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Traffic Speed Estimation Using Mobile Phone Location Data Based on Longest Common Subsequence

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***Abstract*—This paper presents a traffic speed estimation method based on longest common subsequence. The study focuses on user location update mechaninsm of mobile phone network to reconstruct mobile phone trajectory. The main contribution of this paper is development of a systematic framework for estimating vehicle trajectories from mobile phone location data by longest common subsequence matching algorithm. This framework consists of five steps: vehicle trajectories reconstruction, object road handover sequence generation, vehicle trajectories matching, similarity measurement and traffic speed estimation. First, we analyzed the location update theory to reconstruct vehicle trajectories and generate object road handover sequences. Then, we proposed a vechile trajectories matching method under the inspiration of longest common subsequence and designed a similarity measurement algorithm that satisfies the specific condition. Moreover, traffic speed can be estimated. At last, in the experiment part, we compared the results between estimated speed in this paper and detected speed by microwave detectors. The estimated speed is consistent with detected speed and has a good precision.**

Keywords-Mobile phone location data; Trajectories matching; Longest common subsequence; Traffic speed estimation.

I. INTRODUCTION

In recent years, measurements of traffic speed are most useful for traffic applications. Travel time measurements and vehicle trajectories are the basis for speed measurements. Obtaining these traffic details is very important for traffic planning and management. The current approaches for traffic information relies mainly on local detectors that measure traffic volume, speed, occupancy or vehicle types at a specific location along the roadway. Duo to the cost installation and maintenance of local detectors, they are usually installed on a relatively small area of the roadway system. It is difficult to get the whole area traffic data because of the limited coverage of traffic system[1]. With the wide spread of Intelligent Transportation Systems (ITS), floating vehicle with GPS are used for sense traffic speed and travel time instead of local detectors. Traffic information detection by floating vehicle is almost the most popular method although it is also limited in its size and its coverage.

To avoid the coverage limit and equipment costs, mobile phones can be used as sensors to detect vehicles' locations. The project of CAPITAL in America is the first one to detect traffic speed and events while it is not accurate[2]. Yim and CayFord analyzed 44 hours cellular calling data and predicted GPS technology will become more attractive and realistic for vehicle probe activities when GPS is deployed in cellular phone[3]. Herrera et al. took a field experiment named "Mobile Century" which included 100 vehicles carrying a GPS-enable phone[4]. Results suggested that 2-3% penetration of cell phones in the driver population is enough to provide accurate measurements about traffic flow. Smith described the study of anonymous mobile call sampling for transportation applications underway, and used anonymous mobile call sampling method to contraste with other probe and point detection mechanisms[5].

Origin destination (OD) matrices are the basic data for traffic planning and management. Cascetta studied the methodology for estimating or updating origin-to-destination trip matrices from traffic counts[6], and proposed different "dynamic" estimators using time-varying traffic counts to obtain (discrete) time-varying OD flows or average OD flows[7]. White and Wells used origin destination data to provide an estimate of the number of vehicles travelling between points on a network over a given period of time[8], and this method achieved significant effect. With the rapid development of cell phone-locating technologies, a lot of scholars estimated origin destination flows by mobile phone location data. Pan studied investigates a cellular-based method to extract trip distribution data[9]. Calabrese proposed an algorithm to analyze opportunistically collected mobile phone location data[10]. Dong[11] proposed the use of the traffic semantic concept to extract commuters' OD information from mobile phone CDR data, and to use the extracted data for traffic zone division.

II. DATA DESCIPTION

Mobile phone can be detected when users communicate or surf the Internet by phone. Usually, a communication network consists of many base stations (BS) that serve the mobile phones around them. The base transceiver station (BTS) can be considered as access point to the network for mobile phones. The communication network coverage area is divided into many subareas, named location areas (LAC). While one location area is consist of many cells which is the area covered by BTS. The location of BTS can be considered as the locations of mobile phones which are served by this BTS. This location method is called Cell of Origin (COO). Though this method is not very accurate, it is reliable for vehicle trajectories reconstruction designed by this paper.

When a mobile phone move from one LAC to another (from Cell2 to Cell3 in Figure 1, actually LAC1 to LAC2), its location will be sent to the network. Moreover, a mobile phone move from one cell to another while calling or surfing the internet, its location will also be recorded. If all the locations are kept, the trajectories can be reconstructed.

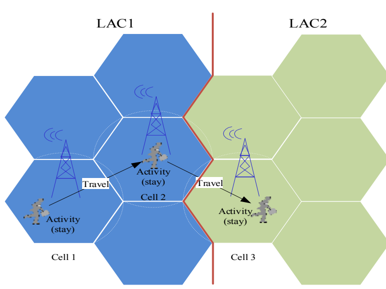


Fig. 1. Location update of cellular network.

In the communication network, the basic is base station. If we want to know where the user is, we must know the base station location information. In the base station table, the main attributes include base station ID (CELLID), its location area (LAC), longitude and latitude. Except base station information, mobile phone location data table contains IMSI that is anonymous user ID and location update time. In this paper, we estimate traffic speed using actual mobile phone location data that were collected by communication operator during one day on February 2, 2015 in Beijing.

This study proposes a detailed implementation method for traffic speed estimation by mobile phone location data. The study includes speed estimation comparison between mobile phone location data and microwave data. The remainder of this paper is organized as follows. The topic of this paper is shown in Section 2 which presents the main methods for estimating traffic speed. In this section, vehicle trajectories have been reconstructed and matched by longest common subsequence algorithm and similarity measurement. Then it shows how to estimate traffic speed. Section 3 performs an experiment with mobile phone location data and compares with microwave detection data to evaluate the approach. The conclusions and future work are discussed in Section 4.

III. METHODOLOGY

A. *Vehicle trajectories reconstruction*

Based on mobile phone location data, this paper reconstruct vehicle trajectories. A vehicle trajectory, denoted by Tr, is a time-ordered sequence of base station location (cellid, t) representing the cellid location of a vehicle at time t. The trajectory of vehicle i is Tr_i, $Tr_i=(p_1,p_2,\ldots,p_n)$, where p_j is the jth location of sequence($n=1,2,\ldots,n$). Due to location update strategy of mobile phone network, the trajectories of different vehicles addressed in this paper have the following four characteristics[12]: different lengths, different and uneven samping rates, different directions and regions and road network constraint.

This paper extracts every vehicle (mobile phone user) trajectories from raw mobile phone data and sort every trajectory in ascending order of time. About 19 million people's trajectories in one day are reconstructed in this paper. The detailed implementation method for each step is presented.

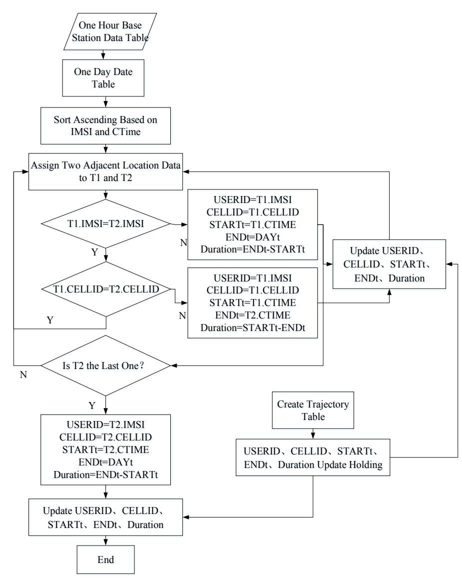


Fig. 2. The framework of user base station trajectory.

B. *Object* road handover sequences generation

Vehicle location will be updated if meeting updating location conditions when vehicle moves. Object road handover sequence is the vehicle location sequences when vehicle moves in perfect condition. Object road handover sequences, including positive sequence L(1,n){ $x_1,x_2,\ldots,x_n$ } and reverse sequence L(n,1){$x_n,x_{n-1},\ldots,x_1$}, are the basis of matching vehicle trajectories. Positive sequence is a 'CELLID' set generated when vehicle moves in a road from start point to end point while reverse sequence from end point to start point. These 'CELLID's are base station ID along the road.

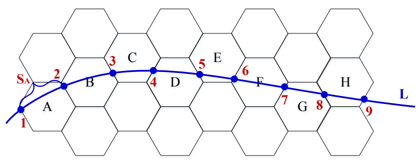


Fig. 3. The handover of base station on the road.

If one vehicle move from A to H on the road L and its location update in time, we can treat the sequence {1,2,…,8} as its handover trajectory instead of {A,B,…,H}. While the vehicle move from H to A, the sequence {9,8,…,2} is used as its handover trajectory instead. Then we can adopt these key point location sequence {1,2,…,8} or {9,8,…,2} to estimate vehicle speed.

In order to obtain object road handover sequences, many road tests should be carried out in the project. A lot of manpower and material resources are needed in road tests. Low efficiency and high cost are obvious. So this paper presents a virtual base station coverage using Voronoi diagram and combined GIS to extract object road handover sequences.

Step 1: Base station Voronoi diagram is created by ArcGIS. Then Voronoi diagram surface layer is converted into boundary line layer.

Step 2: Object road selection and object road line layer interception.

Step 3: Voronoi diagram boundary line layer and object road line layer intersection. We can get key point layer.

Step 4: According to the road direction, the key points are extracted to form object road positive sequence and reverse sequence.

C. Vehicle trajectories matching

a) Theoretical basis

Trajectory matching is a geographical location correction technology belonging to map matching. Vehicle trajectories matching is to determine travel path through base station handover order by combining vehicle trajectories and road network in GIS. Particularly, this paper has two assumptions in the process of vehicle trajectories matching. (1) Vehicles matched successfully are on the road. (2) There is only one mobile phone user in matched vehicle. Multiple users in the vehicle are not considered. In order to apply these assumptions to matching trajectories, this paper extend the definitions as follows.

Definition 1 (vehicle trajectory) A vehicle trajectory is the base station handover sequence generated by the user location update of mobile communication network. A vehicle trajectory Trv is defined by Trv={CELLID_1, CELLID_2,…, CELLID_n}.

Definition 2 (object road handover sequence candidate set) The object road handover sequence candidate set is a set of possible handover sequences when a vehicle moves on the target road.

This paper matches vehicle trajectories and road handover sequences in the object road handover sequence candidate set to determine which road segment the vehicle on. The higher similarity between vehicle sequence and object road handover sequence, the greater likelihood that the vehicle travel on the object road.

b) Longest common subsequence matching algorithm

To find overlapping portions of trajectories, we use the Longest Common Subsequence (LCS) algorithm[14]. The LCS is an algorithm for finding the longest common subsequence of two sequences and originates in the field of string matching, where two strings with different lengths are given to find a set of characters that appear left-to-right, not necessarily consecutively.

The LCS problem can be broken down into smaller, simpler subproblems until becomes trivial. Let S={A,B,C,A}, a prefix of S is the sequence with the end cut off. So the possible prefixes of S are S_1={A}, S_2={A,B}, S_3={A,B,C}, S_4={A,B,C,A}. If we have two sequences X and Y, the function LCS(X,Y) gives the longest common subsequences to X and Y. Suppose two sequences X={$x_1,x_2,\ldots,x_m$}, Y={$y_1,y_2,\ldots,y_n$}, their lengths are m and n, their prefixes X_1 to X_{m-1} and Y_1 to Y_{n-1}. The function LCS(X, Y) relies on the following properties.

(1) if $x_m=y_n$, then LCS(X,Y)={LCS(X_{m-1},Y_{n-1}),x_m}.

(2) if $x_m\neq y_n$, then LCS(X,Y)=LCS(X_{m-1},Y) or LCS(X,Y_{n-1}). Where LCS(X,Y) is the longest sequence of LCS(X_{m-1},Y) and LCS(X,Y_{n-1}).

In any case, this set of sequence is given by the following:

$$LCS(X_i,Y_j)=\begin{cases}0 & \text{if } i=0 \text{ or } j=0\\ LCS(X_{i-1},Y_{j-1})\cup x_i & \text{if } i,j>0 \text{ and } x_i=y_j\\ \text{longest}\,(LCS(X_i,Y_{j-1}),LCS(X_{i-1},Y_j)) & \text{if } i,j>0 \text{ and } x_i\neq y_j\end{cases} \tag{1}$$

It requires a lot of calculation time and storage space to save the actual subsequences. In order to save storage space, we use the length of the subsequence instead. Defining a function lenLCS(X,Y) that calculates the length of LCS(X,Y). So the recurrence relation of LCS can be denoted as follows:

$$\text{len}LCS(i,j)=\begin{cases}0 & \text{if } i=0 \text{ or } j=0\\ lenLCS(i-1,j-1)+1 & \text{if } i,j>0 \text{ and } x_i=y_j\\ \max(lenLCS(i,j-1),lenLCS(i-1,j)) & \text{if } i,j>0 \text{ and } x_i\neq y_j\end{cases} \tag{2}$$

Let two sequences be defined as follows: T_1={$P_1,P_2,P_4,P_5,P_6,P_7,P_9$} and T_2={P_1,P_3,P_5,P_6,P_7}. We can get the completed lenLCS table between T_1 and T_2 , as in the Table 1 below, through the recurrence relation.

TABLE I. LENLCS matrix

	T_1	P_1	P_2	P_4	P_5	P_6	P_7	P_9
T_2	0	0	0	0	0	0	0	0
P_1	0	1	1	1	1	1	1	1
P_3	0	1	1	1	1	1	1	1
P_5	0	1	1	1	2	2	2	2
P_6	0	1	1	1	2	3	3	3
P_7	0	1	1	1	2	3	4	4

Every diagonal move corresponds to the matching of two location, $T_1(i)=T_2(j)$. If $T_1(i)\neq T_2(j)$, the biggest cell among diagonal, left and up cells. If the same maximum cell exists, the priority order is up, left and diagonal. If the current cell is in the first row of the table, it should go left, while in the first column, it should go up. Then we can get the completed trace back table (Table 2).

TABLE II. TRACEBACK MATRIX

	j	0	1	2	3	4	5	6	7
i		T_1	P_1	P_2	P_4	P_5	P_6	P_7	P_9
0	T_2	0	0	0	0	0	0	0	0
1	P_1	0	↖1	←1	←1	←1	←1	←1	←1
2	P_3	0	↑1	↑1	↑1	↑1	↑1	↑1	↑1
3	P_5	0	↑1	↑1	↑1	↖2	←2	←2	←2
4	P_6	0	↑1	↑1	↑1	↑2	↖3	←3	←3
5	P_7	0	↑1	↑1	↑1	↑2	↑3	↖4	←4

The LCS algorithm given below takes a s input sequence $X=\{x_1,x_2,\ldots,x_m\}$, $Y=\{y_1,y_2,\ldots,y_n\}$, computes the LCS between X and Y and stores it in Z[i,j] for all $1\leqslant i\leq m$ and $1\leqslant j\leqslant n$. Besides, Z[m,n] will contain the length of the LCS(X,Y).

The pseudocode is shown below:

```
Procedure lenLCS(X,Y)
Input:
X={x1,x2,⋯,xm};
Y={y1,y2,⋯,yn};
begin
  m=length[X], n=length[Y];
  for i=1 to m do
    for j=1 to n do
      if X[i]=Y[j] then
        Z[i,j]=Z[i-1,j-1]+1;
         L[i,j]="↖";
      else if Z[i-1,j]⩾Z[i,j-1] then
        Z[i,j]=Z[i-1,j];
         L[i,j]="↑";
      else
        Z[i,j]=Z[i,j-1];
         L[i,j]="←";
      end;
  return(Z,L);
end;
```

D. Similarity measurement

To define the similarity measurement for trajectories is to determine a rule for comparing location points in different sequences. During match the sequences, Figure 4(a) shows the situation using a simple no direction object road handover sequence. If distinguish the direction of object road, a vehicle trajectory sequence should match object road handover sequence two times, positive sequence and reverse sequence. This situation is illustrated in Figure 4(b). This case can be divided into two different situation, shown in Figure 4(c) and Figure 4(d).

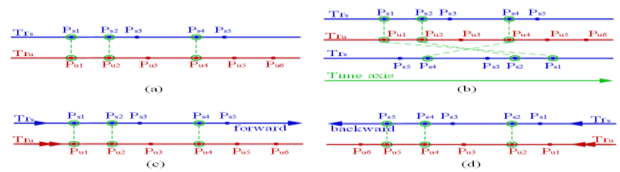


Fig. 4. Trajectory matching.

This paper considers their spatial proximity. Given two sequences Trs={Ps1,Ps2,Ps3,Ps4,Ps5} and Tru={Pu1,Pu2,Pu3, Pu4,Pu5,Pu6}, Trs denotes an object road handover sequence while Tru denotes a vehicle trajectory sequence. lenLCS(Trs,Tru) represents the length of longest common sequence between the Trs and Tru. To obtain the similarity, we define a function Sim(Trs,Tru) as follows:

$$\mathrm{Sim}\ (Tr_s, Tr_u) = \frac{lenLCS\ \ (Tr_s, Tr_u)}{len\,(Tr_s)} \tag{3}$$

E. Traffic speed estimation

In this section, we demonstrate how we can use the LCS and similarity to estimate traffic speed. We set a trajectory similarity threshold δ to judge the quality of matching. If similarity between object road handover sequence and vehicle trajectory sequence were greater than similarity threshold δ, we keep the vehicle trajectory sequence. The whole procedure for traffic speed estimation is provided as follows:

Step 1: Object road handover positive sequence and reverse sequence generation. We calculate the distance of adjacent base stations by ArcGIS. The positive sequence distance vector is expressed as $D_f=\{d_1,d_2,\ldots,d_m\}$ while the reverse sequence disctance vector is $D_b=\{d_m,d_{m-1},\ldots,d_1\}$.

Step 2: Vehicle trajectories reconstruction. The detail description is introduced in 2.1. If we get all the vehicle trajectories, the ith vehicle trajectory sequence is shown as $Tr_{ui}=\{(cellid_{i1},T_{i1}),(cellid_{i2},T_{i2}),\ldots,(cellid_{in},T_{in})\}$, where 'cellid' denotes base station number, 'T' denotes the time when updating location. And then, we need calculate LCS and similarity between vehicle trajectories and object road handover sequences.

Step 3: Single vehicle speed calculation. If the matching succeeds, the relevant vehicle trajectory is kept and the speed is calculated. $V_{i,linkl}$ is the lth link speed of ith vehicle.

$$V_{i,link_l} = \frac{d_{cellid_{l-1}\sim cellid_l}}{T_{i,l} - T_{i,l-1}} \tag{4}$$

And V_i is the average speed of ith vehicle and $cellid_{l-1}\sim cellid_l$ represents the distance of $cellid_{l-1}$ and $cellid_l$.

$$V_i = \frac{\sum_{l} V_{i,\text{link}_l}}{lenLCS\ (Tr_s, Tr_i)} \tag{5}$$

Step 4: Loop Step 2 to Step 3 until no vehicle trajectories need to be matched.

IV. Experiment And Discussion

A. Data description

In this section, we test the proposed traffic speed estimation approach using actual user mobile phone location trajectories. The data was collected by one communication operator on February 2, 2015 in Beijing, China. We reconstructed all the user trajectories from 6 AM to 8 PM to estimate traffic speed. Besides, the coverage of base station is determined by Voronoi diagram through ArcGIS.

B. Object road selection

For our experiment, we selected two road sections as representative of expressway sections. Section 1: the Beijing Western Fifth Ring Road- Xiangquan Bridge to Xingshikou Bridge (sparse traffic flow section); Section 2: the Beijing North Fifth Ring Road-Shangqing Bridge to Laiguangying Bridge (dense traffic flow section).

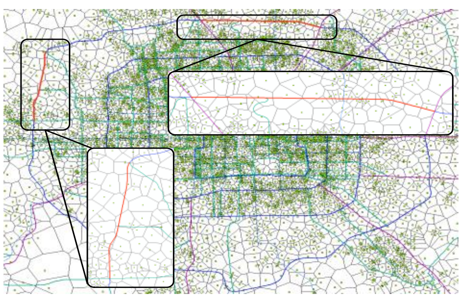


Fig. 5. Research road sections.

Section 1: Xiangquan Bridge to Xingshikou Bridge

This section is about 4.3km and spans 12 base stations. We label these base station new numbers (001~012) instead of their 'CELLID's from south to north, shown in Figure 6. So we define the direction from south to north is the positive direction. Then the object road positive sequence is Trp1={001,002,…,012} while the reverse sequence is labeled as Trr1={012,011,…,001}.

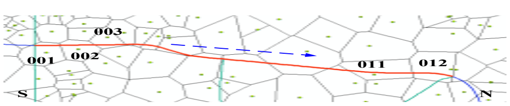


Fig. 6. Base stations relabeling on the object road 1.

Section 2: Shangqing Bridge to Laiguangying Bridge

This section is about 8.8km and spans 25 base stations. We label these base station new numbers (101~125) instead of their 'CELLID's from west to east in the same way, shown in Figure 7. So we define the direction from west to east is the positive direction. Then the section 2 positive sequence is Trp_2={101,002,…,125} while the reverse sequence is labeled as Trr_2={125,124,…,101}.

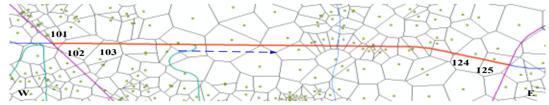


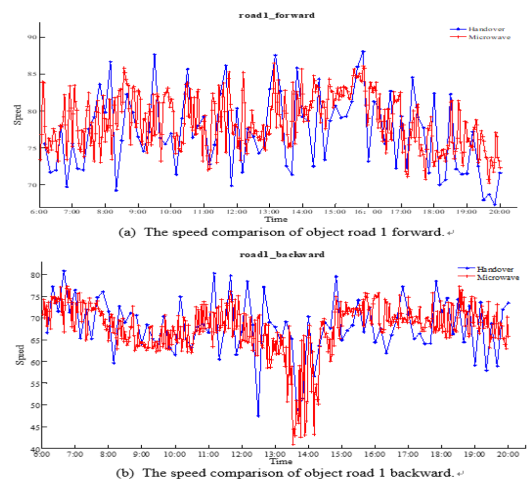
Fig. 7. Base stations relabeling on the object road 2.

C. Object road traffic speed estimation

The traffic speed estimation algorithm is detail description in 2.5. So we estimate the traffic speed of four directions. The selected time period is 6:00~20:00 and time interval is 10min. In order to examine the validity of this algorithm, we compare the traffic speed estimated in this paper and speed detected by microwave detectors. The time interval is 2min.

Section 1: Xiangquan Bridge to Xingshikou Bridge

Figure 8(a) shows the traffic speed comparison of Section 1 positive direction. Figure 8(b) shows the traffic speed comparison of Section 1 reverse direction. The blue lines represent the estimated speed in this paper while the red lines represent the detected speed of microwave detectors. They are shown that the overall trend between estimated speed and detected speed is consistent, but the fluctuation of estimated speed is larger than detected speed.



(a) The speed comparison of object road 1 forward.

(b) The speed comparison of object road 1 backward.

Fig. 8. Base stations relabeling on the object road 1.

Section 2: Shangqing Bridge to Laiguangying Bridge

Figure 9(a) shows the traffic speed comparison of Section 2 positive direction. Figure 9(b) shows the traffic speed comparison of Section 2 reverse direction. The blue lines represent the estimated speed in this paper while the red lines represent the detected speed of microwave detectors. The same with Section 1, the overall trend between estimated speed and detected speed is consistent, but the fluctuation of estimated speed is larger than detected speed. The entrances in Section 2 are relatively more and there are a mount of successful matched vehicles. The impact of the morning and evening peak in Section 2 is larger. The traffic speed is lower at peaks than normal.

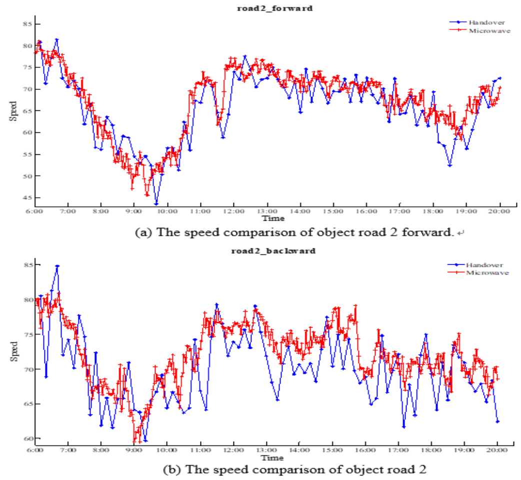


Fig. 9. The speed comparison of object road 2.

D. *Experimental evaluation*

In order to prove the feasibility of the algorithm more accurately, this algorithm is analyzed quantitatively. The time interval of estimated speed is 10min while the time interval of detected speed is 2min. Spline interpolation is performed in this paper to achieve the same time interval. We use the absolute error, the percentage of error and mean square error to assess the quality of the algorithm.

As Table 3 shown, vh denotes estimated speed, vm represents detected speed and n is the total number of speed points. And the traffic speed estimation algorithm has high precision. All absolute errors are below 5.5 km/h and the PEs of Section 1 positive direction and Section 2 are about 5%. The PE of Section 1 reverse direction is 8.01 which is larger than others. The reason of this result is that the number of the successful matched vehicle trajectories is less than others.

TABLE III. LENLCS MATRIX

Road Name	$\overline{v}_h$ (km/h)	$\overline{v}_m$ (km/h)	e (km/h)	PE (%)	MSE
road1_forward	77.14	78.57	4.06	5.15	4.94
road1_backward	68.14	67.70	5.27	8.01	6.68
road2_forward	65.68	67.13	3.37	5.17	4.29
road2_backward	69.94	72.14	3.44	4.74	4.25

V. CONCLUSION

Nowadays, one mobile phone is considered as a sensor for detecting information in many fields. It turns out that the possibility of using it as a sensor to estimate traffic speed. In this paper, we proposed a Traffic Speed Estimation Model. The proposed model utilized mobile phone location data by existing GSM network. Using the effective procedure described in this paper, it is possible to reconstruct vehicle trajectories and generate road handover sequences. Then one can estimate traffic speed by adopting LCS after matching trajectories. In comparison with microwave detection data, the proposed method shows high precision and results have the same trend.

The approach discussed in this paper is appropriate only for freeway and expressway because of location method weakness. If the approach is performed in the complex road network in the inner urban areas, it may show low accuracy. But it is promising to obtain traffic speed from mobile phone location data with the promotion of smart phones. The explosion data will make up the shortcomings.

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