Extracting Urban Mobility QoL Indicators and Individual Activity Pattern from Mobile Phone-based Human Mobility Trajectories

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Abstract: For the human-centric society and improving individual Quality of Life (QoL), extracting and analyzing key QoL indicators are crucial. In this paper, we aim to develop a model to extract key QoL mobility indicators from a city-scale low-sampling rate mobile phone mobility trajectory data. The QoL indicators include commuting time, at-home time, and excursion time, and we evaluate the result based on census and other related panel survey data.

Keywords: mobile phone location data, human mobility, quality of life (QoL)

1. Introduction

1.1. Urban computing

Understanding urban dynamics and large-scale human mobility has become one of the major challenges (Zheng et al., 2014), and Urban Computing aims to utilize emerging new technologies to solve urban issues such as transportation, public safety, and public health. Recently, mobile device-based mobility data enables several applications such as detecting users' significant places and additionally analyzing their mobility patterns including commute (Kobayashi et al., 2019). The commutes in large-scale cities have been one of the key drivers of the cities' productivity growth. However, the recent issues such as work-life balance and work-style reform requires cities to support diverse lifestyles and to consider new indicators for urban planning.

1.2. Urban quality of life

One prominent indicator is for the Quality of Life (QoL), which is increasingly considered as an important concept for cities (Stiglitx et al., 2009). Using real-world mobility data, the QoL indicators can now be estimated for each individual, while aggregation in any spatiotemporal unit is possible that local government can identify QoL problems in the local group and tackle region-specific issues.

Our main idea is to develop a model to extract key urban QoL indicators from a city-scale low-sampling rate mobile phone mobility trajectory data.

2. Related work

Many urban computing studies are now the application-specific studies that aims to tackle certain issues such as life pattern discovery from GPS trajectories (Fan et al., 2014), lifestyle discovery from credit card-purchase data (Di Clemente et al., 2018) and the estimate and comparison of QoL in different cities for planning urban transit infrastructure (Nakamura et al., 2017). The aim of this study is similar to those studies; however, we focus on specific indicators for mobility that improving them would directly impact the people's life every day.

3. Data

3.1. Human mobility trajectory

The human mobility trajectory we use in this study is from

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approximately three million anonymized daily ID users of several mobile phone apps in throughout the Greater Tokyo Area from June 1, 2016 to June 30, 2016 which is collected by Agoop Corp. with the users' agreement. Each user is assigned a new daily ID at 0 am every day, and the data is collected in different intervals depending on the operating system. For example, the data from an Android phone is collected typically in every 30 minutes in background mode. The location of the devices is measured with either Global Positioning System (GPS), WiFi hotspots, or cell tower depending on the availability. The data is not collected in nighttime (1 am to 5 am). The other specification is summarized in Table 1.

Table 1. Specification of human mobility trajectory

Target area	The greater Tokyo Area (Tokyo, Kanagawa, Saitama, Chiba, Tochigi, Gunma, Ibaraki prefecture)
Target time	June 1, 2016 to June 30, 2016
Attributes	Daily ID, timestamp, longitude, latitude, location error (m), velocity, direction, etc.

3.2. Activity and mobility panel statistics

For evaluation of activity detection, two sets of activity and mobility panel statics: Survey on Time Use and Leisure Activities (Statics Bureau, Ministry of Internal Affairs and Communications, Japan, 2017) and National Time Use Survey (Broadcasting Culture Research Institute, Japan Broadcasting Corporation, 2016) are used in this study.

4. Extracting urban mobility QoL indicators

Figure 1 shows the overview of the framework. After the preprocessing of the human mobility trajectory, we adopt our previous work of significant place detection followed by spatiotemporal mobility clustering, which is evaluated and calibrated with national Census data. Then the model detects several activities from the trajectory which is also evaluated and calibrated with activity panel statistics and Person Trip survey data. The model finally extracts several urban mobility KPIs for analyzing individual and regional QoL.

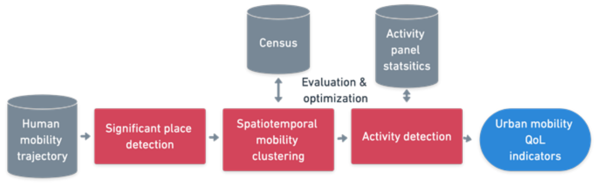

Figure 1. The overview of the framework

4.1. Preprocessing

At first, we filter the data by target area and time period. We also filter users based on several thresholds to extract highly active users. The thresholds are summarized in Table 2.

Table 2. Threshold used for the study

Indicator	Threshold
Location error (m) (each points)	365
Maximum lag time (hours)	8
Maximum distance moved in one trip (km)	150

4.2. Significant place detection and Spatiotemporal mobility clustering

We adopt the result from Kobayashi et al. (2019). Their model detects significant places from human mobility trajectory and apply clustering to extract commuters. Then the model's detection of home location and workplace location from significant places is calibrated to the Census's nighttime population. The extracted users are considered as "commuters" who regularly commute to their workplace in either daytime or nighttime.

4.3. Activity detection

We then detect several mobility-related activities from their users' trajectories. The activities we extract are follows:

- Commute: mobility from their estimated home location and workplace location. The leg from home to workplace the leg from workplace to home are denoted as *HtoW* and *WtoH* respectively. The combined estimated time is compared to the average commuting time on weekdays in the Greater Tokyo Area in National Time Use Survey.

- Staying at home: activity the users stay in their estimated home location. It is estimated from the lack of mobility going outside their estimated home location. The estimated tine is compared to the average at-home time (people with jobs) in National Time Use Survey.
- Excursion: mobility that does not involve their estimated workplace location. The estimated time is compared to the "Moving (excluding commuting)" in Survey on Time Use and Leisure Activities.

The time for each activity is calculated from the human mobility trajectory using the significant places.

5. Result

Table 3 summarizes the result compared to the activity and mobility panel statistics. The commuting time and excursion time are overestimated while at-home time is underestimated. The potential reasons are follows:

- Long trips are inaccurately detected as commutes: typical commute is a direct movement between home and workplace locations with only limited intermissions such as at transportation hubs. Some trips with longer intermissions and activities (e.g. shopping or business trips) may have been included as the commuting, resulting longer average commuting time (Figure 2 and 3).
- The definition of excursion is incomprehensive and lacks formal distinction between mandatory and non-mandatory activities (e.g. picking-up family members and trip for strictly leisure activities), that results the discrepancy between the estimated time and the aggregated time from statistics.

Table 3. Estimated aggregated time for each activities and comparison to the activity and mobility panel statistics

Indicator	Average (hours:mins)	Statistics (hours:mins)
Commuting time	2:06	1:42
At-home time	9:03	13:07
Excursion time	0:50	0:29

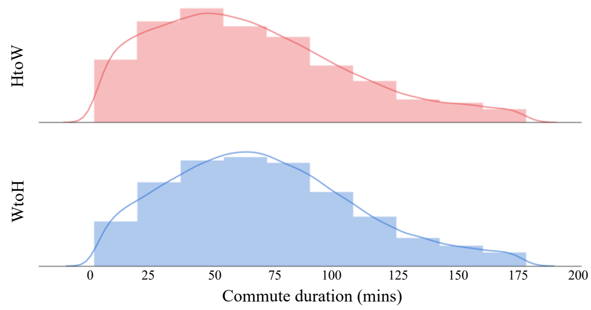

Figure 2. Histogram of estimated commute (*HtoW*: top and *WtoH*: bottom) duration. Some very-long trips are estimated as commute.

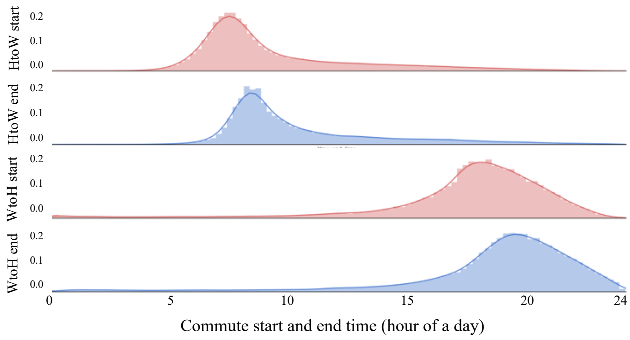

Figure 3. Histogram of estimated commute start and end time of daytime commuters. *WtoH* commute tend to have wider curve, suggesting greater variance of start and end time.

Figure 4 and 5 show the average commuting time and excursion time of municipalities based on each user's estimated home location. Generally, the commuting time increases as the home location gets further from the center of Tokyo, and the users living closer to the center of Tokyo have more excursion time.

6. Conclusion

In this study, we developed a framework for extracting key urban mobility indicators (commuting time, at-home time, and excursion time) for Quality of Life and evaluated with panel statistics. Even though some of the formulation are preliminary, the model extracts spatiotemporal features of the activities.

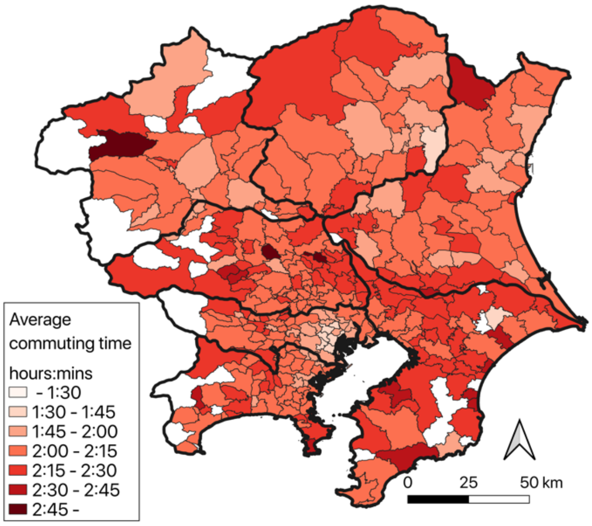

Figure 4. Average commuting time of users in each municipality

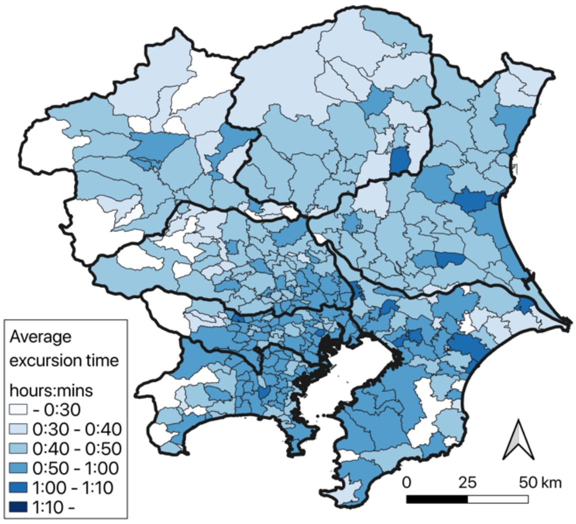

Figure 5. Average Excursion time of users in each municipality

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