Exploring spatiotemporal features of station-free bike sharing trips: case study of Shenzhen

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Abstract

The emerging station-free bike sharing schemes create large quantities of spatio-temporal data and provide opportunities for urban and transportation studies. These schemes are different from traditional city rental schemes (they have no docking stations, etc.). They have at their core a continuous GPS system and generate large amounts of spatially located data for each bike. This study proposes a method to identify the origin and destination of cycling trips. Using Shenzhen as a case study, this research shows how evaluating cyclist mobility patterns allows a better understanding of urban dynamics.
Keywords: Mobility, Big data, Bike Sharing, Transportation

1. Introduction

Bike-sharing systems have been deployed in many cities around the world to encourage the usage of bicycles as an eco-friendly complementary to other mass transit systems. Traditional bike sharing systems typically allow individuals to rent a bike at a rental station, and return it to any stations in the system (DeMaio, 2009; Raviv et al., 2013). With the development of the Internet of Things, station-free bike sharing (SFBS) has emerged, and is replacing traditional bike schemes rapidly. SFBS allow users to search for and rent nearby bicycles through smartphone app; at the end of the trip, users can lock the bicycles in any legal park space. The number of SFBS bicycles in Chinese cities reached 200,000 by the end of 2016. Without the constraints of bike stations, SFBS users can make bike trips closer to their real cycling needs. SFBS bicycles equipped with GPS units produce spatiotemporal data in large quantities. Exploring this big data has the potential to shed light on people's cycling and mobility patterns, and to support bottom-up transportation policy making and urban planning. At the core of research and data analyses of traditional bike rental schemes research are the borrowing and returning records at docking stations (O'Brien et al., 2014; Faghih-Imani et al., 2014). As yet there are no methods for analysing SFBS data and very little research (none to our knowledge) has explored SFBS data in urban and mobility studies. This paper proposed a framework to obtain, process and analyse SFBS data. Various spatio-temporal characteristics of cycling in Shenzhen, China are also identified as a case study.

2. Study area and Data

Shenzhen is the southern mainland China's major financial and high-tech centre with a Population of 11.38 million (by 2015). Shenzhen has a southern subtropical monsoon climate, warm and suitable for cycling in all seasons. There are more than 300,000 SFBS bicycles in Shenzhen by January 2017.

Mobike is one of the top two station-free bike sharing company in China, more than 135,000 Mobike bicycles have been deployed in Shenzhen (by March 2017), which is one-third of the local SFBS market share. All Mobike bicycles are equipped with GPS units and connects to the Internet. Therefore, bicycles are able to provide their real-time location to users and operators. To start a Mobike trip, users can search for nearby vacant bicycles through the smartphone app, then unlock the bike by scanning provided QR code (Quick Response Code). When ending the ride, users park the bikes in legal parking space near destination (public bicycle rack or any publicly accessible location that does not obstruct the traffic flows).

In this study, data are obtained by web crawlers which cyclically searched for current vacant sharing-bicycles in specific locations through the Mobike API. The web crawlers are able to search whole Shenzhen for approximately every 15 minutes. Each obtained record contains following attribute: Time, Bike ID, Bike Model Type, Latitude and Longitude (Table 1). According to Chinese policy, the coordinates have been transformed into GCJ02 coordinate system. When transforming to WGS84 coordinate system, there exists an error range from several to tens of metres.

Time	**Bike Model Type**	**Bike ID**	**Longitude**	**Latitude**
2017-03-21 15:51:31	2	7556086534	113.884947	22.857296
2017-03-21 15:51:31	2	7556118647	113.884821	22.857602
2017-03-21 15:51:31	1	7556073013	113.884901	22.857159
2017-03-21 15:51:31	2	7556028900	113.884769	22.85755

Table 1: Examples of data.

Short-term or daily weather conditions have been proved to have an adverse impact on bicycling commuting (Nankervis, 1999). In order to exclude the impact of weather, bike data in three cloudy and sunny weekdays (2017/3/21,2017/3/23 and 2017/3/28) are examined, the daily average temperature are 25℃, 22℃ and 22℃ respectively, which are all suitable for cycling. A total of 135,914 bicycles' spatio-temporal information has been obtained.

3. Method

Because web crawlers can get the location of vacant bikes at different times with relatively short time interval, bike trips can be detected by examining bicycles' position change. Arrange data records by Bike ID and Time, then calculate neighbouring records' Euclidean distance; if the distance exceeds the threshold value, then the contiguous two records with same bike ID are linked as a trip OD (origin and destination) record. The former record's coordinate is the origin, and the later record provides the destination information. A trip OD record includes following attributes: bike ID, Time1, Time2, Origin Coordinate, Destination Coordinate and Trip Distance(Euclidean). Time1 and Time2 highly depend on the time of web crawler detecting bicycles, so they are not completely accurate trip starting and ending time. To exclude the impact of GPS signal error and the Chinese GCJ02 coordination transformation error, threshold value of trips distance was set to 150 metres in this study.

4. Preliminary Analysis

Hourly bike trip numbers were counted and shown in Figure 1. In weekdays, bike trip numbers rise sharply from 6:00 to 7:00 and then declines over the Morning rush hour (7:00-9:00). The afternoon rush hour (ARH) starts at 17:00 and lasts for two hours. The number of bike trips drops-off slowly over the evening. Figure 2 shows the distribution of cycling trip distance (Euclidean distance between origin and destination). The most popular ride distance is 350-600 metres, after which, the number of trips decreases exponentially. It should also be noted that Euclidean distance is usually shorter than real journey distance.

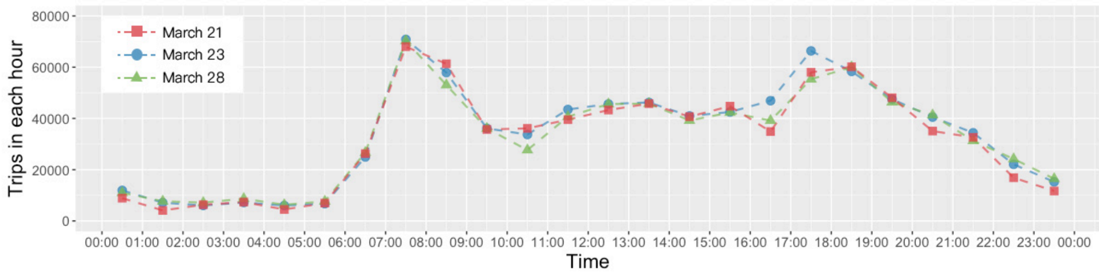

Figure 1: Number of trips in each hour during weekday.

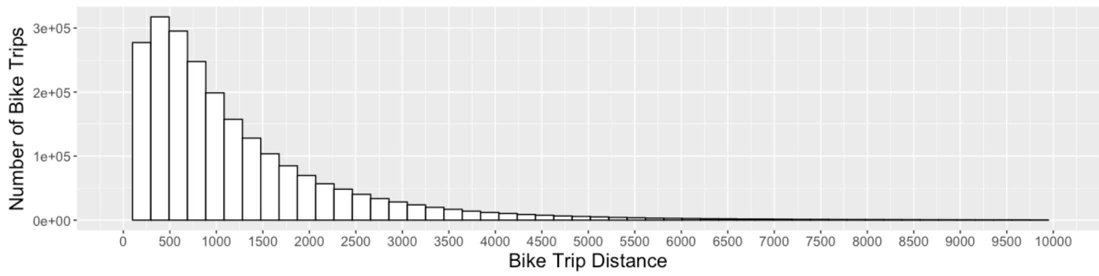

Figure 2: Bike trip distance distribution.

In order to analyse the spatiotemporal features of SFBS trips, this paper divided study area into a grid of 500*500 metres. Figure 3 shows the count of MRH and ARH bike trip origins and destinations in each grid, and various patterns were found. For example, metro stations attract a lot of commuting cyclists, making large numbers of bike trips start/end near metro stations. This concentration indicates that SFBS plays an important role in "bike + metro" travel mode, also as a popular "first/last mile" solution.

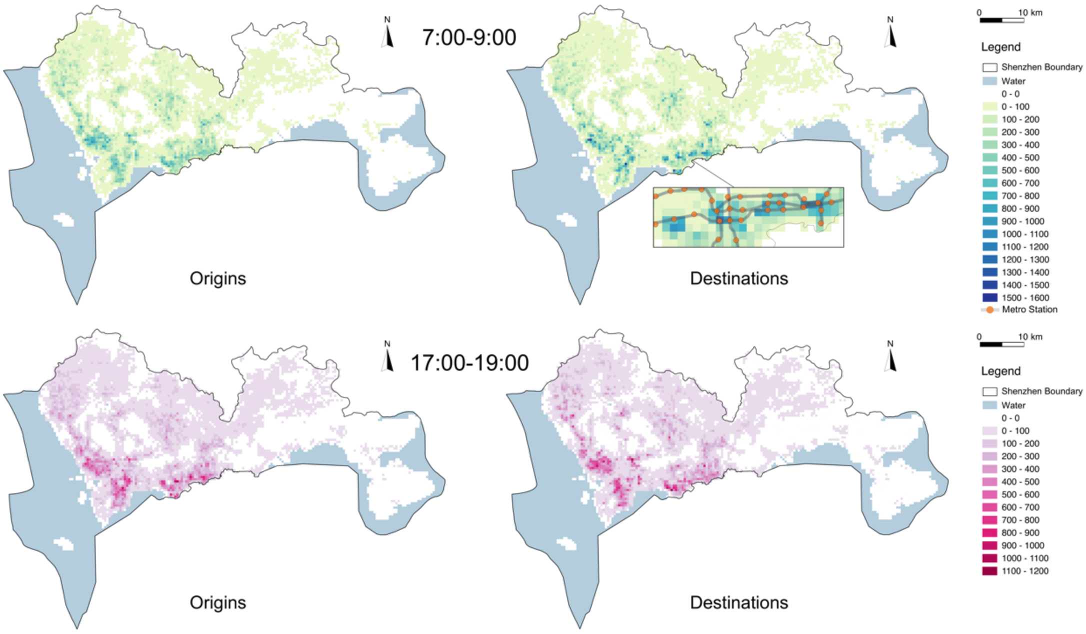

Figure 3: Distribution of origins and destinations in MRH and ARH.

Figure 4 shows the result of the number of MRH ride origins minus the number of ARH ride destinations in each gird. Combining with Land-use information, Figure 4 reveals that some residential areas, such as residential areas close to Foxconn plant (blue cells below), contribute a lot of rides in the morning. But residents did not follow the same route to come back home by bike in ARH. On contrast, more bike trips end in commercial areas(orange) in ARH.

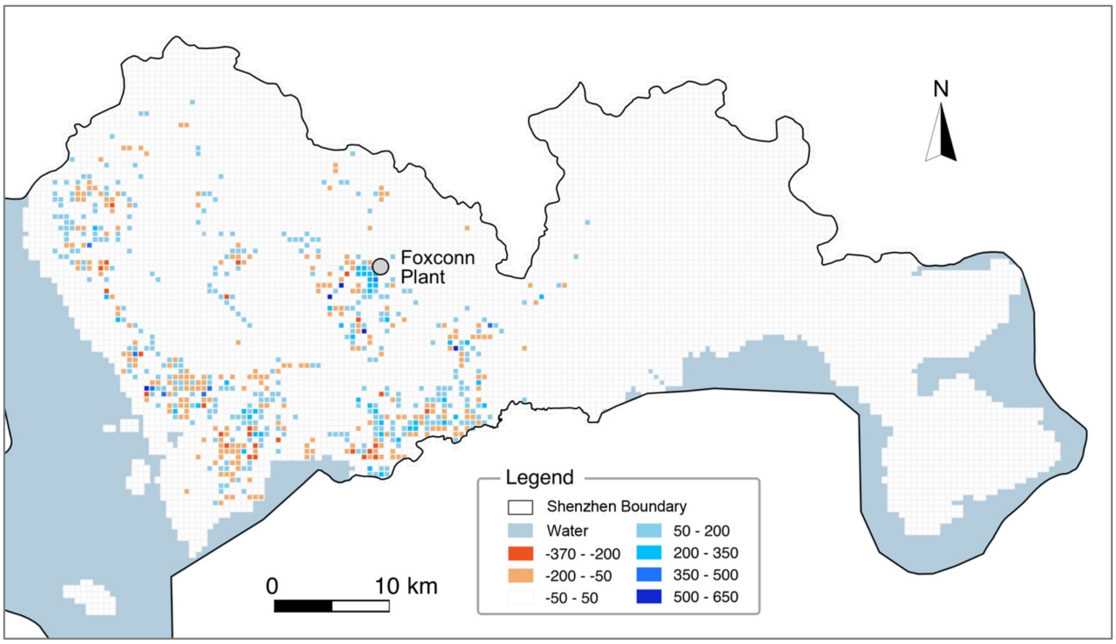

Figure 4: Distribution of MRH ride origins minus ARH ride destinations.

5. Discussion and Outlook

Using the SFBS data collected in Shenzhen, this work presents a framework for processing and analysing this new kind of data. Various of mobility and regional characteristics can be revealed by examining cycling flows. Future work will link SFBS data with Smart Card Data of metro and bus system to gain a better understand of the mass transit system, also get the whole image of flows in cities.

6. Acknowledgements

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