In this study, we term this method a "network-based spatial interpolation." Sekimoto et al. (2008) and Usui et al. (2009) apply a network-based spatial interpolation to large trip datasets to reconstruct the flow of people in Japanese metropolitan areas. They employ animation to effectively geovisualize the change of flow volumes within a day. Thus, the origin–destination datasets are transformed into georeferenced trajectory datasets capable of displaying congestion on a 2-D map by applying various geovisualization methods.

A georeferenced trajectory dataset can be geovisualized in different ways. The 3-D representation of space–time paths (Kwan, 2004) helps in understanding trajectories of few individuals. To simultaneously display many trajectories, employing line density surface of trajectories is more appropriate than space–time paths because people usually use the same streets or railways and their patterns create overlapping routes. Line density surface is a previously utilized method and Demšar and Virrantaus (2010) extend its idea to a space–time domain. By combining it with a network-based spatial interpolation, we can more easily produce detailed spatial patterns of congestion for a large number of people's movements on routes.

Since we collect the origin–destination trip datasets of RU students, we apply network-based spatial interpolation to transform them into georeferenced trajectories and use them for geovisualization. While Sekimoto et al. (2009) and Usui et al. (2009) incorporate road and railway networks for route estimation, they do not include bus networks. Because buses are essential modes of commuting in Japanese cities, particularly for students, modeling bus transportation is vital for network-based spatial interpolation. In addition, the number of bus routes in big cities is significantly larger than that of railways and subways. Therefore, this paper presents a method to construct a large multimodal public transportation network dataset in a GIS environment.

3. Datasets and methods

3.1. Study area

Kyoto, with a population of approximately 1.47 million, is one of three large cities in the Kansai region. RU's Kinugasa campus is located in a northwestern suburb of the city (Fig. 3). The campus covers an area of about 200 by 200 m. The approximate number of students who commuted to the Kinugasa campus in 2010 was 17,788. According to Kirimura and Kondo (2010), during the last decade, RU students tended to reside further away from the campus because of their preference for living in the city and because of greater availability of part-time jobs in the city center.[5] This trend resulted in an increase in the travel distance and time of student commuters. Currently, 69% of students live more than 2 km (based on direct distance from the centroid of the campus) away from the campus (Ritsumeikan University, 2011).

Regional railway companies provide access to the campus by connecting Kyoto with other major cities. In Kyoto, dense public transportation networks serve commuters and tourists; they include two subway lines, city buses, and buses run by private companies. During the semester, city and JR buses ply from major railway stations to the campus at 3–5-min intervals every morning, and travel times are approximately 10–30 min. In addition, express bus services with minimal stops ease congestion during rush hours (usually 8:30–9:00 a.m., before the first lecture of the day).

3.2. Online travel survey and student commuting patterns

The trip dataset used in this study was collected through an online survey conducted from October 13–19, 2010. All students

[5] According to a national survey conducted by the Japan Student Service Organization, 73% of students have part-time jobs (Japan Student Service Organization, 2012).

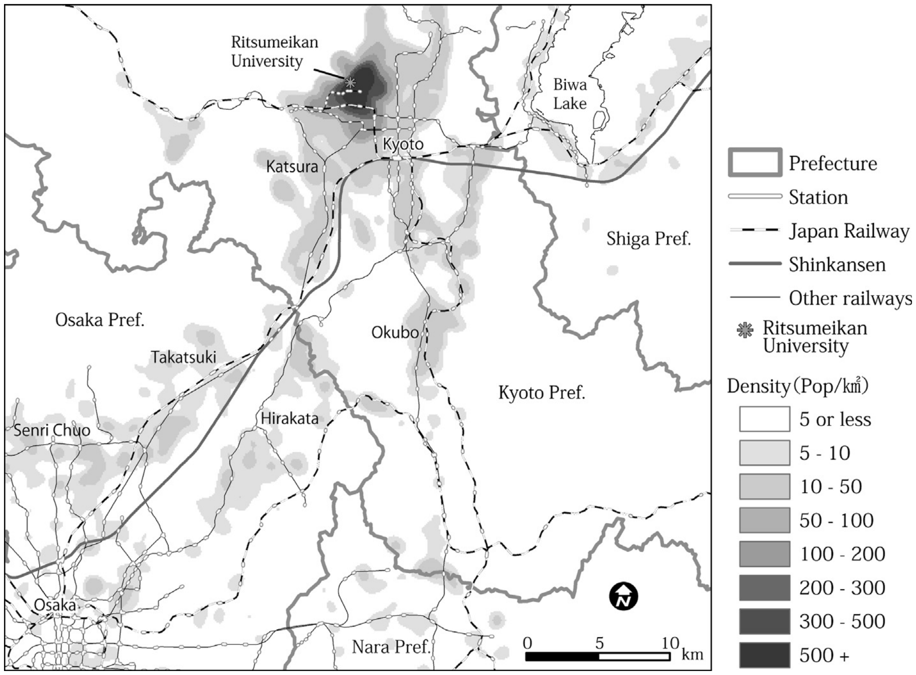

Fig. 3. Residential locations of Ritsumeikan University students.

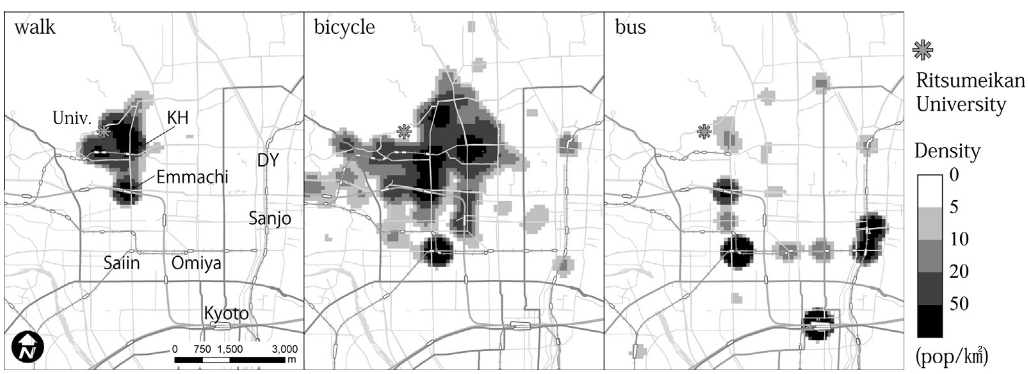

Fig. 4. Density of student trip origins by travel mode. Kernel density estimations of points of student trip origins. DY: Demachi Yanagi, KH: Kitano Hakubai Cho. *Source*: student travel survey.

participated in the student travel survey via emails or through the university home page. The questionnaire inquired about the students' personal data (grade, sex, department, and home address), whether they held a season ticket, their mode of transportation to the campus (and travel times), and travel records (date, origin, destination, mode, traffic company, and purpose). Their journey's origin and destination were recorded by selecting the locations on an online map created in Google Maps.

We collected 1196 samples, and after disregarding samples containing errors in the answers, 1105 were used to describe student commuting patterns, and 1048 were used for the network-based interpolation. The sample covered approximately 6% of the student population at the Kinugasa campus.[6]

For every student's commute, we divided a commuting trip (one way from a student's home to the RU campus) into a set of trip records comprising the origin and destination. A total of 1672 trip records were reported by the 1048 students, with the average being 1.60 trip records per student. Students' home addresses, railway stations, and bus stops were georeferenced beforehand.

Using the same dataset, we divided each person's trip by travel mode and calculated the densities of their origin locations (the starting point of a walk or a bicycle or bus trip) in Fig. 4. Starting points (origin) of trips to the campus are geographically structured by travel modes and are varied according to their distance from the campus. With regard to walking, areas with higher trip origin densities are generally clustered within 1.5 km (direct distance) of the campus. Moreover, because some railway commuters walk for approximately 25 min from a station, areas with a higher density of pedestrians are also found around a nearby railway station, located 2 km from the campus. A high density of origins of bicycle commuters' trips is found within 3 km of the campus, and the density declines as the distance from the campus increases. However, higher densities are found around major railway stations because many commuters ride their bicycles to the station and park them in station parking spaces. Origins of bus trips are concentrated at five railway stations from which city and JR buses depart for the

[6] The survey over-represents female students (the proportion is 62.6% based on the survey samples but 49.7% based on university statistics).

campus. Based on the map, these areas are candidates for RU's commuting management project because of their potential to convert bicycle commuters to bus commuters.

3.3. Building a spatial network dataset

We built a spatial network dataset using the ArcGIS 10 Network Analyst extension, which provides a wide range of spatial data processing and analysis functionalities to handle multimodal transportation network datasets.

We used a digital road network dataset published by Hokkaido-Chizu Co., Ltd. as well as railway and bus route network datasets downloaded from the National Land Numerical Information of Japan. In the study area, railway services are frequent but the frequencies of bus services vary depending on the route. Students usually commute in the morning and do not use bus routes with low frequencies. Therefore, using the information regarding the daily frequencies of bus services on weekdays provided with the bus route network datasets, we disregarded routes with less than 10 daily services. This was an arbitrary decision; however, we did not omit major bus routes to the campus in the morning. Creating time tables is time consuming; using average queuing duration is acceptable because passengers are generally aware of the schedule when they have to wait for long periods (Tribby and Zandbergen, 2012). Without a bus time table, students select the first arriving bus regardless of when they arrive at the bus stop. This may affect travel time because some bus services take detours or stop at bus stops more frequently.

Our method for constructing spatial network datasets is similar to that presented by Tribby and Zandbergen (2012). To model transfers at railway stations and bus stops, roads and stations/stops were connected by lines and queuing duration for trains and buses were added to the lines as attributes. Network Analyst provides two methods to model multimodal public transportation networks: "hierarchy" and "elevation." Hierarchy was used by Tribby and Zandbergen (2012), but setting hierarchies of many bus routes and railways via their user interface is time consuming when transportation networks are complex. Therefore, in our study, values of elevation were used to distinctly consider each bus route or railway. They were added in attribute tables of bus routes/railways, stops/stations, and connection lines to roads (=entrance/exit). In addition, hierarchy was used to distinctly consider transportation networks such as railways, bus routes, and roads. The nested structure of transportation networks was achieved by using the hierarchy attribute representing transportation mode and the elevation attribute representing routes or lines of each transportation mode.

On the basis of Ishida et al. (1999), we set travel speed by mode in Kyoto as follows: 36.7 km/h for railways, 13.9 km/h for buses and trams, 6.8 km/h for bicycles, and 4.0 km/h for walking. According to the author's experience, we assumed that the speed of a motorbike is the same as that of a bus (13.9 km/h). Queuing durations at railway stations and bus stops are 5 min. In addition, considering time tables of public transportation, we assumed that 5 min and 1 min were required for passengers to transit from trains and buses to other travel modes, respectively. Trains and buses stop for 12 and 30 s at each railway station or bus stop, respectively for embark and disembark passengers. A train transfer between stations requires an additional 10 min including queuing duration. Moreover, we distinctly considered three major bus companies: city bus, JR bus, and other buses.

To estimate a route between an origin and a destination, we assumed the chosen route for a given origin–destination pair as the shortest path. Network Analyst calculates the shortest routes using Dijkstra's algorithm, which is widely used for routing applications (e.g., Macharis and Pekin, 2009). We used the ArcGIS Model Builder to read a pair of origin and destination points for each trip, set the travel mode and parameters, and calculate the shortest path between them. During the iteration process, we saved topologies of estimated trajectories together with travel distance and time by mode. Finally, we merged all trajectories into one shapefile and calculated line densities of estimated trajectories for geovisualization. The line density tool is provided in the ArcGIS Spatial Analyst.

3.4. Post-intervention simulation setting

In the commuting management project, RU encouraged students to use buses and walk instead of using bicycles. As noted in Section 3.2, the origins of bicycles trips are within 5 km of the campus. Therefore, to analyze the maximum impact of the commuting management project, we changed commuters' travel modes from bicycle/motorbike to bus or on foot according to zone divided by the distance from the campus. First, for trips starting within 1 km of the campus, all bicycle/motorbike commuters were required to walk to campus. Second, for trips starting within 1–5 km of the campus, all bicycle/motorbike commuters were required to use a bus or walk, whichever was quicker. We considered 25 "within 1 km" trips and 464 "within 1–5 km" trips.

4. Analysis

4.1. Pre-intervention situation

The results of a network-based spatial interpolation of the origin–destination trip dataset are geovisualized using line density (Fig. 5). Line density of trajectories is regarded as the daily volume of student commuters. Since approximately 5500 students registered for the first lecture, starting at 9:00 a.m. on weekdays, and another 3000 registered for the second lecture, starting at 10:40 a.m. (Ritsumeikan University, 2011), a large volume of commuting trips are concentrated on short time periods before the lectures in the morning.

Thus, densities of trajectories tend to be higher near the campus. Since students commute by bus or train, higher densities are found along these routes, particularly around two railway stations (Emmachi and Saiin) south of the campus. On the other hand, most students living near the campus commute on foot or by bicycle. A radial pattern of these high densities is observed on the street network. In addition, maps in Fig. 5 reveal two congested routes leading to the north and east gates of the university, which correspond to some of the actual locations of congestion reported by RU (2011).

Fig. 5 indicates that the route to the north gate is primarily used by bus commuters because a bus terminal is located in front of the gate, while the east gate is used by students commuting by bicycle or on foot. For all student commuters other than bus commuters, high densities are observed along the streets from railway stations in the south to the east gate of the campus. This pattern indicates that most students walk or use bicycles after disembarking from trains and that the route leading to the east gate is the shortest from the nearby railway stations. Thus, compared with the straight line representation in Fig. 2, line density representation based on interpolated commuting routes provides more information on the geographical patterns of student commuting.

4.2. Post-intervention simulation

Based on the intervention setting mentioned in Section 3.4, network-based spatial interpolations were reapplied to the origin–destination trip dataset. Line densities of estimated trajectories

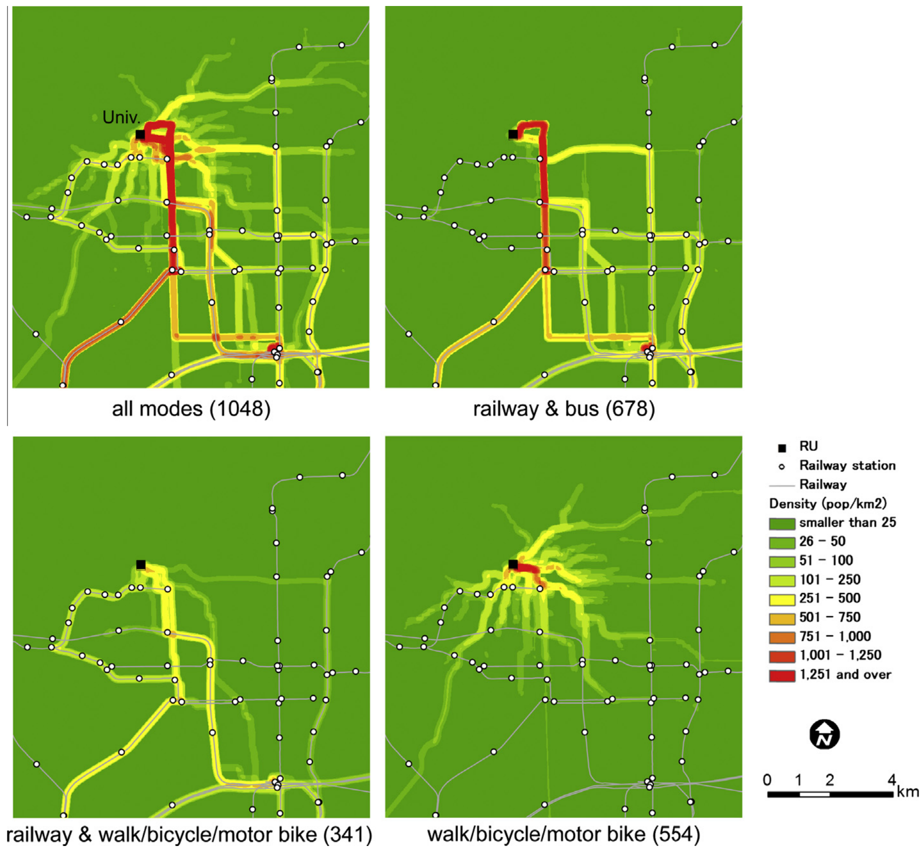

Fig. 5. Line density mapping of interpolated trajectories by travel mode. Values in brackets: the number of students.

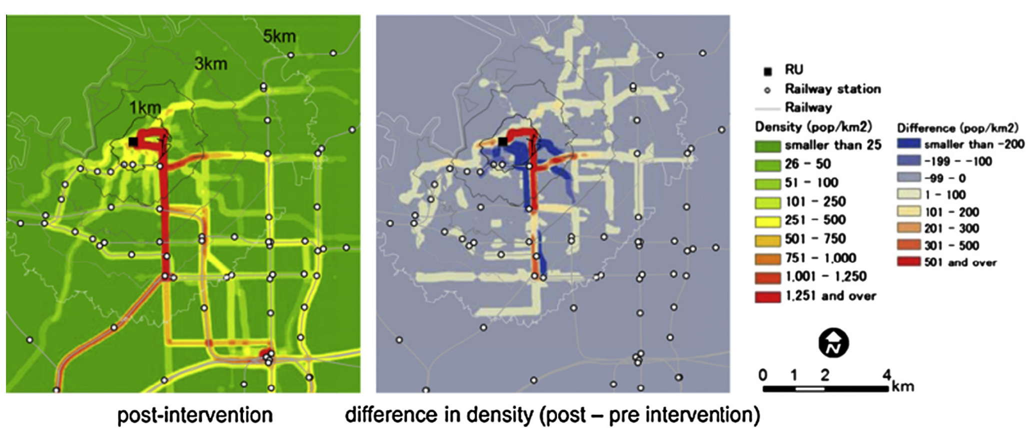

Fig. 6. Line density mapping of trajectories (post-intervention simulation). Gray lines show street network distances from the campus.

were geovisualized in Fig. 6. Because all previous bicycle/motorbike commuters traveled by bus or on foot, higher densities are found along bus routes to the campus. Based on these results, traffic congestion along a route to the east gate appears to be easing, while that along routes to the north gate has worsened. A map of the difference in densities between the present situation and the simulation reflects such route changes.

Table 2 summarizes the changes in travel distance and time by zone divided by the distance from the campus. Within 1 km, students traveled 693 m on average by bicycle, equivalent to a 5-min bicycle ride. If all students who previously commuted by bicycle/motorbike walked to the campus, the average travel time would increase by two times, from 5.1 to 10.4 min. Within 1–5 km, average travel time increased by approximately 10 min, from 17.7 to 28.2 min, when bicycle/motorbike commuters used the bus or walked to the campus. In addition, the travel distance was approximately 270 m greater. The magnitude of this increase should not be ignored.

The results of the post-intervention simulation illustrate the utility of multimodal public transportation networks and geovisualization of estimated trajectories to understand spatial impacts on student commuting and traffic congestion. Furthermore, they provide numerical information to students about changes in travel time and distance when commuting by public transportation or on foot. The combined use of geovisualization and numerical information on simulated trajectory data is important for persuading students to use public transportation instead of private vehicles.

Table 2
Result of post-intervention simulation by the distance from campus.

Zone by the distance from the campus	0–1 km	1–5 km
	"bicycle/ motorbike" → "walk only"	"bicycle/ motorbike" → "bus or walk"
Present		
Total distance (m)	692.9	2432.8
Total (min)	5.1	17.7
Railway (min)	0.0	0.0
Bus (min)	0.0	0.0
Walk (min)	0.0	0.0
Bicycle (min)	5.1	18.0
Motorbike (min)	4.4	12.4
Scenario		
Total distance (m)	692.9	2703.4
Total (min)	10.4	28.2
Railway (min)	0.0	0.0
Bus (min)	0.0	8.1
Walk (min)	10.4	14.3
Bicycle (min)	0.0	0.0
Motorbike (min)	0.0	0.0
Difference		
Total distance (m)	0.0	270.7
Total (min)	5.3	10.5
Trips (n)	25	464
Trips (n) = 1672 (all students)		

5. Discussions

5.1. Strategies to induce modal shift among students

This study simulated trajectories when all bicycle/motorbike commuters used public buses or commuted on foot. Our results showed that while a route to RU's east gate is used significantly less under the intervention setting, a route to the north gate is more congested owing to an increase of bus commuters. This indicates the requirement for more bus services on the north route under the intervention setting. Accordingly, the Kyoto City Bus provided new rapid bus services (two additional buses in the morning) experimentally between a main railway station and the campus along the north route for only five days. It reduced both the number of students standing in a queue and congestion on other buses (Ritsumeikan University, 2011).

Whether the results induced a modal shift from bicycles to buses was not examined; however, improving bus services would stop a modal shift from buses to bicycles, at least. RU is responsible for providing a better commuting environment for students without disturbing the living environment of residents in the area. Currently, there is limited space for installing additional bicycle parking on the RU campus and, as previously mentioned, increasing the bicycle parking capacity does not solve commuting problems around the campus. Student's understanding and cooperation are important factors in shifting their mode of commuting.

Our study provided numerical information suggesting that students must allow for an additional 10 min and 300 m to their commute if they use a bus or walk. Regarding this, the university's online survey revealed that 83% of the sampled students have begun realizing how they can contribute to easing traffic congestion, and 58% of the sampled students have agreed to begin their commute earlier (Ritsumeikan University, 2011). Given these high percentages of students adopting a cooperative stance toward solving traffic congestion around the campus, we assume that some students will accept the longer travel time and distance presented in post-intervention simulation.

If students use buses more frequently, our results suggest that the narrow road to the north gate will be highly congested by buses. Moreover, these buses will be crowded. Therefore, for introducing feasible strategies to induce a modal shift using efficient bus services, it is also important to implement bus traffic management strategies such as non-stop direct bus services, alternative routes to the east or west gates of the campus, time table optimization, and announcements concerning the arrival of the next bus to average passenger loads.

5.2. Limitations and future directions

The results of estimated trajectories were not formally validated to actual student trajectories. They must be validated in comparison with a benchmark dataset of actual routes collected by GPS receivers or a questionnaire survey of sampled students. A future study should be directed to compare the interpolated results with such actual trajectory data or that of the traffic census conducted by transportation companies and RU in order to tune parameter settings and the route-finding algorithm to minimize differences between observed and estimated traffic counts.

A limitation related to the abovementioned issue is that our dataset did not include travel speed by transportation mode, and thus we referred to other sources from surveys in different cities. The average travel speed/time should be articulated by measuring each individual's actual travel speed by mode as well as queuing duration at bus stops and train stations. Furthermore, the route-finding algorithm (Dijkstra algorithm) in this study assumed that students always select the shortest path based on travel time. However, selections of commuting routes may vary depending on individual preference, such as to street environment, traffic volume, the physical characteristics of streets, and traffic signs for route selection (Sener et al., 2009). Such physical and functional elements need to be considered in the route-finding algorithm.

Further consideration should include temporal elements (e.g., GTFS_NATools, developed by Morang and Pan (2012)). Our application assumed that students begin commuting in the morning because the public transportation time table and detailed traffic census information were not readily available. However, since traffic congestion and frequencies of public transportation change during a day, travel speed and queuing duration need to be dynamically modified to estimate realistic trajectories. In addition, incorporating stated preferences against queuing for public transportation and travel durations is important to simulate route selection as well as estimate impacts on modal shift and congestion patterns introduced by transportation interventions (Abdel-aty et al., 1997).

Regarding geovisualization, raster maps of line densities of interpolated commuting trajectories effectively display bundles of routes and congested points on real road networks. However, since directional information was removed by the conversion, it is difficult to simultaneously visualize people's paths if there are multiple destinations. A merit of network-based interpolated trajectories is that they are easily mapped to the real space. Therefore, to preserve the positional accuracy of the trajectories, combining line density mapping and flow animation of people's movements along the trajectories could help us intuitively understand not only spatial patters of congestion but also the directions to destinations.

6. Conclusion

In the commuting management project, an online travel survey was conducted at RU to understand student commuting behavior.

The origin–destination trip dataset was transformed into a georeferenced trajectory dataset by using a network-based spatial interpolation method that incorporated multimodal public transportation networks, particularly the bus network. For geovisualization, line densities of estimated trajectories were calculated and displayed on maps. The geographical distributions of high trajectory densities indicated a radial area near the campus, where students commute on foot, which followed bus and railway networks within a distance from the campus that enabled students to use public transportation. Unlike a linear representation of people's movements that connects origins and destinations, interpolated trajectories help us understand the exact locations of congestion and spatial patterns through effective geovisualization methods.

Once a transportation network dataset was constructed, a post-intervention simulation was easily implemented by modifying the route-finding setting in Network Analyst. This study simulated and geovisualized trajectories on maps when all bicycle (including motorbike) commuters used public buses or commuted on foot. Our results showed that while a route to RU's east gate is used significantly less under the intervention setting, a route to the north gate is more congested owing to an increase of bus commuters. This indicates the requirement for more bus services on the north route under the intervention setting.

Several limitations in the route-finding algorithm and geovisualization of people's movements need to be addressed. However, a network-based spatial interpolation technique effectively produced commuting trajectories from an origin–destination trip dataset. Furthermore, in comparison with simple straight line representations, the datasets and representations based on interpolated trajectories provide more insight into assessing congestion of student commuting around the RU campus under pre- and post-interventions.

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