Abstract: Understanding the dynamics of the inhabitants’ daily mobility patterns is essential for the planning and management of urban facilities and services. A system for real time monitoring of urban mobility patterns can measure the daily mobility patterns of citizens and evolution of these patterns with social-economic and land use changes. This paper reports on the Urban Mobility Landscape System (UMLS) in South China where has experienced rapid growth of economics, population and urban scale in last 30 years. The project used the multiple real time data sources (5,000 floating car GPS data and 5 million smart card data for both bus and metro) for the real time evaluation of urban mobility dynamics. This research reports on exploring real time analytical methodologies for spatio-temporal data of inhabitant daily travel patterns in a real metropolitan urban environment. The research objective is to spatially and temporally quantify, visualize, and examine urban mobility patterns to provide real time decision support for the city. In terms of spatiotemporal analysis, 3D visualization helps to qualitatively analyze the spatio-temporal patterns for inhabitant movements. And cluster technique is adopted to qualitatively analyze the trip relationship between different locations, relationship between daily travel and land use and to calculate the pendulum value of daily travel. The research results show that the system provides more accurate and dynamic method to understand daily urban mobility patterns and explore the relationship for mobility with land use, social-economic changes. For the first time a large dense urban area, which covered most of the city of Shenzhen, was monitored in real time using a variety of sensing systems - hopefully opening the way to a new paradigm to understand and optimize urban mobility dynamics by providing integrated urban mobility patterns in real time.

Keywords: urban mobility landscape, intelligent transportation system (ITS), GPS, smart card, visualization

1. INTRODUCTION

The city never sleeps. The human movement constitutes the pulse of the city. Observing and modeling human movement in urban environments is central to traffic forecasting, understanding the spread of biological viruses, designing location-based services, and improving urban infrastructure. However, little has changed since Whyte (1980) observed in his "Street Life Project" that the actual usage of New York’s streets and squares clashed with the original ideas of architects and city
planners. A key difficulty faced by urban planners, virologists, and social scientists is that obtaining large, real-world observational data of human movement is challenging and costly (Brockman et al., 2006).

In recent years, the large deployment of pervasive technologies in cities has led to a massive increase in the volume of records of where people have been and when they were there. These records are the digital footprint of individual mobility pattern. As websites have evolved to offer geo-located services, new sources of real-world behavioral data have begun to emerge. For example, Rattenbury et al. (2007) and Girardin et al. (2008) used geo-tagging patterns of photographs in Flickr to automatically detect interesting real-world events and draw conclusions about the flow of tourists in a city. In addition, as city-wide urban infrastructures such as buses, taxis, subways, public utilities, and roads become digitized, other sources of real-world datasets that can be implicitly sensed are becoming available. Ratti et al. (2006), Reades et al. (2007) and González et al. (2008) used cellular network data to study city dynamics and human mobility. McNamara et al. (2008) used data collected from an RFID-enabled subway system to predict co-location patterns amongst mass transit users. Such sources of data are ever-expanding and offer large, underexplored datasets of physically-based interactions with the real world.

In this paper, we introduce a novel method for real time monitoring human mobility in dense urban area based on two major digital footprints: taxi GPS traces and millions of smart card data from Shenzhen, south of China. We show how these data regarding the position and intensity of digital footprint can be used to infer cultural and geographic aspects of the city and reveal urban mobility pattern, which corresponds to human movement in the city.

In particular, the main contributions of this paper are: (1) demonstrating the potential of using taxi traces and smart card as data sources to gain insights into city dynamics and aggregated human behavior; (2) exploring the relationship between spatiotemporal patterns of taxi/smart card usage and underlying city behavior and geography; and (3) studying patterns in taxi/smart card usage, including an analysis of how factors such as the time of the day affect this prediction. In our analysis, we emphasize not just what the taxi/smart card usage data reveals about urban mobility patterns but also how these patterns reflect the culture and the spatial layout of the city.

We believe this work not only has direct implications for the design and operation of future urban public transport systems (e.g., more precise bus/subway/taxi scheduling, improved service to public transport users), but also for urban planning (e.g., for transit oriented urban development), traffic forecasting, the social sciences (Latour, 2007)—in particular, studying how people move about a city—and the development of novel context-based mobile services. In addition, we expect that similar types of analyses can be applied to other sources of urban digital traces such as those provided by parking management (e.g., San Francisco’s SFpark) and cellular networks (González et al., 2008). Our work thus emphasizes the increasing role that data mining and visualization techniques will play to assist the aforementioned fields in analyzing traces of human behavior. Our work seems to open the way to a new approach to the understanding of urban systems, which we have termed “Urban Mobility Landscapes.” Urban Mobility Landscape could give new answers to long-standing questions in urban planning: how to map vehicle origins and destinations? How to understand the patterns of inhabitant movement? How to highlight critical points in the urban infrastructure? What is the relationship between urban forms and flows? And so on.
This paper is organized by the following sequences: first, it describes the real time monitoring platform to collect, process data and visualize results; second, it describes the data sets and the feature extraction process; third, it describes the spatial and temporal patterns of urban mobility; fourth, the implications to the urban planning is explored; finally, we draw the conclusion and discuss the future work.

2. REAL TIME MONITORING AND VISUALIZATION PLATFORM

Urban mobility landscape is the integrated urban mobility system in the metropolitan area, which could integrate different pervasive data sources from the city, process the data and visualize the data for better understanding of urban transport problems and provide real time decision support for the municipality.

The framework of urban mobility landscape is showed in Figure 1. The digital footprint of citizens made through both taxi GPS traces and smart card are transmitted to traffic information center through the wireless and internet connections in real time. The traffic information center processes the data and visualizes the results.

![Figure 1 Urban Mobility Landscape Platform](image)

3. THE DATASETS

The datasets used to describe urban mobility patterns cover most of public transport modes, i.e. bus, subway, taxi. The data sources are from 5,000 taxi GPS traces and 5 million smart card data. For taxi traces, considering there are 10,305 taxicabs serving in Shenzhen, the sample rate is 50%. For smart card data, according to the survey conducted by the smart card company, there are 55% passengers using smart card in bus trip and 61% passengers using smart card in subway trip (ShenzhenTong Survey, 2008).

3.1 Smart card data

The smart card data is from 5 million smart card users’ transit records for one month, through December 1st, 2008 to December 31st, 2008. Every day there are 1.5 million transit records from the users. The smart card data description and sample is showed in table 1.
From the smart card data, we could infer two major public transit modes: bus and subway. For bus journey, we could get the boarding time and travel fare; for the subway journey, we could get the time and location of check-in and check-out, from which we could infer the OD feature of trip. Moreover, the transfer information could be derived from the smart card data.

### 3.2 Taxi GPS traces

Taxicab is the most flexible public transport mode. Taxi is frequently used because of the high economic vitality in Shenzhen. GPS traces (description in Table 2) has been collected from taxis with GPS equipment, reporting their location (Longitude, Latitude) with certain intervals, operation status (no passengers or with passengers), spot speed, azimuth and equipment status. The GPS traces used in this study are collected from December 1st, 2008 to December 31st, 2008.
From the raw GPS traces, through the data pre-processing to clean the data, transforming the coordinates to the local coordinate system and mapping the GPS traces to the road networks, we could get the important mobility features, such as trip distance, trip time, OD (origin-destination) matrix and trip zones. The process of feature extraction is showed in figure 2.

Figure 2 taxi traces feature extraction

4. TEMPORAL AND SPATIOTEMPORAL PATTERNS

Before exploring the implications of urban mobility landscape to urban planning, we discuss temporal and spatiotemporal patterns and highlight how these patterns reflect underlying cultural and spatial characteristics of Shenzhen.

4.1 Mobility patterns for smart card users

4.1.1 Temporal patterns of public transit passengers

Through statistics of smart card records of the bus and subway in different day, their temporal mobility patterns could be infered. The temporal pattern of bus trip and subway trip is showed in figure 3.
Figure 3 public transit temporal patterns in different day

Figure 3(a) and 3(b) shows that during weekday there are obvious peak hours for bus trips. AM peak begins from 7am and reaches the peak at 8am; PM peak begins from 17pm and reaches peak at 18pm. This rhythm reflects the daily life patterns of citizens in Shenzhen, most of government institution and enterprises begin their work around 9am and finish their work around 18pm. The morning peak proportion is 26%, the evening peak proportion is 20%, the sum of two peaks achieves 46%, and the trips in peak hours almost occupy the half of daily travel demand. On Sunday, the peak hour is 10am, 14pm and 17pm, but in total is smooth, because the inhabitants can choose the free travel time on Sunday. The night activity is more frequent during night on weekend than on weekday, which means more citizens choose to go out for recreation. The morning peak of passengers on Saturday is still big, it is 10.2%, it means on Saturday a large proportion of citizens work during Saturday (From the proportion, it contribute half of daily working population), this reflects the corporation composition of Shenzhen, because most of HongKong, Taiwan and Japan enterprises ask employees to work half day on Saturday, their daily travel cause the peak hour on Saturday, and the small noon peak. In some sense, the travel feature of Saturday is the combination of weekday and Sunday, in the morning it likes the weekday and after the noon it is the same like Sunday. However, the Saturday peak hour is 18PM.

Figure 3(c) and 3(d) shows the temporal mobility pattern for subway. During weekday, the subway trip mobility pattern is almost the same with bus trip mobility pattern. The only difference is that subway AM peak hour is one hour after bus AM peak hour, which means subway is more reliable than bus. The inhabitants spend less travel time in subway than in bus.
4.1.2 Spatiotemporal patterns of subway passengers

4.1.2.1 Land use information of different subway stops

Because the bus trip only has the terminal id and no other location information, so we could not infer the spatiotemporal pattern from the smart card records. Thus in this study, we only study the subway passenger spatiotemporal pattern.

Shenzhen Metro Phase 1 is composed by east part of line 1 and south part of line 4. The east part of line 1 is from Luo Hu Railway station to Shijiezhichuang; the south of line 4 is from Futian Port to Shaoniangong. The total length of Shenzhen Metro Phase 1 is 21.866 kilometers, and there are 19 subway stops in total (the detailed information is showed in figure 4). The land use information is in table 3.

![Shenzhen subway stop description](image)

Figure 4 Shenzhen subway stop description [Shenzhen Metro, 2008]

Table 3: land use information of different subway stops

<table>
<thead>
<tr>
<th>code</th>
<th>name</th>
<th>Land use</th>
<th>code</th>
<th>name</th>
<th>Land use</th>
</tr>
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<tr>
<td>1</td>
<td>Luohu</td>
<td>External transport</td>
<td>12</td>
<td>Chegongmiao</td>
<td>business</td>
</tr>
<tr>
<td>2</td>
<td>Guomao</td>
<td>Business</td>
<td>13</td>
<td>Zhuzilin</td>
<td>Ex- transport</td>
</tr>
<tr>
<td>3</td>
<td>Laojie</td>
<td>Recreation</td>
<td>14</td>
<td>Qiaochengdong</td>
<td>residential</td>
</tr>
<tr>
<td>4</td>
<td>Dajuyuan</td>
<td>Business (CBD)</td>
<td>15</td>
<td>Huaqiaoacheng</td>
<td>residential</td>
</tr>
<tr>
<td>5</td>
<td>Kexueguan</td>
<td>government</td>
<td>16</td>
<td>Shijiezhichuang</td>
<td>transport</td>
</tr>
<tr>
<td>6</td>
<td>HuaqiangRd</td>
<td>Business and recreation (CBD)</td>
<td>17</td>
<td>Futiankouan</td>
<td>Ex-transport</td>
</tr>
<tr>
<td>7</td>
<td>Gangxia</td>
<td>residential</td>
<td>18</td>
<td>Fumin</td>
<td>residential</td>
</tr>
<tr>
<td>8</td>
<td>HuizhanZhongxin</td>
<td>business</td>
<td>19</td>
<td>ShimingZhongxin</td>
<td>government</td>
</tr>
<tr>
<td>9</td>
<td>GouwuGongyuan</td>
<td>business</td>
<td>21</td>
<td>Shaoniangong</td>
<td>government</td>
</tr>
<tr>
<td>11</td>
<td>Xiangmihu</td>
<td>recreation</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

4.1.2.2 Daily check-in and check-out of different subway stops

Through detailed analysis of daily check-in and check-out in different subway stops,
we could get the spatiotemporal patterns of subway travel. The proportion of check-in and check-out in different day is showed in Figure 5.

![Figure 5 Check-in(check-out) proportion in different stops in different day](image)

<table>
<thead>
<tr>
<th>Date</th>
<th>0</th>
<th>2</th>
<th>4</th>
<th>6</th>
<th>8</th>
<th>10</th>
<th>12</th>
<th>14</th>
<th>16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sunday</td>
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<td>6</td>
<td>4</td>
<td>2</td>
<td>0</td>
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<td>8</td>
</tr>
<tr>
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<td>6</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>Tuesday</td>
<td>4</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
</tr>
<tr>
<td>Wednesday</td>
<td>2</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
<td>14</td>
</tr>
<tr>
<td>Thursday</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
<td>14</td>
<td>16</td>
</tr>
<tr>
<td>Friday</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
<td>14</td>
<td>16</td>
<td>18</td>
</tr>
<tr>
<td>Saturday</td>
<td>0</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
<td>14</td>
<td>16</td>
</tr>
<tr>
<td>Sunday</td>
<td>2</td>
<td>4</td>
<td>6</td>
<td>8</td>
<td>10</td>
<td>12</td>
<td>14</td>
<td>16</td>
<td>18</td>
</tr>
</tbody>
</table>

Figure 5 (a) and 5 (b) is basically the same, which means that the check-in and check-outs is almost similar. The proportion remains the same during different date and different bus stops, which means they have great similarity. The largest proportion subway stop is Dajuyuan, Huaqiang Road and Shijiezhichuang. The proportion of Saturday and Sunday are similar, the three largest proportion data is Laojie, Huaqiang Road and Shijiezhichuang.

From the proportion change of from weekday to weekend, Laojie Subway station(Dongmen Pedestrian Street) has largest increase, then is Huaqiang Road, Luohu Station and Futian Port station. Meanwhile, the proportion decreases in Guomao, Dajuyuan, Guowu Gongyuan and Chegongmiao. This describes the life rhythms of citizens’ lives. The working place activity decrease during the weekend, while the two biggest recreation center- Laojie and Huaqiang Road increase the activity.

This smart card datasets open a new way to measure the mobility pulse in the city, which give us the intuitive sense about the cultural and life character of the city.

4.1.2.3 Daily connections of different subway stops

From figure 5 we could know the unique mobility pattern for individual subway stop. however, what we are more concerned is the connection between different subway stops. While the most efficient way to measure the connections between different subway stops is deriving OD matrix. According to check-in and check-out timestamps and locations for each individual passenger, we can inter the OD matrix for arbitrary time period, which is a 19*19 matrix.

From the analysis results, we find the OD pair between different two points is in the same magnitude and there is little difference between them. So we sum the OD pair, and display them through GIS platform to compare directly. The summarized OD pair is showed in Figure 6.
From figure 6(a), it is easy to understand that the largest connections in weekday are Guangxia and Huaqiang Road, Shijiezhichuang and Huaqiang Road, Shijiezhichuang and Dajuyuan, Huangqiang Road and Laojie. The first three shows the working travel, the last one is the recreation. The working travel is more than the recreation travel.

Figure 6(c) shows the largest connections in Sunday are Laojie and Huaqiang Road, Shijiezhichuang and Huaqiang Road, Huaqiang Road and Gangxia. The recreation trips are more than working trips.

Figure 6(b) indicates the mobility pattern of Saturday is the mix of weekday and weekend, work travel and recreation travel. Though Saturday travel is less than weekday, but the connections are more concentrated, i.e. several stops have more connections than weekday.
4.1.2.4 Spatiotemporal patterns during the AM and PM peak hours

Through temporal analysis we can know the AM and PM peak mobility pattern. But how do they distribute in spatial scale and do they have obvious directions? Through spatial mapping of AM and PM peak flow, we can answer these research questions.

Generally, the check-in during AM peak hour is more close to the residential center, and the check-out is more close to the working zones. On the contrary, the check-in during PM peak is more close to the working zones and the check-out is more close to the residential area. Based on these assumptions, we could detect working zones and residential zones.

Through analyzing different proportion of check-in and check-out in AM peak 8am and PM peak 18pm, we could use simple figure to detect residential area and working area. Check-in(check-out) proportion in different stops in peak hour is showed in Figure 7.

From Figure 7, obviously Shijiezhichuang and Gangxia represents the residential centers, the two biggest communities, Shijiezhichuang represents western communities, including Nanshan district and Xin’an and Xi’xiang community in Bao’an district; Gangxia represents northern communities, including Meilin, longhua communities. While Guomao, Dajuyuan, Huaqiang Road, Gouwu Gongyuan, ChegongMiao are the center of working area.

![Figure 7](image_url)

Figure 7 Check-in(check-out) proportion in different stops in peak hour

Through analysis of different proportion during the peak hours, we can distinguish the residential area and working area, but we can not tell the directions of the travel. Thus we must calculate the related OD matrix and show it on GIS platform, from which we could obtain the direction of morning and evening direction. AM and PM peak OD in different day is showed in Figure 8.

From Figure 8 we could understand that the AM peak in weekday represents very obvious rules: from residential area to working area is unidirectional flow, and the main flow direction is from west to east. The center of trip generation is Shijiezhichuang and Gangxia, which represents the western and northern residential center.
The spatiotemporal pattern is also very obvious during PM peak in weekday, which is from working area to residential area, and the main flow direction is from east to west. The center of the trip generation is Huaqiang Road and Dajuyuan.

![Figure 8 AM and PM peak OD in different day](image)

In sum, if we summarize the travel OD in peak hours, we could find the daily mobility patterns is simple and clear, every morning the inhabitants move from residential area to working area, while in the evening they travel from working zone back to residential area, some of them choose to go to recreation area.

In all of the subway stations, Shijiezhichuang and Gangxia are the center of residential area, representing western and northern inhabitants; Guomao, Dajuyuan, Kexueguan, Huaqiang Road, Gouwu Park and Chegongmiao are the center of working zone; Laojie and Huaqiang Road are the center of shopping and recreation. Inside of these, Huaqiang Road has special statuses, which is the center of both working area and recreation area. The mobility patterns of peak hours show the uni-CBD model in Shenzhen, which causes the clock pendulum movement of urban citizens.

### 4.1.2.5 Daily Urban Mobility Pendulum

Considering the mobility direction during the peak hours, we could have intuitive sense of daily mobility pendulum. From spatiotemporal pattern of inhabitant travel during peak hours in different day, we could get the obvious pendulum rule for subway travel: AM peak from residential area to working or recreation area, PM peak from working or recreation area to residential area.

Here we develop a novel method to calculate the daily urban mobility pendulum. The core thought is letting the trip proportion in different stops in Peak hour as weight; we could calculate the trip centroid of inhabitant’s daily travel. Then we could quantify the origin, destination and pendulum.

The method to calculate the trip pendulum:

Let $i=0,1,...,23$ represents different time periods in one day, and let $j=1,2,...,19$ represents different subway stops, $p_{ij}$ represents the different proportion in different time period, $x_j$ represents x coordinate of j stop, $y_j$ represents y coordinate of j stop, then the trip centroid $x_i$, $y_i$ in different hour are
\[ X_i = \sum_{j=1}^{19} p_i x_j \]  
\[ Y_i = \sum_{j=1}^{19} p_i y_j \]  

From equation (1) and (2), we could calculate the trip centroid in peak hour in different day. Comparing the PM peak value to the morning peak value, we could calculate the offset value. This offset value describes the range of daily trip pendulum. The origin, destination and pendulum are showed in table 4 and Figure 9.

<table>
<thead>
<tr>
<th>Day</th>
<th>Peak hour</th>
<th>X (m)</th>
<th>y (m)</th>
<th>Zone</th>
<th>X offset(m)</th>
<th>Y offset(m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekday</td>
<td>8</td>
<td>113719.4174</td>
<td>18993.27589</td>
<td>233</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>116333.1562</td>
<td>19029.79979</td>
<td>208</td>
<td>2613.738757</td>
<td>36.5239047</td>
</tr>
<tr>
<td>Saturday</td>
<td>8</td>
<td>113755.5205</td>
<td>18995.37395</td>
<td>233</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>116718.9405</td>
<td>19085.36763</td>
<td>209</td>
<td>2963.419997</td>
<td>88.9936754</td>
</tr>
<tr>
<td>Sunday</td>
<td>8</td>
<td>114171.1622</td>
<td>18987.75928</td>
<td>202</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>17</td>
<td>116915.9519</td>
<td>19079.8178</td>
<td>209</td>
<td>2745.789689</td>
<td>92.0585176</td>
</tr>
</tbody>
</table>

From table 4 and figure 9 we could know the AM peak centriod is in the western zone 233 and 202, i.e. center area of Futian area; while PM peak is zone 208 and 209, close to Huaqiangbei business district. The trip centroid swing between the center line of Lianhuashan of Shenzhen, in the morning from west to east, in the PM peak from east to west. The pendulum is Saturday>Sunday>Weekday. The centroid of peak hours on weekend is move to the east, which describes the daily trip behavior is towards Luohu, Shangbu area.

The trip pendulum shows the separation between working area and residential area and shows the uni-center in the city. Trip pendulum and its evolution is the effective index to measure the distribution of people residence and employee and is also important to urban transport planning.
4.2 Mobility patterns for taxi passengers

4.2.1 Temporal patterns of taxi passengers

According to the one month sample data, we calculate the average trips in different day in one week and the trips in different time of different day. The results are showed in Figure 10.

Figure 10(a) shows that taxi trips are largest in Saturday, then are Friday and Sunday, which means taxi trips concentrate on weekend and taxi trip is leaner to recreation and shopping journey. Figure 10(b) shows the taxi trips in different time: there are three peaks in weekday, i.e. 8-11am, 14-17pm and 19-22pm. The temporal patterns of taxi trips are essential for a more refined urban taxi system, for example, controlling taxi supply according to the travel demand in space and time.

4.2.2 Spatiotemporal patterns of subway passengers

4.2.2.1 Daily taxi trip connections between different zones

According to the boarding and alighting location and time, we could infer daily taxi trip OD matrix. Because there are 491 traffic analysis zones (TAZ) in Shenzhen, it is too complicated to understand the OD matrix in GIS platform. Thus we sum the OD between different TAZs. Meanwhile, to highlight the most connected zones, we only visualize the OD pair which trips are larger than 100. Connections between different TAZs in different day are showed in Figure 11.

Figure 11 shows the major trips are concentrated on Luohu, Futian and Nanshan district where the most vital special economic zones are. Besides these, there are strong connections between airport and these three districts. In all of the connections, the largest one is the connection between zone 224(Huanggang port) and zone 221(Huanggang village). Huanggang village is close to the biggest land port in Asia, Huanggang port. There are many Hongkong citizens living here. And the second largest connection is between Luohu Port and Guomao CBD, where many Hongkong citizens work.

Taxi trip connections could be useful to understand the spatial distribution of Hongkong Citizens in Shenzhen, which provides valuable support for Hongkong and Shenzhen municipalities to better plan the facilities and services.
4.2.2.2 Spatiotemporal patterns for trip generation in different day

Through comparing the trip generation in different day, we could better understand the activity distribution and changes inside the city. The trip generation in weekday and compare between Sunday and weekday are showed in figure 12.

Figure 12 Trip generation in weekday and compare between Sunday and weekday

Note: for (a) From blue to red, the trip increases; for (b), blue means decrease and red means increases.

Figure 12(a) shows the taxi trip generation inside city during the weekday, which could be a natural reflection about the urban dynamics and activities. Figure 12(b)
compares the difference between Sunday and weekday. From the difference we could understand that the life patterns shift in the city: On Sunday, the trips in working area decreases, while the trips in residential, recreation, consumer area and two major ports connecting Shenzhen and Hongkong increases. Through taxi trips we could grasp the land use and daily mobility patterns, which in turn can be use to better schedule and manage the urban taxi system.

5. IMPLICATIONS OF URBAN MOBILITY LANDSCAPE

As urban infrastructures are increasingly digitized, human behavior data will become ubiquitous. Urban mobility landscape will be necessary to sort through and analyze the large amounts of real-world behavioral data being produced. We have shown how taxi GPS traces/smart card data can reveal not just patterns of taxi/bus/subway usage, but also the underlying temporal and spatial dynamics of a city.

Urban mobility landscape will not only give us real time understanding of urban mobility dynamics, but also open the new way to plan the urban furniture and economic development. Moreover, it provides the essential and valuable materials for urban planner and transport planner to design the quick responsive inter-modal urban transport system, from which we can select the most proper transport mode for individual mobility demand, decease the energy consumption and green house gas emission, finally we can achieve the goal of sustainable development.

6. CONCLUSION AND FUTURE WORK

In this paper we have presented an innovative approach for monitoring human mobility in real time which we call ‘Urban Mobility Landscape’. It paves the way to new analyses and researches on complex urban systems, such as metropolitan areas, polycentric territorial systems and megalopolis. The framework of urban mobility landscape is described in detail. The case study in Shenzhen is carry out and analysis results show that it is of great importance to understand the functioning of metropolitan mobility systems in order to enhance life quality, to protect the environment and to achieve sustainable development.

In the future, we would like to incorporate contextual features into our urban mobility landscape system, such as weather, season, special events (e.g. concerts or soccer matches), public transportation schedules and locations, and data from additional urban infrastructure (e.g., cellular networks). We also plan to fuse the different data sources to derive high level understanding of urban dynamics. The most important aspect of the research is to understand how these urban monitoring and modelling systems can become a tool for urban planning and policy making. The real challenge is enhancing connectivity between research and policy making in sustainable development. The overabundance of analytical data and information on the urban environment doesn’t facilitate the tasks of the policy makers and urban planners, who often can’t manage to interpret the complexity of urban phenomena in an effective and functional way. From this point of view, the Urban Mobility Landscape systems have to be used not only as tools to manage and map urban mobility patterns, but also as Urban Mobility Decision Support Systems (UMDSS).

The setting up of an UMDSS entails, besides the technical elements, a conceptual framework including the knowledge of the context and the ability to evaluate risks, consequences and impacts of any alternative decision. Real-time monitoring systems
can be a support to policy makers and town planners in their setting up and assessment of alternative scenarios of urban development. By using these tools, the operational choices can be more transparent and flexible, because they can be effectively monitored with respect to their effects and impacts on the urban environment.

ACKNOWLEDGEMENTS

We would like to thank Shenzhen Urban Transport Planning Center (SUTPC) and Shenzhentong Company’s generous providing the data for research. In special, we would like to thank Dr. Guan Zhichao from SUTPC and Dr. Jia Jingga from Shenzhentong for their valuable comments. We would also like to thank MIT-Portugal Program to provide the research funding. Of course, any shortcomings are our sole responsibility.

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