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# Aggregated versus Individual Passenger Traveling Patterns in Urban Metro System

**Jian Ma[1], Juan Chen[2], Siuming Lo[3]**
[1]National United Engineering Laboratory of Integrated and Intelligent Transportation, School of Transportation and Logistics, Southwest Jiaotong University, Chengdu, China
majian@mail.ustc.edu.cn
[2, 3]Department of Architecture and Civil Engineering, City University of Hong Kong, Hong Kong SAR, China
juanchen6-c@my.cityu.edu.hk; bcsmli@cityu.edu.hk

***Abstract*** **-** Data of the automatic fare collection system of the city Shenzhen in China was analysed to extract passenger traveling distance and the corresponding dwelling time for each passenger in the metro system, so as to compare passenger trip patterns at both aggregated and individual level. It is found that the traveling distance pattern transit from exponential decaying at short distances to power-law scaling decaying at long distances. Further analysis indicates the passenger volume plays an important role in affecting the dwelling time, which forms the special distance distribution. At individual level, passenger trip features, including the day-to-day traveling distance distribution, as well as inter-travel time distribution have been investigated. Results indicated that although passenger entering and exiting the metro station show a time-clusterized behaviour at aggregated level, we can hardly find any universal pattern for individual trips. Further quantifying a relatively long-time traveling features of the passengers, we can see that some of the passengers are characterized by a regular or quasi-periodic behaviour in time; some others are characterized by Poissonian behaviour.

***Keywords*****:** aggregated passenger traveling pattern, individual traveling pattern, urban metro transportation, trip analysis

## 1. Introduction

Uncovering spatiotemporal human traveling pattern in urban areas is of fundamental importance to the planning, designing and management of urban transportation system. Recently, the development of modern tracking technologies make it possible to track daily movement of large amount of people, various data, e.g., GPS records from mobile equipment [1] and the trajectories of bank notes [2], have been used to analyse aggregated human traveling patterns. Results of the displacement distribution, the inter-event time distribution indicate that human traveling pattern exhibit approximately power-law characteristics. However, the scaling of human mobility by single transportation mode is exponential rather than power-law Lévy flight pattern [3]. This may resulted from that real daily commuting is accomplished by several different transportation modalities [4]. By decomposing the commuting trip into different classes according to different transportation modes, a recently proposed mixture model could reproduce the empirically observed Lévy flight pattern [5]. That is to say, individual level of trip pattern cannot be directly inferred from aggregated ones. Thus the present paper focuses on both aggregated and individual level of passenger trip pattern to refine our understanding of human traveling pattern in metro transportation system.

The rest of the paper is organized as follows. Data used in this study will be firstly introduced in Section 2. Section 3 comes to the main result of the aggregated level and individual level of traveling patterns and the discussions. Section 4 presents the concluding remarks.

## 2. Data description

The automatic fare collection (AFC) system was designed for revenue management in metro transportation system, thus each smart card in this system has a unique sequential number. This number can be used to extract and reconstruct passengers trip records. In the present study, AFC data from Shenzhen metro lines were studied. In Fig.1 we show a scheme of the Shenzhen metro system, which is composed of in total five lines, namely, the Huanzhong line, the Longgang line, the Longhua line, the Luobao line and the Shekou line. There are 131 metro stations, of which 13 stations are line transfer stations for passengers. Distance between each neighbouring stations was measured manually from Baidu online Map.

The daily passenger volume of Shenzhen Metro system was about 1 million in the year 2013. We extracted the data for the entire October of 2013 to build the data set. The reason we choose this month is that there is a National Day Holiday from 1 Oct to 7 Oct, thus the total amount of passengers using metro system is relatively larger than other months. On each day, there were about 1.15 million trip records. The sequential number information of these records were used to reconstruct passenger trips.

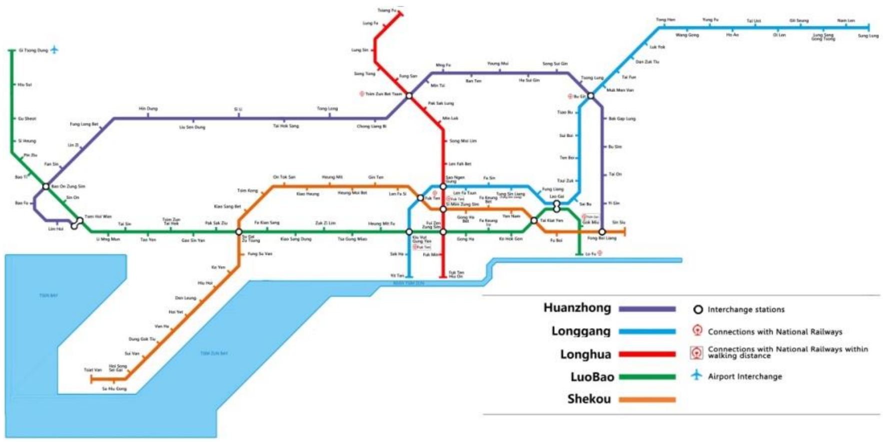


Fig. 1: Scheme of Shenzhen metro lines.

## 3. Results and discussion

Passenger trip pattern at both aggregated and individual level will be explored and discussed in this section. With the above mentioned data sets, we firstly extracted the traveling distance, as well as the corresponding dwelling time, for each passenger from his/her origin to the destination. With the trip data, passenger trip patterns in metro system at an aggregate level has been investigated. Then, we calculated the inter-arrival time for successive passengers in some stations to explore the passenger arrival feature. At last we identify the traveling records for different passengers for one month, and analyse their trip mode.

### 3.1. Aggregated passenger traveling pattern

Spatiotemporal mobility features of passengers in metro system was firstly analysed and shown in Fig.2. In Fig.2a we can find the traveling distance distribution in Shenzhen. It can be found that the number of passengers, whose traveling distance were smaller than 25km, decays exponentially with the increase of the traveling distance. Once larger than 25km, the decaying factor changes dramatically. It show a power-law scaling decaying features. The transit from exponential decaying to power-law scaling decaying may result from the inter-line transfer behaviour. As can be found in Fig.2b, the relationship between dwelling time and the corresponding traveling distance show there is an upper speed limit for passengers in Shenzhen metro system. When traveling distance is smaller than 25km, we can see that the speed value is about 11.54m/s, i.e., about 40km/h. This speed was the metro train speed for most of the lines in Shenzhen. When the traveling distance is larger than 25km, we can see that the speed limit gradually drops. The reason for this feature is passengers have to changes lines to get to their destination. The line-transfer in station is accomplished by walking to another level of floor, which may cost several minutes. In the case rush hour, the line-transfer would cost even longer time. Thus the dwelling time goes up, however the traveling distance along the metro line remains the same.

We then explore the dwelling time distribution and show the result in Fig.3. As can be found in Fig.3, almost all (99%) of the passengers can archive their destination in about 1.5h. About half of the passengers can arrive in about half an hour. It can also be found that a few passengers spend over 4h in the metro system, however, their traveling distance is only a few kilometres.

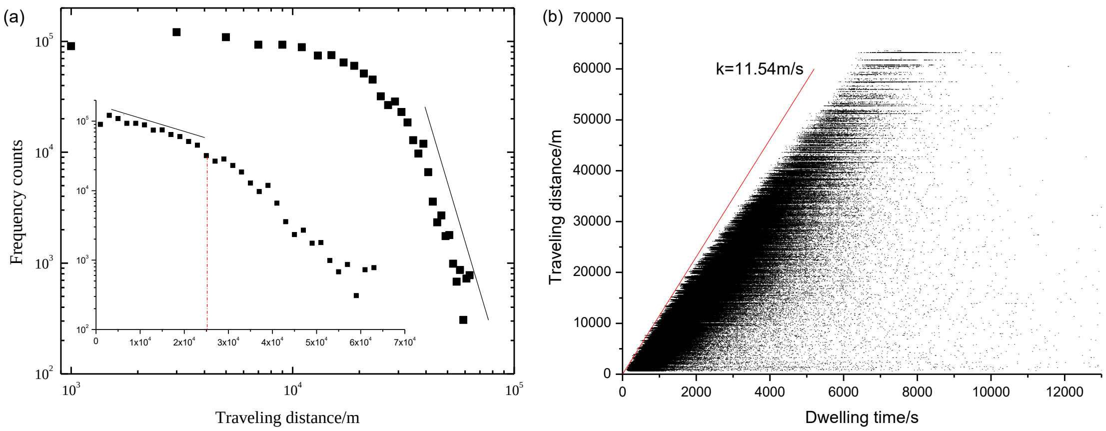

Fig. 2: Spatiotemporal mobility features of passengers in metro system.

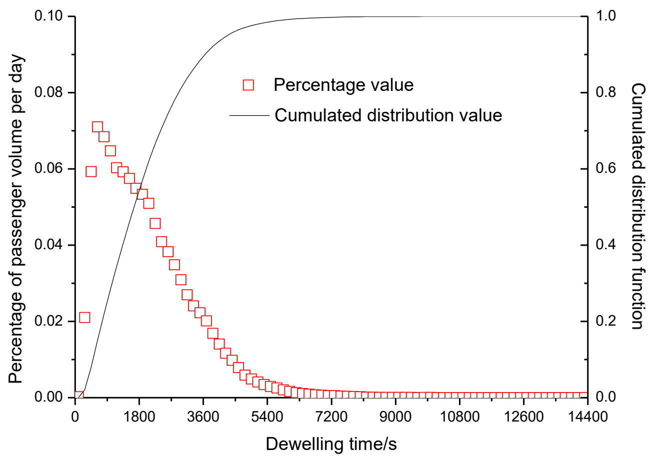

Fig. 3: Passenger dwelling features in metro system.

To further quantify passenger arrival at and leaving from station features, we plotted inter-arrival time for successive passengers in Fig.4. Surprisingly, both of these feature show a pow-law scaling mode rather than exponential distribution. This means passengers entering and exiting the metro station are not independent, but with a time-clusterized pattern, i.e., most of the time, the time interval between successive passengers would be very small, with only few occasions of large gap.

### 3.2. Individual passenger traveling pattern

Now that at aggregated level, passenger trips show special patterns, can we deduce individual trip pattern from the overall movement pattern? We further extracted AFC records of different passengers in October, and summarized the corresponding traveling distance distribution. As typical examples, results for two different kind of traveling pattern were shown in Fig.5. For the 1$^{st}$ passenger shown in Fig5a, he moves in between different station in this month, and statistically his movement show a near-Poissonian feature. However on contrast, the other person shown in Fig.5b moves only between two stations, meaning his movement is regular or quasi-periodical. Summarizing these different patterns, we can hardly find one universal pattern for all individual trips. That may indicate the aggregated pattern are emerged and cannot be used to predict individual traveling pattern.

## 4. Conclusion

Passenger trip pattern at aggregated and individual level were investigated by using automatic fare collection records from Shenzhen metro system. At aggregated level, the passenger traveling distances distribution show a transition feature, while on contrast, individual trip patterns indicate aggregated trip pattern cannot be used to predict individual traveling patterns.

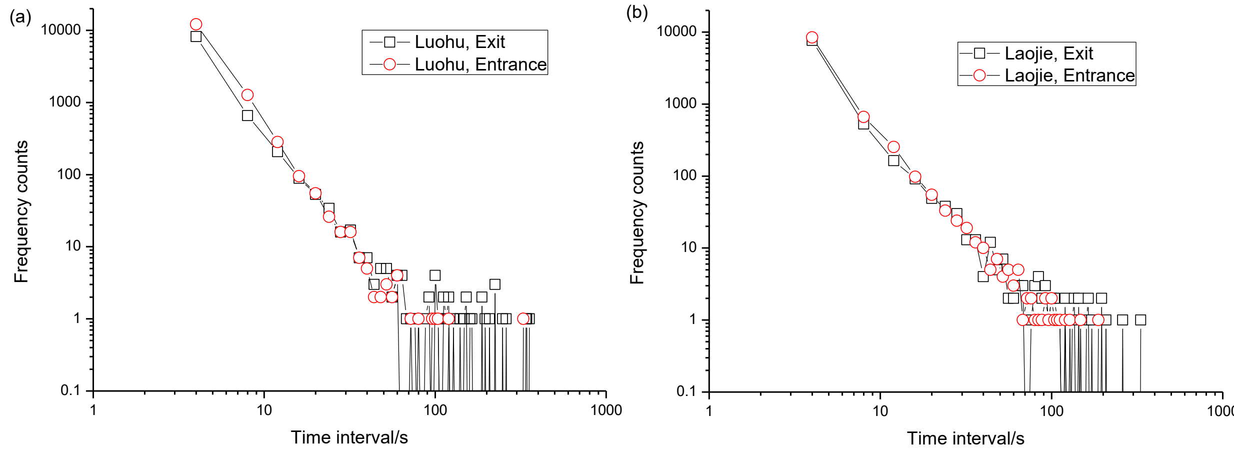

Fig. 4: Passenger exit and entrance features for different metro stations.

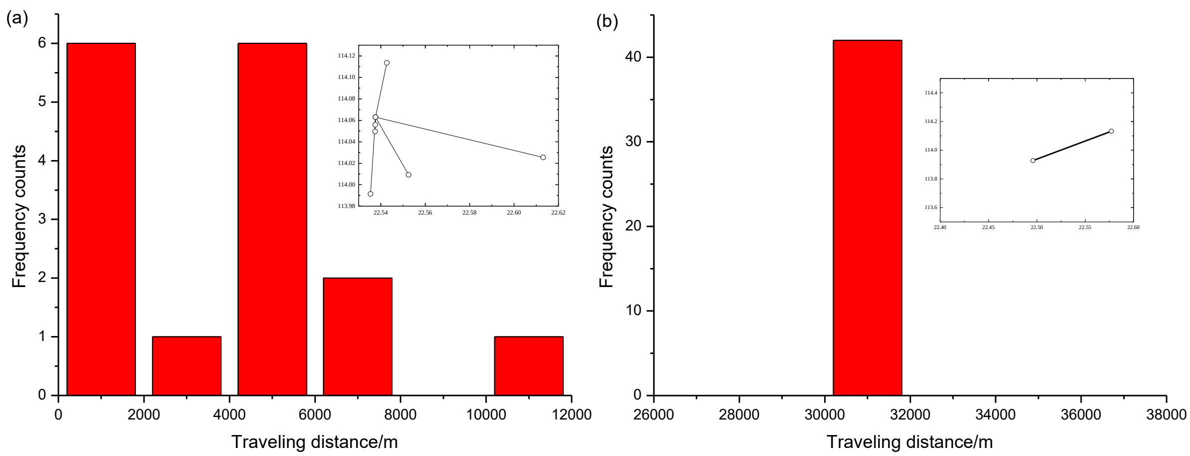

Fig. 5: Individual traveling distance distribution and the corresponding mobility pattern.

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