Research on Urban Spatial Structure in Shanghai from Human Mobility View Based on Cell Phone Data

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Abstract: With the development of traffic information technology and acceleration of life and work rhythm, in modern metropolises like Shanghai, the high frequency mobility of massive population has caused huge influence on urban internal structure. How to measure human mobility and explain its dynamic structure in the city is of great significance to understand the law of intra-urban population flow. Previous research has mainly focused on human mobility patterns. In this paper, we aim to go one step further from exploring how the whole structure look like when individuals' mobility are aggregated into spatial analysis units using relatively high-precision and large-scale cell phone data. Shanghai as a typical metropolis of China is selected for research. To address such question, we divide Shanghai into 5432 census tracts and calculate basic population in every spatial unit by identifying every user's stable location during 4:00 p.m. to 6:00 p.m. when human mobility is the lowest. Then we compare basic population with daily visit frequency to calculate the amount and the ratio of human flow in each spatial unit. Finally, we combine the strength of human flow with the influential range, the composition, and the temporal law of human flow to extract a dynamic structure of urban space in Shanghai. The result shows that People's Square enjoys the highest amount of human flow, approaching 2.95million visitors passing by per square kilometer, which is more than 10 times of its residents, while in suburban areas the average level of human flow is just 4.80 thousand visitors per square kilometer. Additionally, the dynamic structure of human mobility extracted from four dimensions of index is composed of four kinds of features: dynamic surface, from city center to subarea, shows the strength level of daily human mobility; dynamic center, including five center and eleven subcenter, becomes the most influential areas in the flowing network; dynamic cluster, can be divided into six groups according to the structure, influential range, and temporal variation of human mobility; dynamic corridor, strongly related to metro lines, highways, and Huangpu River, provides transportation supports for crowd flux. The findings of the paper help to illustrate a dynamic structure caused by human flow upon the static material spatial structure. The relationship between human mobility and urban structure can also be considered as s key issue which is continue focused on in housing, community development, and transportation field.

1. Introduction

With the development of traffic information technology and acceleration of life and work rhythm, the high frequency mobility of massive population has caused huge influence on urban internal structure, which has brought new challenge to urban spatial policy. How to measure the intensity of human mobility and explain its dynamic structure in the city is of great significance to understand the law of intra-urban dynamic structure and support real-time population management. Traditional population surveys such as nationwide censuses are conducted every 10 years. These survey data reflect only long-term changes. While human activities often result in large-scale population movements within a short period of time. Such rapid and irregular changes in urban space exceed the scope of traditional census data, which has become a shortcoming of population management in recent years. How to describe, measure and evaluate collective human mobility in urban space? Does the distribution of human behavior fit into the urban spatial form and structure? These problem are difficult to solve with the traditional urban structure model and static spatial analysis method.

The developing succession of urban spatial structure is influenced not only by the external influences of the region's natural and humanistic environment, but also by factors such as internal division of functions and land use. The structural laws behind it are constantly revealed by scholars. Relative researches has reached a considerable depth in the evolution and morphology of urban spatial structure with a series from classical theories such as concentric circle models, fan-shaped models and multi-core models Burgess (1925), Hoyt (1939), Harris and EL Ullman (1945) to Further empirical research by some scholars like Zhang Tingwei (2001), Wang Xufeng et al (2011), Bumsoo Lee (2007), Qi Feng et al. (2012). However, limited by the research data and methods, there is always a certain distance between macroscopic scale structure and the real human behavior. Whether our urban structure conforms to real law of urban life, there isn't a quantitative explanation that can be generally accepted.

In the era of big data, an increasingly broad array of user-generated data like cell phone data derived from location-based services and Global Positioning System (GPS) provides new possibilities to analyze human behavior and their spatial distribution. Mobile positioning big data have opened up the interaction between human behavior and urban spatial structure, which not only enables quantitative analysis of urban structure under greater spatial and temporal granularity, but also breaks the long-term research barrier of "interpreting space with space", revealing the spatial law behind complex form of the city from the perspective of collective human activity. Relative research has proved that the cell phone data can be used to identify these daily activities, such as commuting, traveling, and space-time path (Ahas et al., 2015; Widhalm, P et al., 2015; Phithakkitnukoon, S. et al., 2010; C. Song et al., 2010; John Doyle et al., 2014). However, cell phone data still have great potential that needs to be exploited to further advance human behavior studies. At the same time, it should be noted that along with the opportunities it brings, there exist many remaining challenges that need to be dealt with when taking the application of mobile phone data further (Csáji,B.C., et al., 2013).

Therefore, the paper aims to explore urban dynamic spatial structure from the perspective of collective human mobility by revealing the strength, structure, and spatial-temporal variation of daily human mobility, and describing the feature of its spatial distribution. Two-week cell phone data of 2G users in Shanghai are used as basic data. The remainder of this paper is organized as follows. Section 2 gives a panorama of relative research on urban structure and human behavior. Section 3 makes a detailed introduction to how cell phone data can be applied to urban spatial structure research. Section 4 illustrates the results of the case study performed, which shows collective human behavior in Shanghai. In Section 5, we make some discussion about the results, presents a conclusion of this paper, and provides insights for further research. The results can provide reference for the formulation of urban space policy and population management strategy.

2. Literature Review

This study, firstly, analyzes the spatial characteristics of urban population flow based on cell phone data, and then summarizes the urban spatial flow structure. In the end, recommendations on spatial policy are proposed after comparing the results with urban spatial structure. Before conducting such research, it is necessary to understand some basic theories through literature review: 1)The definition of human mobility in urban area and its relevant research 2) Previous research on human mobility with cell phone data 3) Measurement on human mobility, in other words, how to describe and evaluate human mobility and its spatial structure?

2.1 Definition

The Chinese household registration system makes population movement more complicated in cities of China compared with other countries, therefore, some general definitions are not applicable in China. However, some scholars have proposed their understanding on population movement in cities of China. Zhao(2005) compared population statistical stats of different countries and suggested to divide population movement into three types: "Population Migration" -- defined as movement that cross the boundaries of certain jurisdictions, which might bring changes in household registration; "Population Move/Movement" -- simply referring to the changing of residence within a certain period of time, including short-term, long-term and permanent relocation. It can also be classified into regional and inter-regional relocation; "Human Mobility" -- reflecting spatial positional changes in a short period of time. It usually occurs inside the city and continuously changes over time. In this research, we focus more on the human mobility in cities of China.

Dynamic spatial structure of human mobility is always an important topic in the field of Population Geography. Many scholars have visualized spatial and temporal patterns of human mobility based on traditional data such as survey and census (Qin et al., 2013). Some have stimulated dynamic spatial distribution of population (Wang et al., 2014), and analyzed the internal mechanism of population mobility and industry, land use and other related elements (Yang et al., 2015; Rao et al., 2015). However, due to the spatial and temporal limitation of conventional data, for example, there are missing data on temporary population who stay less than half a year as well as the data of short-term population changes; Besides, the research scale of previous study are mainly at regional level (Bian, etc., 2013), interprovincial level (Li et al., 2015) or city and county level (Wang Lu et al., 2014); and the data utilized are mostly in years (Pan et al., 2013). Few research are conducted in smaller scale and focus on the changes over several years. In addition, a small number of studies mainly use data such as census (Foley DL, 1952), population flow observational statistics (Foley DL, 1954), OD matrix (Akkerman A, 1995), travel survey data (Roddis SM et al , 1998) and high-resolution remote sensing data (Sleeter R et al., 2006) to visualize, estimate and predict the spatial distribution of human mobility (Mao et al., 2010; Qi, 2013; Kavanaugh P, 1990). In brief, few studies are able to analyze dynamic spatial structure of human mobility through agglomerating individuals' activities, thus, further research are needed, especially with the advent of big data.

2.2 Human mobility with cell phone data

In recent years, with the increasing availability of big data, cell phone data is widely used in the human behavior and urban spatial studies. The reliability of cell phone data on human mobility research has also been verified by many scholars.

In terms of identifying behavioral activities, Ahas et al. (2010) used one-year cell phone data of Estonia to construct a stop point recognition model so that to identify individuals' stop points (including residence, work place, other places, etc.), after which the population registration data were utilized for comparison and verification. Based on communication data from 100,000 people in Portugal, Csáji et al. (2013) simplified data through clustering and principal component analysis. He identified their residences and workplaces, and compared them with census data. Widhalm (2015) explored cell phone data and call detail (CDR) data in Vienna, Austria and Boston. Considering low accuracy of cell phone data, Widhalm constructed Markov network model and propose a method for identifying the behavior patterns of residents.

When it comes to the description of behavioral patterns, Phithakkitnukoon (2010) visualized and analyzed nearly one million cell phone data of users in Boston central region. He found that people from same workplace have strong correlations in their daily activities. Ahas (2015) defined four indicators: “midnight”, “morning start-time”, “noon” and “day length” based on the call details (CDR) data of three cities -- Harbin, Paris and Tallinn. By comparing those indicators within and among cities, he revealed the differences in the spatial and temporal behaviors of residents in different cities and in the central and suburban areas within cities. Yuan (2012) used cell phone data of Harbin to study the correlations among mobile phone usage and radius, eccentricity and entropy. The results proved that characteristics such as age, gender, social time and built-up environment had impact on the usage of mobile phone and residents' activities. Ran (2013) identified user's travel trajectory through call detail (CDR) data, and analyzed the distribution of resident population and employment population, commuting pattern, OD matrix, commuting pattern in specific regional and commuting characteristics of floating population.

At the same time, recently, some research topics have gradually shifted from the identification and description of behavior to the simulation of human mobility. C. Song (2010) explored the possibility and limitations of cell phone data for predicting human mobility. It is considered that irregular human mobility (except for commuting and leisure travel) is inherently unpredictable. In the same year, C. Song (2010) used cell phone data to construct a random walk (CTRW) model so that to quantitatively stimulate human mobility. John Doyle (2014) visualized population movements across Ireland with call details (CDR) data, by using Markov chain model to rank population hotspots, John found that the results are strongly correlated with census data. Till now, research on the simulation of human mobility are still in their infancy.

Existing research have proved the feasibility that cell phone data can be used to identify daily activities, such as commuting/leisure travel, temporal and spatial patterns, etc. Some studies have further explored the possibility of simulating human mobility with cell phone data. However, on the other hand, most of research focus more on the description or restoration of travel activities, while the explanation of influencing factors is insufficient in these research, as well as practical guidance on spatial policy, which will be the focus of this research.

2.3 Measuring human mobility

Measuring human mobility usually includes description and evaluation of spatial structure. Existing research are mainly from the perspective of spatial-temporal distribution and dynamic space of flows. The spatial-temporal distribution of human mobility mainly refers to the city's population density distribution of different periods. Akkerman A (1995) evaluated the densely populated areas of Saskatoon in Canada based on the matrix of residents' residences and workplaces; Qi (2013) Constructed a “population-day and night-land use” model based on the understanding of cities of different spatial-temporal behavior characteristics. He then used grid as the unit to estimate Beijing's day and night population and analyzed its spatial distribution characteristics; With cell phone data of Oregon, Sleeter R (2006) stimulated the population density of coastal communities, based on which these community space were evaluated. Zhong and Wang (2017) used cell phone data to build a dynamic "population-time-behavior" analysis framework and then explored the dynamic spatial structure of population and activities in Shanghai.

While the perspective of dynamic space of flows focuses on population OD flow and urban spatial network structure. Castells M 's (1996) research did not follow the proximity theory, which greatly promotes the study of dynamic urban spatial network; Shen and Gu (2010) defined space of flows based on the analysis of the flowing society. The concept of space of flows consists of three spatial elements: nodes, lines and surfaces; Cheng and Zhang (2016) used spatial data from branches of the Yangtze River Delta to analyze the spatial organization characteristics of urban agglomeration and quantified its evolution trend, indicators that they used includes centrality, inflow and outflow ratio, etc. Xi and Qi (2013) constructed the residential mobility index system, which covers four aspects: human flow, cargo flow, information flow and activity flow. They employed entropy to measure the mobility of residents.

All in all, three conclusions can be drawn through literature review. Firstly, based on research with conventional survey and census data, the intrinsic mechanism and spatial coupling relationship of population flow has already been deeply studied, but it is necessary to integrate big data and focus more on smaller research scope. Secondly, existing studies have proved that cell phone data could support the identification of human mobility, but for further analysis , most studies are still working on the description of the results, while the impact factors and application need to be further deepened. Thirdly, the measuring of human mobility has two perspectives: spatial-temporal distribution and dynamic space of flows. These two perspectives can be considered together with the support of big data. Therefore, this research will analyze the space of flows based on human mobility collected from cell phone data, which could provide some new perspectives.

3. Methodology

3.1 Data preprocessing

First, we address the station drift of cell phone location data to obtain the correct location for each user. Station drift has a specific characteristic whereby a personal movement trajectory drifts, in a short period of time, from one place to another place that is almost impossible to reach in that time interval. When the speed of a user is faster than 100m/s, we treat such point as a station drift. Moreover, if the lac cell ID of several points next to each other is the same, we merge these points and use the latest timestamp.

Next we change preprocessed data into travel-chain data which includes information like the location(longitude and latitude) and timestamp of every origin(O points) and destination(D points) in a user's travel trajectory. We use a distance threshold to judge whether users leave their O points. Considering the distance between two lac cells grows longer from city center to subareas, our distance threshold should change accordingly in order to maximize the identification of travel trajectory. Figure 1 shows the calculation of distance threshold: 1) divide 6 sectors with the base lac cell as the center, each 60 degrees; 2) calculation linear distance from the nearest lac cell in each sector, and get 6 distances; 3) choose the maximum value in these 6 distances as distance threshold. We use a time threshold which is 20 minutes(duration of two nearest timestamp should be longer than 20min) to judge whether users arrive their D points instead of just passing by. Table 1 shows the final processed travel-chain data which includes 14 days' travel-train information of 16.34 million users, this table is prepared for further analysis.

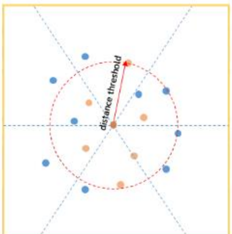

Figure 1: Calculation of Distance Threshold

User ID	O_lng	O_lat	O_timestamp	D_lng	D_lat	D_timestamp
48503	121.3809	31.1129	2014-0315-06:30	121.3885	31.1234	2014-0315-07:02
48503	121.3885	31.1234	2014-0315-09:20	121.4437	31.5324	2014-0315-09:33
48503	121.4437	31.5324	2014-0315-12:13	121.2487	31.2234	2014-0315-12:24
48503	121.2487	31.2234	2014-0315-17:35	121.3809	31.1129	2014-0315-18:36
64598	121.6897	31.0897	2014-0316-09:25	121.4578	31.1239	2014-0316-10:19
64598	121.4578	31.1239	2014-0316-18:20	121.2809	31.2908	2014-0316-19:02
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Table 1: Travel-chain Data

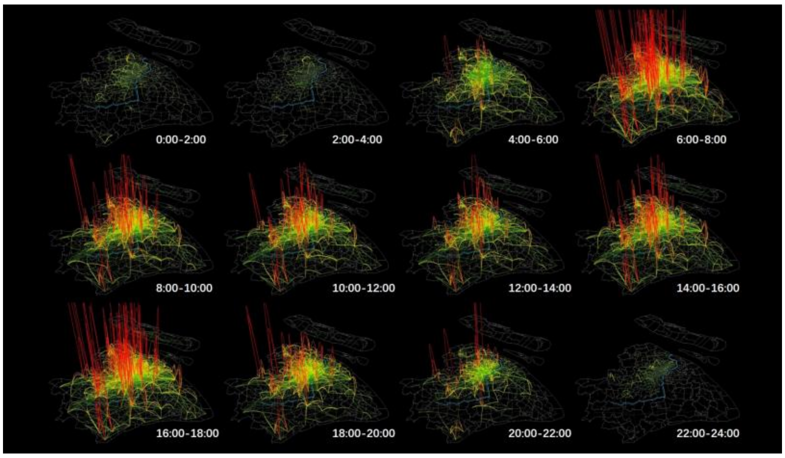

Figure 2: Travel-chain OD visualization

3.2 Description of collective human mobility

We describe collective human mobility from four dimensions, they are respectively mobility strength, mobility structure, influential range, and temporal variation. Figure 3 shows the indicator system of collective human mobility.

Mobility Strength	Shows the vigor of human activities in certain area	**Crowd flux volume :** [14days_D_avg]/Shape_Area **Crowd flux rate :** [14days_D_avg]/[14days_basic_avg]	Strength
Mobility Structure	Shows the main group of people visiting certain area	**External proportion :** [days<=4]]/[14days_D_avg] **Radom proportion :** [radom]]/[14days_D_avg] **Stable proportion :** [stable]/[14days_D_avg]	Structure
Influential Range	Shows how large the influential range of certain area is	**Travel distance : [sum(distance)]/[count(msid)]** **Coverage rate : [count(distinct O_pcq)]/5432** **Primary Index : max[OD_num]/max2[OD_num]**	Range
Temporal Variation	Shows the change of mobility strength according to time	**Day/night ratio :** [Avg_8-16_num]/[Avg_18-22_num] **Workday/Weekend ratio**:[Avg_wd_num]/[Avg_we_num]	Variation

Figure 3: Indicator System

Mobility strength shows the vigor of human activities in certain area, including crowd flux volume. We aggregate D points into 5432 census units and calculate their density, so crowd flux volume reflects how many people per km2 choose a certain census unit as a destination every day. Since crowd flux volume is strongly influenced by population density, we divide it with basic population of each census unit(stay more than 3 hours here from 0:00 to 6:00) and get crowd flux rate which reflects how many times is every-day visiting population larger than basic population here.

Mobility structure shows the main group of people visiting certain area. We divide visiting population of each census unit into three parts. If a user have O/D points which are no more than 4 days in two week, he/she will be identified as external population since he/she maybe a tourist or come Shanghai for business. If a user choose a census unit as a destination only once in two weeks, he/she will be identified as random population since he/she won't come here again in a relative long period of time. If a user choose a census unit as a destination more than 5 times in two weeks, he/she will be identified as stable population since he/she has a strong relationship with this place.

Influential range shows how large the influential range of certain area is. We calculate average travel distance of people visiting each census unit, the longer travel distance means the census unit can attract visitors from a larger range of area. Coverage rate presents the percentage of area a certain census has relationship with(more than 50 number of OD links). Primary index is introduced to judge whether travel from a census unit have a direction oriented connection with others.

Temporal shows the change of mobility strength according to the time. We calculate average crowd flux volume per hour from 8:00 to 16:00 as day volume and from 18:00 to 22:00 as night volume, then day/night ratio equals day volume divided by night volume. Also, we calculate average crowd flux volume in workdays and weekends, then workday/weekend ratio equals workdays volume divided by weekends volume.

4. Results

4.1 Mobility strength and structure

High mobility area in Shanghai can be divided into four grades according to their crowd flux volume (Figure 4-left): the first grade enjoys a visiting population larger than 100 thousand person per km2 such as the People's Square, Jingan Temple et al., the second grade has a visiting population between 60 to 100 thousand per km2 such as sub centers like , Daning, Wujiaochang, the third grade has a visiting population of 40 to 60 thousand person such as some community centers, and the fourth grade are several new towns like Songjiang, Jiading et al.. The distribution of basic population(stay more than 3 hours in a certain census units at 0:00-6:00) is similar to the distribution of resident population from the 6th National Population Census, with Pearson Correlation Coefficient reaching 0.699(Figure 4-middle). Employment center Lujiazui has the largest crowd flux ratio of nearly 12.0, indicating that the number of visiting population in Lujiazui is 12 times that of the basic population. Pudong airport, Hongqiao transportation hub and area along line 2 inside the inner ring road are obvious high value areas and crowd flux ratio in Chongming and the southeast of Shanghai is low(Figure 4-right).

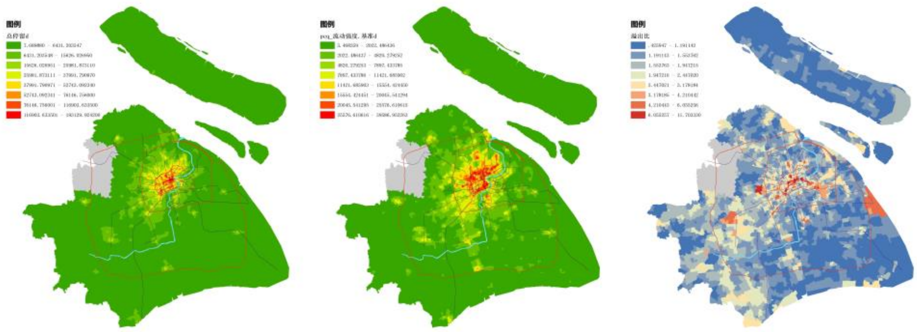

Figure 4: Crowd Flux Volume, Basic Population, and Crowd Flux Ratio

Combine crowd flux volume and ratio we can get comprehensive mobility strength of these census units in Shanghai(Figure 5). The areas with highest mobility strength in Shanghai are in turn: city center > sub center (high volume) and transportation hub (high ratio) > regional center > new town. Songjiang has higher mobility than other new towns, followed by Jiading, Baoshan, and Jinshan, while Nanhui new town has a low mobility.

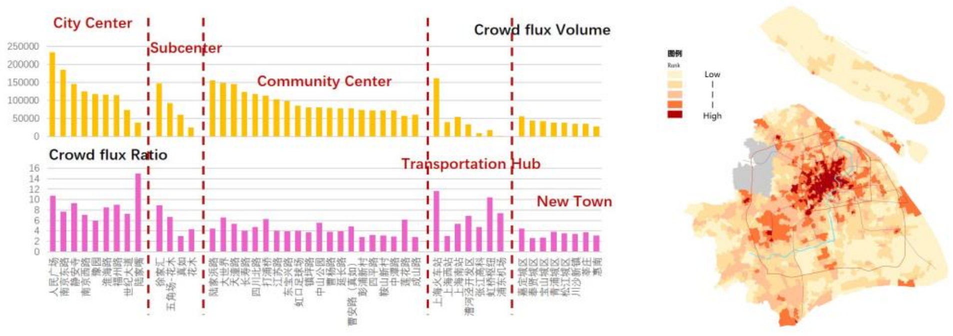

Figure 5: Comprehensive Mobility Strength

Hongqiao transportation hub has the highest external proportion, 27% of the visiting population is external population, external proportion of transportation hubs is obviously larger, and the second is the main employment center(Figure 6-left). The random proportion city center, employment center and transportation hub are relatively high, for example random proportion of the People's Square, Lujiazui and Hongqiao hubs are all over 55%(Figure 6-middle). Residential areas and outer suburbs with small visiting population have relatively high stable proportion. For example, Nanhui new town has extremely high stable proportion of 60%(Figure 6-right).

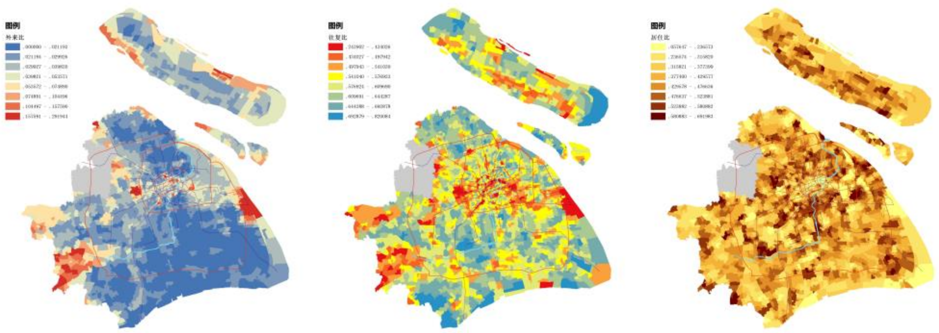

Figure 6: External, Radom and Stable Proportion

According to the proportion of the three groups of people, 5432 census units can be divided into random oriented type, stable oriented and basic oriented three types(since average external proportion in Shanghai is low compared with other index, we put external population into random population). The Figure 7 shows the distribution of these three types. It can be seen that there is almost no basic dominant in high mobility areas, so for these high mobility regions visiting population should be taken into consideration as well as resident population.

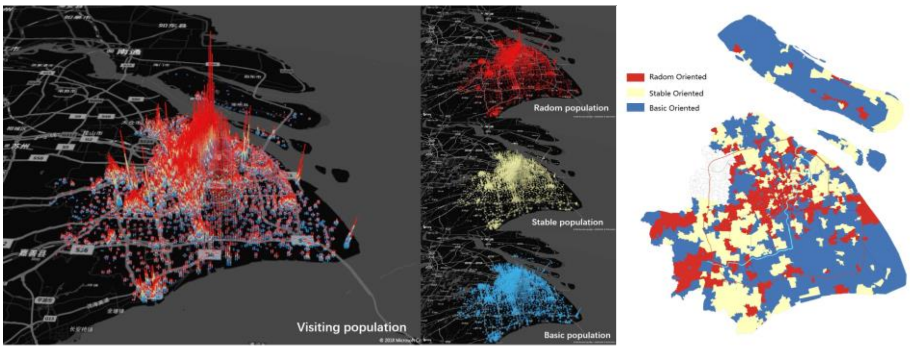

Figure 7: Comprehensive mobility structure

4.2 Influential area and temporal variation

The travel distance of transportation hub is longer, with Pudong airport reaching 18.8km. Areas inside the inner ring road have relatively short travel distance, while there are some exceptions such as the people’s square, Tiantong road, Lujiazui, and Xujiahui. These areas can attract visitors from an average distance of 5.5-6.5km(Figure 8-left). When it comes to the coverage rate, areas along Line 1, 2, 8 form a "cross high value area", Lujiabang Road has the highest coverage rate reaching 25.7%, which means it connects a quarter of census units in Shanghai(Figure 8-middle). Nanhui new town, Pudong airport and Changxing island have a high primary index, reaching 6.0, that is, the crowd flux of the largest OD link is 6.0 times the second large OD link(Figure 8-right). Primary index of employment zones is relatively high, indicating that the attractiveness of employment has a clear direction. Since primary index shows the special link between two areas, we won’t put it into the calculation of comprehensive influential range.

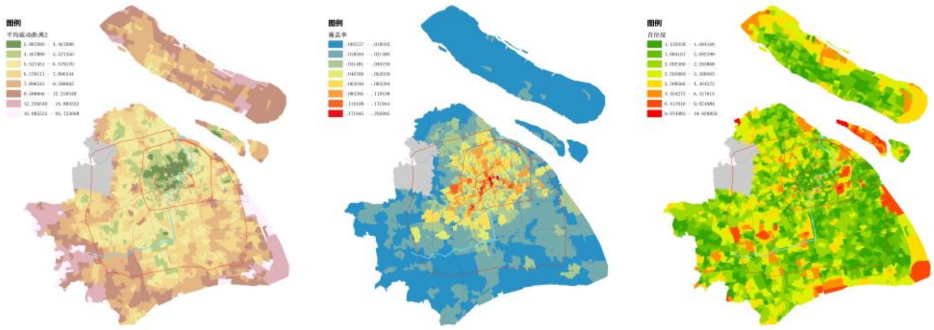

Figure 8: Travel distance, coverage rate, primary index

Combine travel distance and coverage rate we can define whether the influential range of a certain census unit is large or small. We can see from Figure 9 that influential range of suburban areas are the most extensive. The people’s Square, Lujiazui, Xujiahui, Shanghai Railway station inside the inner ring road have large influential range. The high value zone is banded and has strong coupling with metro lines, indicating that the metro station can indeed expand the influential range of areas nearby. Moreover, transportation hub and employment zones have a larger range, while the residential areas and community centers have a smaller range.

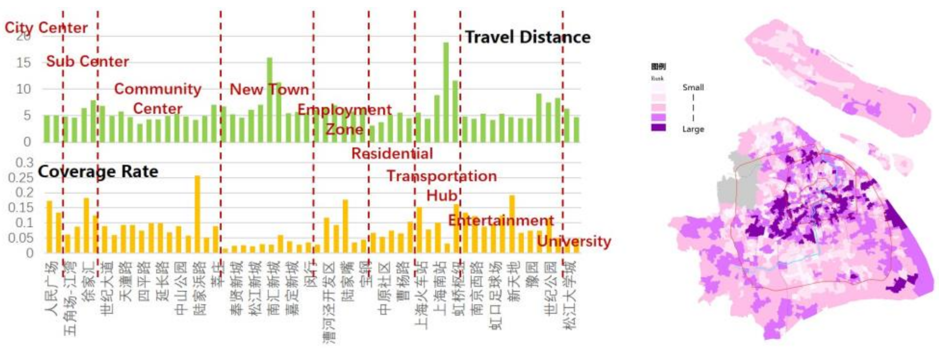

Figure 9: Comprehensive Influential Range

Caohejing Development Zone, Gucun Park, Town God’s Temple (employment center, view spot with opening time) are high in day and night, reaching 2.2 respectively, day/night ratio of city center is about 1.5, and day/night ratio of residential areas is about 0.9. Day/night shows a "high-low-high" distribution pattern from the central city suburb to outer suburbs(Figure 10-left). Workday/weekend ratio of Caohejing was the highest, its visiting population in workdays is 2.1 times as large as that of weekends. While workday/weekend ratio of sub centers and view spots is lower, such as Wujiaochang and Gucun park reaching 0.8(Figure 10-right). On weekdays, visiting population in the center city is slightly higher than other areas, and visiting population in employment zones are much higher than those of others. The comprehensive temporal variation of the central city and outer suburbs is relatively high, that is, the mobility strength of these regions varies greatly with time(Figure 11).

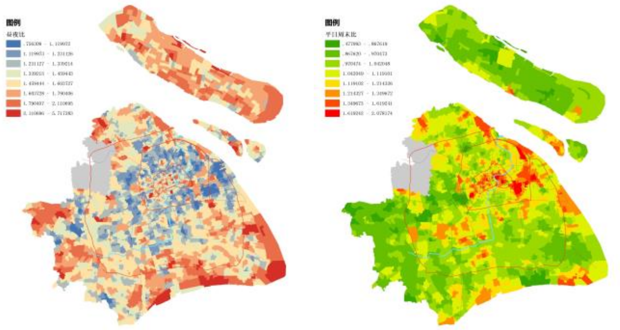

Figure 10: Day/Night Ratio and Workday/Weekend Ratio

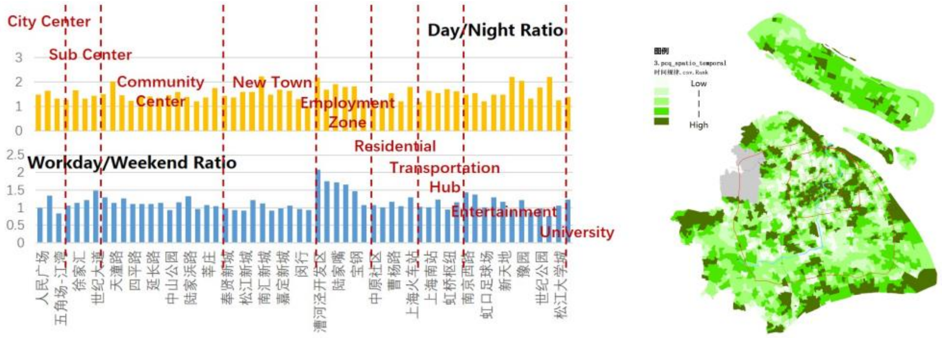

Figure 11: Comprehensive Temporal Variation

4.3 Spatial structure under view of human mobility

Figure 12 shows how we extract spatial features from four dimensions of indicators. The spatial structure under view of human mobility extracted from four dimensions of index is composed of four kinds of features: dynamic surface, from city center to subarea, shows the strength level of daily human mobility; dynamic center, including five center and eleven subcenter, becomes the most influential areas in the flowing network; dynamic cluster, can be divided into six groups according to the structure, influential range, and temporal variation of human mobility; dynamic corridor, strongly related to metro lines, highways, and Huangpu River, provides transportation supports for crowd flux.

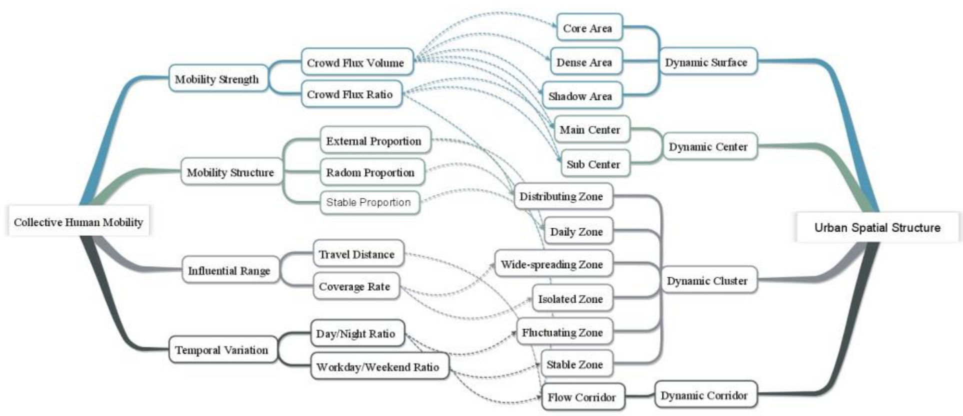

Figure 12: Spatial Elements Identification

Figure 13 shows the final spatial structure under the view of human mobility, we can see that the central city is mainly covered by core area, six dynamic clusters mainly distribute between the outer ring road and the beltway. New towns like Jiading, Songjiang and Qingpu are main mobility centers, other local community centers in suburbs compose sub mobility centers. The spatial distribution of dynamic corridor has strong relationship with metro lines and Huangpu river.

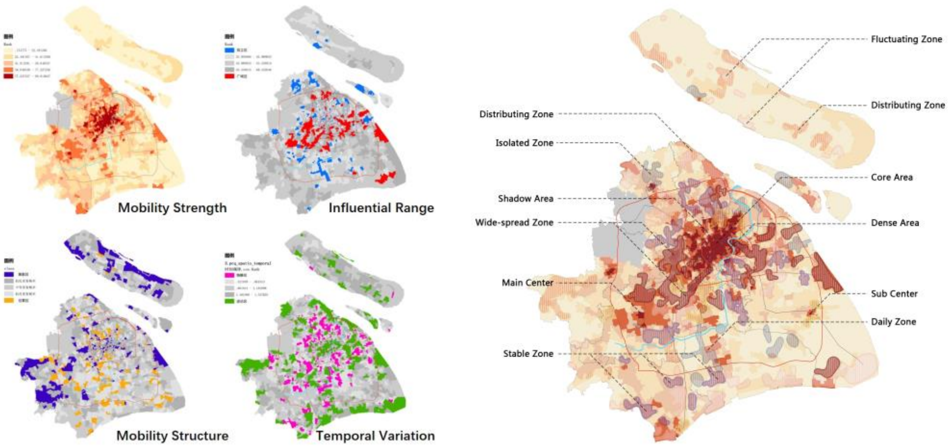

Figure 13: Spatial Structure under View of Human Mobility

5. Discussion and Conclusion

Urban spatial structure has been widely discussed in studies with conventional data. Recently, more and more scholars have used big data to conduct similar research. However, in Shanghai, the findings are mostly focus on human mobility pattern instead of the whole structure from collective human mobility view. In this study, we used cell phone data to provide some new findings about urban spatial structure, especially dynamic spatial distribution from crowd flux perspectives to make up the research gap in the context of Shanghai.

Four dimensions of indictors are employed to illustrate collective human mobility. New findings of this study suggest that:
(1)The visiting population associated with a census unit is about 5 times that of the resident population. The characteristic of collective mobility can be revealed using mobility strength, mobility structure, influential range, and temporal variation.
(2)The spatial distribution of mobility strength in Shanghai is in the form of "central hard core + suburb mobile center". Radom and stable population obviously larger than basic population in high mobility areas, so for these high mobility regions visiting population should be taken into consideration as well as resident population.
(3)From location perspective, influential range of suburb areas is the most extensive, high value zone is banded and relationship with metro lines is strong, temporal variation of edge areas in Shanghai is more obvious, and its spatial distribution presents "high-low-high" from the central city to outer suburbs. From function perspective, residential areas and local community centers have a smaller scope of influential range, mobility strength of employment centers and view spots varies greatly with time.
(4) Spatial structure can be extracted from four dimensions of indicators, which is composed of four kinds of spatial elements: dynamic surface, dynamic center, dynamic cluster, and dynamic corridor. The results can be further drawn into a spatial structure under mobility view showing the general rule and classification characteristics of urban space.

However, there are still some limitations exist and could be discussed in future work. Firstly, due to the limitation to data source, we only used two-week cell phone data in 2014 for study. The results may not have great significance to reflect current situation. Secondly, the predefined rule that we used to identify travel chain need further proved, different time and distance threshold may brings certain difference in results. Thirdly, the relationship between spatial structure under mobility view and traditional view needs to be analyzed quantitively. For further work, it is necessary to discuss the reliability and rationality of this measurement whether it is the most appropriate way to characterize different groups of visiting population. Moreover, detailed comparison should be conducted to find relationship between spatial structure under mobility view and traditional view in order to provide reference for the formulation of urban space policy and population management strategy.

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