Extracting Dynamic Urban Mobility Patterns from Mobile Phone Data

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Abstract. The rapid development of information and communication technologies (ICTs) has provided rich resources for spatio-temporal data mining and knowledge discovery in modern societies. Previous research has focused on understanding aggregated urban mobility patterns based on mobile phone datasets, such as extracting activity hotspots and clusters. In this paper, we aim to go one step further from identifying aggregated mobility patterns. Using hourly time series we extract and represent the *dynamic mobility patterns* in different urban areas. A Dynamic Time Warping (DTW) algorithm is applied to measure the similarity between these time series, which also provides input for classifying different urban areas based on their mobility patterns. In addition, we investigate the outlier urban areas identified through abnormal mobility patterns. The results can be utilized by researchers and policy makers to understand the dynamic nature of different urban areas, as well as updating environmental and transportation policies.

Keywords: Mobile phone datasets, Urban mobility patterns, Dynamic Time Warping, Time series.

1 Introduction

Identifying urban mobility patterns has been a continuing research topic in GIScience, transportation planning, and behavior modeling. Since the time-dimension is considered an important factor for most social activities, understanding the dynamics of the daily mobility patterns is essential for the management and planning of urban facilities and services [1, 2]. However, most of the previous research in this field is based on data acquired from travel diaries and questionnaires, which is a widely adopted data collection method when studying individual travel behavior [3]. Due to the limited number of people covered by travel diaries, these datasets fail to provide comprehensive evidence when studying the characteristics of the whole urban system, such as identifying clusters of urban mobility.

Meanwhile, the development of information and communication technologies (ICTs) has created a wide range of new spatio-temporal data sources (e.g., georeferenced mobile phone records), leading to research that focuses on characterizing urban mobility patterns from mobile phone datasets (e.g., the real-time Rome project at the MIT SENSEable City

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Lab[1]). Undoubtedly, mobile phone datasets opened the way to a new paradigm in urban planning, i.e., Real-time cities [4], as well as facilitating studies on behavior analysis and spatio-temporal data mining [5]. Researchers believe that urban structure has a strong impact on urban-scale mobility patterns, indicating that different areas inside a city are associated with different inhabitants' motion patterns [6, 7]; therefore, previous research has focused on extracting aggregated patterns in different urban areas from mobile phone data, such as hotspots, clusters, and points of interest (POIs) [8]. However, there has not been sufficient research on characterizing and classifying mobility patterns in different urban areas from a *dynamic perspective*, i.e., analyzing these patterns with respect to time. Although the extraction of aggregated patterns (i.e., hotspots and clusters) offers valuable input for maintaining the sustainability of urban mobility, it fails to provide sufficient information for understanding the "rhythm" of an urban system. The objective of this research is to go a step beyond the aggregation of individual mobility. We analyze the hourly patterns (time series) of mobility aggregation in different urban areas and demonstrate their differences. For instance, time series associated with a central business district (CBD) would be different from suburban areas. Exploring these patterns will be helpful for policy makers in understanding the dynamic nature of different urban areas, as well as updating environmental and transportation policies. Moreover, the methodology can also be applied to identify abnormal mobility patterns in some special districts, for example, a high crime rate area.

The analysis in this research is based on a mobile phone dataset from northeast China. We will measure the similarity of different urban areas based on a Dynamic Time Warping algorithm (DTW): this is a well-developed algorithm in the field of speech recognition and signal processing for matching two time series, but it has rarely been used for urban mobility modeling [9]. Next, we will classify the time series based on hierarchical clustering, which allows for the detection of outlier urban patterns. The results can also be used as a reference for residents' activities, including long-term choices such as where to live, and short-term choices such as daily activity scheduling.

The remainder of this paper is organized as follows: Section 2 describes related work in the areas of mobility modeling, mobile phone data analysis, and Dynamic Time Warping. Section 3 introduces the basic research design, including the description of the dataset and the methodology. Section 4 presents the data analysis, and we conclude this research in Section 5.

2 Related Work

2.1 Mobility Modeling and Mobile Phone Data

Modeling human mobility patterns has become an important research question in various fields such as Geographic Information Science, Transportation, and Physics. Much progress has been made regarding the theories, methodologies, and applications. Larsen [10] identified five types of mobility: 1) Physical travel of people (e.g., work, leisure,

[1] `http://senseable.mit.edu/realtimerome/`

family life); 2) Physical travel of objects (e.g., products to customers); 3) Imagination travel (e.g., memories, books, movies); 4) Visual travel (e.g., internet surfing on Google Earth); and 5) Communication travel (e.g., person-to-person messages via telephones, letters, emails, etc.). In this research, when referring to "human mobility" we mainly focus on characterizing the 1st category of human mobility (Physical travel of people).

Due to the widespread usage of mobile phones, several studies have been conducted with a focus on extracting the characteristics of human mobility from georeferenced mobile phone data [11]. Since individuals are atoms in an urban system, the spatio-temporal characteristics of an urban system could be viewed as a generalization of individual behavior; therefore, mobile phone data also provide new insights in analyzing the aggregated mobility patterns of phone users in urban systems. Researchers have identified two major perspectives when exploring human mobility patterns from mobile phone data [12]:

- **(a) Individual perspective:** This category of research mainly focuses on identifying individual trajectory patterns, which is related to the theme of pattern recognition in Physics and Computer Science. For example, Gonzalez et al. [13] studied the individual trajectories of 100,000 mobile phone users based on tracked location data for over six months, providing new input to understanding the basic laws of human motion. Song et al. [14] examined the regularity of human trajectories based on mobile phone data, and their results indicate that human mobility is highly predictive. Some researchers have combined the location information with social attributes of the phone users, such as with the social positioning method (SPM) [15]. Since the usage of mobile phones can affect the mobility patterns of their users, previous studies have also focused on the interaction between ICTs and human activity-travel behavior [16, 17].
- **(b) Urban perspective:** Cities can be considered complex systems that are constituted by different processes and elements [2]. The rapid development of ICTs not only provides a rich data source for modeling urban systems, but also resulted in inevitable changes in the spatio-temporal characteristics of urban mobility. Researchers have focused on the following two aspects when studying the development in urban and regional planning based on mobile phone data:
  - (i) Spatial division and morphology: For example, Kang et al. [18] investigated how patterns of human mobility inside cities are affected by two urban morphological characteristics, i.e., compactness and size.
  - (ii) Spatial clustering and spread: The study of hotspot clustering patterns has been addressed in many studies. In the real-time Rome project conducted by the MIT SENSEable City Lab, researchers studied the congregation of tourists and the gathering of people during special events[2]. Another similar project is "Mobile Landscape Graz in Real Time", which concentrates on the activity distribution of phone users in the city of Graz, Austria[3].

[2] http://senseable.mit.edu/realtimerome/
[3] http://senseable.mit.edu/graz/

The analysis in this research is conducted from the urban perspective. As stated in Section 1, most previous research has concentrated on exploring aggregated patterns when analyzing urban mobility from mobile phone datasets. Here we focus on the temporal patterns of urban mobility. We use DTW to characterize and classify the mobility time series associated with different urban areas, which extends previous research on spatial clustering and mobility spread. The DTW algorithm has been identified as one of the most useful methods to measure the similarity between two time series, which minimizes the effects of shifting and distortion in time [19]. Section 2.2 provides the background of DTW and its applications.

2.2 Dynamic Time Warping and Its Applications

One important research question regarding time series data is finding whether two time series represent similar behavior [20]. Traditional distance measures, such as Euclidean distance, are not suitable for measuring the distance between time series data. For example, consider two time series A[1,1,1,1,2,10,1,1,1] and B[1,1,1,1,10,2,1,1,1]: the Euclidean distance between A and B is $\sqrt{128}$. This is a fairly large number, which implies dissimilarity between the two given time series; however, the structures of the two series are actually very similar to each other. Therefore, researchers started to look for new algorithms to measure the similarity between two time series. Moreover, in the fields of Computer Science and Mathematics, researchers also used Discrete Fréchet Distance to measure the similarity between two curves [21]; however, this method is very sensitive to outliers and displacements [22], therefore it is not very appropriate for time series data. Here, Dynamic Time Warping (DTW) is proposed to find an optimal match between two given time-dependent sequences [23]. This algorithm has been well developed to measure the similarity between time series in various research areas, such as speech recognition, motion detection, or signal processing [24]. DTW has also been used for analyzing human trajectories and motion patterns, for example, Lee et al. [25] utilized DTW to classify the trajectories of moving objects.

Fig.1 represents the process of calculating the DTW distance between two example time series. First a DTW grid is constructed. Inside each grid cell a distance measure is applied to compare the corresponding elements (here we use absolute differences) of the two time series. In order to find the best match between these two sequences, one needs to find a path through the grid which minimizes the total distance; this is considered the DTW distance between the two series.

The biggest advantage of DTW is that one can obtain a robust time alignment between reference and test patterns with a high tolerance of element displacement [26]. It can also match series with different lengths, which is very useful for some applications such as handwriting recognition. However, sometimes DTW tends to over-distort the series to create an unrealistic correspondence between elements; therefore, it is applicable to set local constraints and global constraints on the path. This prevents very short features matching with very long ones [19].

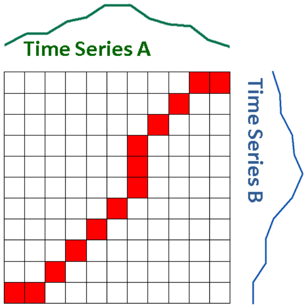


Fig. 1. DTW algorithm

As mentioned in Section 1, although DTW has been applied to analyze individual trajectory patterns, only a few studies have utilized this method to explore urban-scale patterns, most of which concentrate on remote sensing data [27, 28]. Researchers have proposed several other methodologies to compare two time series, such as Longest Common Subsequence (LCSS), but DTW has a high performance for series in which the same classes are best characterized by their shapes rather than their values. In this research we focus on the internal structure of the mobility time series instead of their magnitude. Since DTW can be used to warp the time series, it allows us to group similar mobility patterns together, even though the corresponding elements in the two series are not exactly aligned with each other (see example in Section 3.2). More specifically, here we will use DTW to measure the similarity of hourly population density trends of different urban areas. The results of the similarity measure will serve as the basis for urban classification and outlier detection. In addition, we will discuss the issue of comparing the mobility pattern of a reference area, i.e., a benchmark, to other urban areas.

3 Research Design

3.1 Dataset

The analysis is based on a dataset from city A[4] (acquired from a major mobile phone operator in China), which is a commercial and transportation center in northeast China. The dataset covers approximately one million mobile phone users (20% of the city population) and includes mobile phone connection records for a time span of 9 days (4 weekend days and 5 weekdays). It includes the time, duration, and approximate location of mobile phone connections, as well as the age and gender attributes of the users. Table 1 provides a sample record. The phone number, longitude, and latitude are not shown for privacy reasons. For each user, the location of the nearest mobile phone base tower is recorded both when the user makes and receives a phone call, resulting in a positional data accuracy of about 300m-500m.

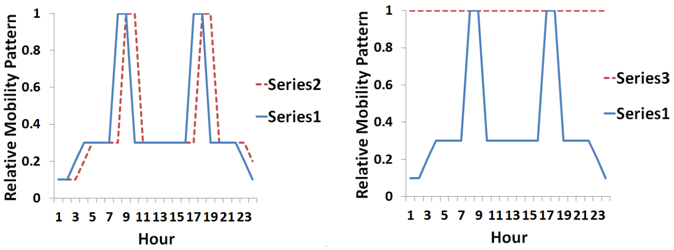
[4] The name of the city is not shown as requested by the data provider.

Table 1. Sample record from the dataset

Phone number	Longitude	Latitude	Time	Duration
1360*******	126.*****	45.*****	12:06:12	5mins

3.2 Methodology

As discussed in Section 2, we use DTW to measure the similarity of hourly mobility patterns between different urban areas. This algorithm allows us to group similar patterns together, as well as identifying outlier patterns. Due to the complexity of urban systems, it is highly possible that similar mobility patterns may have various forms in terms of their time dimensions. Fig. 2a shows two example series that are similar (series 2 is created from series 1 using the lag operator lag=1, the y axis of both figures are normalized to [0, 1] for simplicity). Both series have two peak time periods (one in the morning, the other in the afternoon). For comparison, Fig. 2b shows two series that are highly distinct from each other (series 3 is a flat series).



(a) (b)

Fig. 2. Example series: (a) Two similar patterns; (b) Two distinct patterns

The distances measured by DTW, Euclidean distance and the Discrete Fréchet Distance are presented in Table 2.

Table 2. DTW, Euclidean and Discrete Fréchet distance for example series

	Dis1 (Series 1 vs Series 2)	Dis2 (Series 1 vs Series 3)	Distance Ratio (Dis2/Dis1)
DTW	0.00208	0.31	149.04
Euclidean	1.41	3.33	2.36
Fréchet	0.70	0.90	1.29

As can be seen, the distance ratio indicates that DTW shows a much better performance of distinguishing different time series than the other two methods; therefore, it is a more useful method for researchers to quantify the similarity of dynamic mobility patterns.

In this research, the data analysis will be conducted in the following three steps:

3.2.1 Summarize Dynamic Population from Cell Phone Records

To summarize the dynamic mobility patterns in different urban areas, we first need to divide the study area into sub-areas. One option is to divide the study area into grid cells [18]; however, it is difficult to decide on the appropriate cell size. Moreover, it is highly possible that the number of base towers in each cell varies, resulting in higher mobility in areas with higher tower density. Therefore, we decided to divide the study area into Voronoi polygons based on the spatial distribution of cell phone towers (Fig. 3), and then to summarize the hourly phone call frequencies for each polygon. Each Voronoi polygon is associated with a time series to represent its hourly phone call frequency pattern. To further extract the number of people (i.e., active mobile phone users) in each cell, we eliminated the repeated phone calls made by the same user.

Note that all the numbers here are on an average daily basis. To normalize the results, each population count is divided by the size of the given polygon. Since the analysis for large polygons has relatively low spatial accuracy resulting from the low density of base towers in the surrounding area, we only perform the analysis for polygons smaller than 10 km^2. As indicated in Fig. 3, these polygons (highlighted) cover the majority of the downtown area.

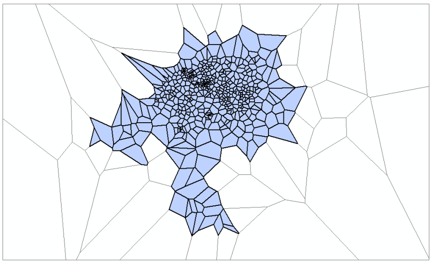


Fig. 3. Voronoi polygons smaller than 10km^2

Last, we calculate relative mobility patterns for each polygon. In relative time series, for each cell its values are divided by the maximum of the 24 hourly values. This standardizes the magnitude of data and also helps in further investigating the internal structure of each time series. Since the main focus of this research is not on the absolute value of each series, we use relative time series instead of the original ones to measure the similarity of mobility patterns between polygons.

3.2.2 Calculate DTW Distance Matrix

Based on the algorithm described in Section 2, we construct the DTW distance matrix for the relative time series associated with each of the selected Voronoi polygons. The output is a distance matrix D, in which D_{ij} represents the DTW distance between cell polygon i and j. We use a global constraint "Sakoe-Chiba band", which has a fixed windows width in both horizontal and vertical directions [23]. Here the window size is set to be 4, indicating that the maximum allowable absolute time deviation between two matched elements is 4 hours. This constraint helps to prevent unrealistic distortion in the time dimension, such as matching the evening hour patterns with morning patterns.

3.2.3 Analyze Urban Mobility Patterns Based on DTW Distance Matrix

Based on the DTW matrix, one can explore the dynamic patterns of urban areas from various perspectives, either addressing the “similarity” or “dissimilarity” of urban divisions. In this paper we will conduct two example analyses for both circumstances based on the distance matrix constructed in step 2. The first one focuses on mapping the mobility similarity to reference areas, whereas the second example concentrates on detecting outlier patterns. Note that to further clean up the data, polygons with zero-phone call frequencies are eliminated. The analysis is presented in detail in Section 4.

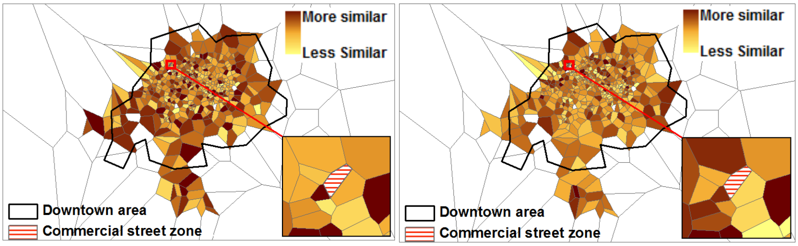
4 Data Analysis

4.1 Mapping the Similarity to Reference Areas

In urban studies, it is common for researchers to select one or more particular areas as case studies for data collection and analysis. Many of these studies are related to human mobility patterns, such as crime trends, traffic congestion, etc. Although there are usually many other control variables in the analysis, identifying the mobility similarity between a selected area (reference area) and other areas can provide references for further analysis.

Fig. 4 represents the similarity measure of mobility patterns between a reference polygon (marked red, where a major commercial street is located) and other urban areas. Dark brown color indicates a more similar mobility pattern (shorter DTW distance), whereas the light yellow color indicates a less similar one. As can be seen from Fig. 4, the average DTW distance on weekdays (2.73e-2) appears to be slightly smaller compared to that on weekends (2.85e-2) based on a paired two sample t test ($p<0.001$), indicating that the mobility patterns on weekdays are closer to the pattern in the reference area. A potential reason is that most human social activities during weekends (i.e., grocery shopping, leisure activities) do not have such strict time constraints as the ones on weekdays (i.e., go to school / work), so it is highly possible that there are more irregular patterns during weekends (further confirmed in the outlier analysis in Section 4.2). In addition, it appears that the polygons surrounding the commercial street show a more similar pattern to the reference area on weekends than on weekdays (see the zoomed-in subfigures of Fig. 4a, b), indicating a potential mobility correlation among those areas during weekends. This also represents the opposite of the general trend of the whole study area, where mobility on weekdays is closer to the pattern in the reference area. This indicates that spatial scale plays an important role in this analysis. However, in order to generate further conclusions for other urban study questions (e.g., traffic congestion), we will need additional socio-economic data to conduct additional correlation analyses. Fig. 4 is only a first step of measuring the similarity between different urban areas in terms of dynamic mobility patterns, and it provides an initial reference for socio-economic studies.

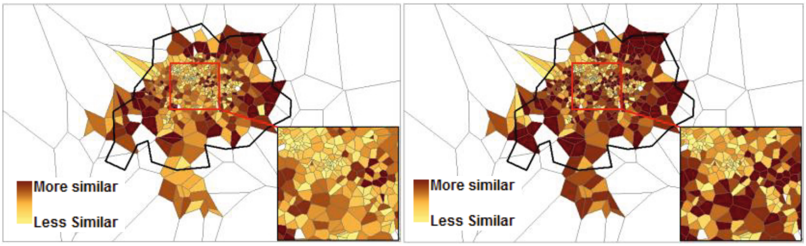
One can also define the reference (benchmark) series manually. For example, we define the benchmark series as [1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1], representing an evenly distributed mobility pattern during both day and night hours.



(a) (b)

Fig. 4. Mapping the DTW distance between reference area and other areas. (a) Weekdays; (b) Weekends

Fig. 5 shows the distribution of DTW distances between the benchmark series and the study areas. This method is very useful for interpreting the internal structure of dynamic mobility patterns for a particular cell polygon. In this case, polygons with a smaller DTW distance have more evenly distributed mobility patterns.



(a) (b)

Fig. 5. Mapping the DTW distance between a benchmark series and other series. (a) Weekdays (b) Weekends

As can also be seen from the histogram (Fig. 6), in the first three groups (DTW distance < 0.2), there are more polygons on weekends than on weekdays, indicating that the mobility patterns on weekends are closer to an evenly distributed pattern. This is consistent with common sense that activities during weekends have less time constraints.

Similarly, we can define other benchmark series. For example: [0,0,0,0,0,0,0,1,1,1,1,1,1,1,1,1,1,1,1,0,0,0,0,0] represents a pattern that expresses the fact that there is only one peak during the day. Note that the numbers in benchmark series can be any value between 0 and 1, and it is not necessary to use binary values. The principle here is similar to the studies utilizing DTW to detect a particular hand-writing style or speech tone pattern. By matching pre-defined benchmark series with study areas, we can investigate various patterns that are of interest.

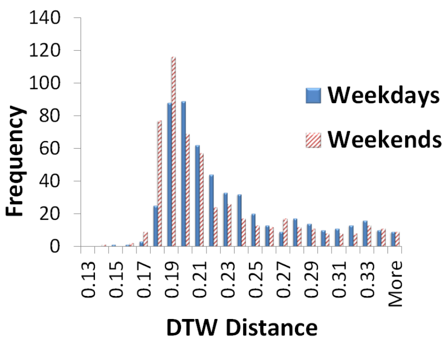


Fig. 6. Histogram of DTW distance for weekdays and weekends

4.2 Outlier Detection

As discussed in [29], outlier mining techniques can be used to investigate abnormal activities such as traffic accidents. From a broader perspective, since urban-scale mobility patterns are strongly affected by the urban structures, identifying abnormal mobility patterns can be helpful for researchers and policy makers to investigate the functioning patterns of different urban areas, as well as optimizing the distribution of urban services (e.g., Police patrol). Moreover, this technique can also be applied to detect potential incidents by comparing given patterns in a certain area to its regular pattern. Therefore, in the second analysis we explore outlier detection based on the DTW distance matrix discussed in Section 3. Our objective is to identify cell polygons with abnormal mobility patterns. Since hierarchical classification can operate directly on the distance matrix, we adopt this method to classify the mobility time series. The algorithm is defined in Fig.7.

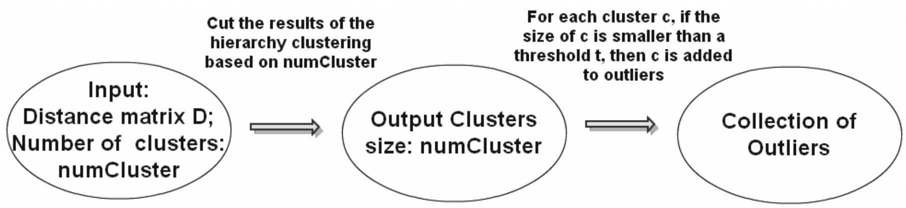


Fig. 7. Outlier detection algorithm

There are several methods to set the number of clusters in hierarchical classification; however, this value is often affected by specific application scenarios. As an example analysis, here we adopt the criteria discussed in [30], where numCluster = max(2; sqrt(n/2)), n is the number of entries, and threshold t is defined as 3.

In the classification, we detected 15 outliers for weekdays and 18 for weekends. All the other cells are aggregated into one class. To further investigate the structures of the outlier series, we first define what a typical "normal series" looks like. Fig. 8

shows an average series for both weekdays and weekends after removing the outlier polygons. As can be seen, a normal series has two mobility peaks each day: one is around 9am; the other is around 6pm. The mobility density reaches the lowest point between 2-4am. This is consistent with common sense. On weekends the mobility density is slightly higher during night hours in this case, but there is no substantial difference between weekdays and weekends regarding the average patterns.

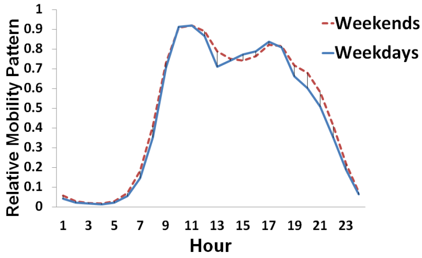


Fig. 8. Average normal series

Fig. 9 shows the results of the outlier detection. The detected outliers are marked red, other cell polygons are marked light blue. We can see that there are slight differences between weekdays and weekends.

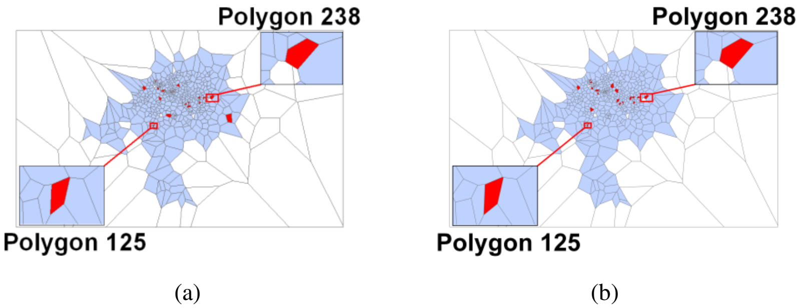


Fig. 9. Outlier polygons. (a) Weekdays; (b) Weekends

As a comparison, Fig. 10 shows two example outlier time series (zoomed-in polygons in Fig. 9). Referring back to the landmarks on Google Map[5], the plot leads us to the following hypothesis to explain the abnormality of the areas:

In polygon 238 there are many night clubs and other leisure facilities for night hours. This may explain the abnormal high density rate after midnight. Since there is a big international trade center only open during weekdays, this possibly explains why the mobility during daytime is not consistent with regular work hours on weekends.

[5] `http://maps.google.com`; The map with landmarks is not shown as required by the data provider.

In polygon 125 there are several community colleges and training schools. There are not many night clubs in this area. The mobility density continues to be high between 8am and 8pm on weekends, indicating a noticeable difference in mobility patterns between weekdays and weekends.

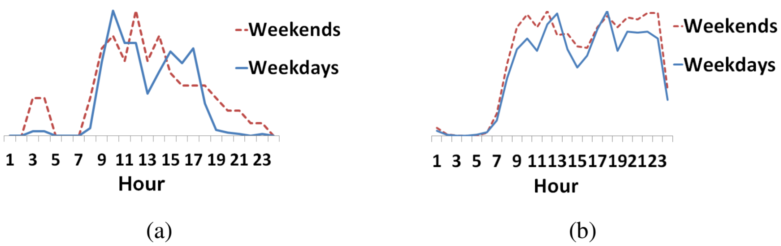


Fig. 10. Outlier patterns. (a) Polygon 238; (b) Polygon 125

Additional information is needed to test the above hypothesis, which is not the focus of this research. Generally, the above provides us with a novel method of detecting the abnormality of urban mobility patterns, as well as a better understanding of the "pulse" of a particular city.

5 Conclusion

This research focused on investigating the dynamic mobility patterns of urban areas. We demonstrated that DTW is a highly effective method for exploring the similarity / dissimilarity of urban mobility patterns. The results indicate that the study area has the highest mobility density around 9am and 6pm, and this pattern exists for both weekdays and weekends. We also looked into the internal structures of the abnormal series. In addition, we provided a method to examine the similarity between a benchmark series and study areas based on the DTW distance matrix. The outlier detection method discussed in Section 4.2 can also be used to identify abnormal mobility patterns in future urban studies, as well as providing reference for transportation and urban planning.

This research provides us with new insights for modeling the changing mobility patterns for urban areas. Here we used Voronoi polygons to divide the study area, in future studies we will use grid cells (500m*500m) and compare both results. Moreover, in this paper the data is segmented into 1 hour granularity. It would be interesting to investigate how different temporal granularities impact the results. Age and gender factors of phone users should also be included in further studies. Another potential direction for future research is to investigate how the predefined local and global constraints affect the DTW distance and classification results. The methodology discussed in this paper can be applied to other cities. Moreover, DTW can also be used to examine individual mobility patterns of phone users (i.e., characterizing user trajectories based on the abnormality of visited areas).

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