Space Matching Fusion Model for Arterial Speed Estimation in ITS

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Abstract—To improve the accuracy of arterial mean speed estimation through data fusion in road traffic, this paper presented a speed estimation method based on space-matching fusion model. In the method, an urban road model is proposed, which divided road into several equal length segments. The loop detector data is matched to each segment by the adjusted coefficient. Because of the strongly complementary between loop vehicle detector data and probe vehicle data in space, a weighted fusion model is proposed. The model is used to calculate arterial mean speed by link mean speed of each segment. In the weighted fusion model, Newton method is used as training method to get the weights. The simulation results show that this method is effective and reliable to improve the accuracy of arterial link mean speed, and the computation is reduced owing to relatively simple training process.

Keywords—Information fusion; space matching; loop vehicle detector; probe vehicle

I. INTRODUCTION

The traffic flow data processing system is an important foundation of the urban traffic management system. It mainly provides Intelligent Traffic Management System (ITMS) and Advanced Traveler Information System (ATIS) with effective traffic data to evaluate the current traffic state, and achieves the purposes of easing traffic jams, reducing energy consumption and eliminating traffic accidents by releasing the traffic state to travelers. Therefore, the accuracy of the traffic data has a positive influence on the control strategies of Intelligent Transportation System (ITS).

More and more different types of vehicle detectors such as loop detectors as in [1], [2], probe vehicles as in [3], [4], microwave detectors and videos as in [5], [6] are employed to collect traffic information with the rapid development of sensor technology. However, it is still difficult to obtain low error traffic data by a single detector because of the factors of environment, damaged detector and the drawbacks of detector itself. Take the loop detectors and probe vehicles, which are most widely used, as the example. Loop detectors can only detect traffic information of road sections in the case that the data obtained are of high precision. Probe vehicles can collect traffic information of different location of road, and provide more speed data of each vehicle, but they can not show the traffic flow characteristics of all vehicles on road.

As the one of important methods of information processing, information fusion technology has been introduced into ITS as the core component of the entire traffic information processing system. It helps to get more accurate and complete traffic parameter estimation than a single detector by fusing data from various traffic vehicle detectors. In this field, a number of methods have been proposed so far. In [7], [8] proposed a data fusion algorithm using loop detectors and probe vehicles, which was based on average speed calculating model and BP Neural Network. The drawback of this algorithm is needs to train lots of data by neural network and can’t meet the needs of real time processing in practice. In [9] fused multi-sensor data by mix-structure neural network in order to estimate travel time and verified it in practice. However, it takes lots of time to estimate travel time by mix-structure NN. In [10] also proposed a fusion algorithm that simultaneously utilizes data from both point and interval detection systems. Although it satisfactorily predicted the travel time with the mean absolute percentage errors, traffic variable prediction by points can cause discontinuities between points and lead to performance degradation in traffic model. In [11] introduced travel time prediction method and discussed advantages and disadvantages of two neural-network-based fusion models: one is Space Discretization Travel Time Calculation Algorithm (SDTCM) and the other is Speed Integral Travel Time Calculation Method (SITCM). Both of two algorithms are time consuming because of complex data training. This paper introduced a new...
algorithm which has relatively simple data training process and high accuracy.

In the proposed fusion algorithm, an urban road model is presented firstly, which divided entire link into multiple equal length segments. Then the speed data of segment which loop detectors are coded in are collected by loop detectors, and other segments’ data are collected by probe vehicles when they travel by. In order to get more accuracy speed data, loop detectors data are matched to other segment by the adjustment coefficient. These data are further used in the proposed fusion model which actually is weighted average method. In the method, Newton method is used to train weights to reduce the train time. The structure of this paper is as follows: Section II shows the network system of loop detectors and probe vehicles. Section III proposes the speed estimation model of urban road. Section IV and Section V discuss the data preprocessing of probe vehicles and loop vehicle detectors. Section VI presents the fusion model of the speed estimation. The experiment result is concluded in Section VII.

II. NETWORK SYSTEM OF DETECTORS

In order to apply the speed estimation model to practice, a network system of detectors is presented to collect traffic flow data, and then the identification results are release to travelers in different ways. In this system, probe vehicles and loop vehicle detectors are used to collect traffic flow data owing to their characteristics and advantages. Probe vehicles and loop vehicle detectors have different means of communication, and sensor networks should be composed respectively. The network system of traffic flow data collection is shown in Fig. 1. In the figure, the whole system is divided into three parts: wireless transmission network of GPS, loop vehicle detectors transmission network based on Ethernet and information processing center.

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III. SPEED ESTIMATION MODEL OF URBAN ROAD

On the purpose of improving the estimated precise of the speed, a speed estimation model of urban road is proposed in this section. In this model, road with cross intersection is selected for simulation, taking the urban road as background in this paper. The speed estimation model of urban road is shown in Fig. 2.

Suppose any vehicle on the road, the link mean speed can be described by the travel time

$$\bar{v}_i = \frac{L_r}{t_i}$$  \hspace{1cm} (1)

where \(\bar{v}_i\) is the link mean speed of the \(i\) th vehicle, \(L_r\) is the travel length of the link, \(t_i\) is the travel time of the whole link.

Suppose the link is divided into infinite segments, so the speed of each segment should be invariant essentially, and the travel time of each vehicle is equal to sum of its travel time of each segment, which can be described as

$$\bar{v}_i = \frac{L_r}{t_1 + t_2 + \cdots + t_M} = \frac{L_r}{\sum_{j=1}^{M} t_j} \quad M = 1, 2, \cdots, \infty$$  \hspace{1cm} (2)

where \(t_j\) is the travel time of \(i\) th vehicle in the \(j\) th segment.

According to the formula described above, we can divided the entire road into finite segments of equal length, and then estimate the link mean speed of the road approximately on the basis of that the speed of vehicles remain constant at a certain distance.

As shown in Fig. 2, the whole link is divided into upstream and downstream segments, with lengths \(L_1\) and \(L_2\) respectively. The downstream segment contains no useful traffic information for estimating link mean speed on account of vehicle queue affected by the traffic signals. Therefore the upstream segment is only used in our speed measurement. In the model, the length of the link is 710m, while \(L_1\) is equal to about 640m and \(L_2\) is equal to about 70m. Loop detectors are coded in every lane, with length \(b\) from the downstream intersection. The upstream segment is divided into \(M\) segments with length \(L\). The link mean speed of each segment is estimated by the speed of their middle location, which can be collected from loop detectors if there has a loop detector.
IV. DATA PREPROCESSING OF PROBE VEHICLE

In order to get useful information from probe vehicles, the space-time matching approach is firstly introduced, including two procedures that extracting data from the same sampling period and removing the data not belong to the link measured. Further processing is to remove the information of the empty vehicles parking beside the road for a long time, because they are not helpful to speed measurement. It is also needed to verify the validity of the speed data. The number of probe vehicles will directly impact on the accuracy of the travel speed estimated and it is analyzed in [12], in which the link mean speed is expressed as follows.

\[ \overline{v} = \frac{1}{n} \sum_{j=1}^{n} \overline{v}_j \]  

(3)

where \( \overline{v} \) is the link mean speed estimated, \( \overline{v}_j \) is the link mean speed of the \( j \)th probe vehicle, \( n \) is the number of probe vehicles measured.

The error between actual value and estimated value of link mean speed is small when there are enough probe vehicles, and it gets bigger in the case of few probe vehicles. For the purpose of making the result more precise, the number of probe vehicles must reach to the minimum value \( n_{\min} \) according to [11]

\[ n_{\min} = \frac{Z_{\alpha/2} \cdot \sigma}{\epsilon} \]  

(4)

where \( Z_{\alpha/2} = \Phi^{-1}(1-\alpha/2) \), \( \Phi(x) \) is the standard normal distribution function, \( \sigma \) is the standard deviation of the standard normal distribution, \( \epsilon \) is the maximum permissible error.

In this paper, an adaptive weighted exponential smoothing method shown in [9] is adopted to deal with the speed of probe vehicles, and the model is shown as follows

\[ \overline{v}(k) = f(k) \cdot \overline{v}(k-1) + (1-f(k)) \cdot \frac{1}{n} \sum_{j=1}^{n} \overline{v}_j \]  

(5)

\[ f(k) = \begin{cases} \frac{1}{n} & (0 \leq n < n_{\min}) \\ 0 & (n \geq n_{\min}) \end{cases} \]  

(6)

where \( \overline{v}(k) \) is the estimation link mean speed of the current interval, \( \overline{v}(k-1) \) is the estimation link mean speed of the previous interval, and \( f(k) \) is the adaptive weight.

After preprocessing, the link mean speed and the number of probe vehicles of each segment are imported to the fusion model.

V. DATA PREPROCESSING OF LOOP VEHICLE DETECTORS

The mean speed of loop vehicle detectors can be computed by using the following equation

\[ \overline{v} = \frac{1}{k} \sum_{i=1}^{k} v_i \]  

(7)

where \( \overline{v} \) is the estimated mean speed of all vehicles in the interval measured, \( v_i \) is the mean speed collected from \( i \)th loop detector placed in internal lane, \( k \) is the number of the loop detectors. The traffic information collected may be false owing to noise of detectors, so in order to improve the accuracy of the data, a data screening and data resume procedure is needed to guarantee the data quality.

Generally, there are three kinds of false data among traffic data collected: missing data, error data and abnormal data, which are usually caused by environment noise, damaging detectors and network connection error as in [13, 14]. All of these false data must be identified and processed further.

Step 1: basic screening. Before macro data screening, data needs for testing to determine whether it contains a negative or missing data. Traffic flow \( q \), speed \( v \), and occupation \( o \) three basic traffic parameters are considered as a whole, through analyzing relation of three parameters find out regularity between them, so that incorrect data can be identified. Possibility of three parameters are analyzed, then validity and corresponding approach are listed in TABLE I.

<table>
<thead>
<tr>
<th>No.</th>
<th>Parameter state</th>
<th>Validity</th>
<th>Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>( q = 0, o = 0, v = 0 )</td>
<td>Missing or true</td>
<td>Further test</td>
</tr>
<tr>
<td>2</td>
<td>( q \neq 0, o = 0, v = 0 )</td>
<td>Error</td>
<td>Delete</td>
</tr>
<tr>
<td>3</td>
<td>( q = 0, o \neq 0, v = 0 )</td>
<td>Error</td>
<td>Delete</td>
</tr>
<tr>
<td>4</td>
<td>( q = 0, o = 1, v = 0 )</td>
<td>Stop vehicle</td>
<td>Further test</td>
</tr>
<tr>
<td>5</td>
<td>( q = 0, o = 0, v \neq 0 )</td>
<td>Error</td>
<td>Delete</td>
</tr>
<tr>
<td>6</td>
<td>( q = 0, o \neq 0, v \neq 0 )</td>
<td>Error</td>
<td>Delete</td>
</tr>
<tr>
<td>7</td>
<td>( q \neq 0, o \neq 0, v = 0 )</td>
<td>Error</td>
<td>Delete</td>
</tr>
<tr>
<td>8</td>
<td>( q \neq 0, o = 0, v \neq 0 )</td>
<td>Uncertain</td>
<td>Further test</td>
</tr>
<tr>
<td>9</td>
<td>( q \neq 0, o \neq 0, v \neq 0 )</td>
<td>Uncertain</td>
<td>Further test</td>
</tr>
</tbody>
</table>

Step 2: the threshold screening. Vehicles on the road are limited to travel by a max speed according to links. The principle can be used to identify error data that exceed the threshold.

Step 3: abnormal data filtering. Changes in traffic flow of the network are a stationary random process under normal traffic conditions. The variation value of the speed maintain in a certain range though randomness exists among it. Therefore, a false data identification method is presented by using average value \( \overline{v} \) and variance \( \sigma \) of the \( n \) data collected previous in the time length of \( t \)

\[ \begin{align*} 
|v_i - \overline{v}| & \leq 2\sigma, & \text{normal} \\
|v_i - \overline{v}| & > 2\sigma, & \text{error} 
\end{align*} \]  

(8)

Missing data are recovered by further process after data screening. Different data resume methods are utilized according to the number of the missing data. In this paper, a time-series-based data recovery method is proposed when the quantities of the missing data are less than 5.
The Kalman Filter method is used to forecast the current speed with the historical data when missing data exceed 5.

VI. FUSION MODEL BASED ON SPACE MATCHING

Because most of probe vehicles are car, they have relatively higher speed compare with other vehicles which are not car; loop vehicle detectors can collect speed of all of vehicles with high accuracy, but it can’t well estimate link mean speed because of just collecting spot speed. In order to make solution about these problems, it is need to make space-matching data of loop vehicle detectors between data of probe vehicles. In other words, eliminate the difference between data of loop vehicle detectors and data of probe vehicles with data correction.

\[ \lambda = \frac{v_f}{v_i} \]  

Where \( v_f \) is the mean speed of probe vehicle at spot of loop vehicle detector (km/h), \( v_i \) is the mean speed collected by loop vehicle detector (km/h).

A. Weighted Average Method

According to Fig. 2, the mean speed in every link can affect arterial mean speed, so it can be estimated arterial mean speed through the weight sum of mean speed in every link.

\[ \bar{v} = \sum_{i=1}^{M} w_i \bar{v}_i + b \]  

Where \( \bar{v} \) is arterial mean speed (km/h), \( \bar{v}_i \) is link mean speed of \( i \) th segment (km/h), \( w_i \) is the weight of corresponding link. \( w_i \in [0,1] \). \( b \) is the deviation, which is used to Correct fusion result. So the function of total error is

\[ En = \frac{1}{2} \sum_{i=1}^{n} [\bar{v}(i) - v(i)]^2 \]  

Where \( \bar{v}(i) \) is estimated mean speed of the \( i \) th sample, \( v(i) \) is the actual mean speed of \( i \) th sample.

B. Training By Newton Method

To find weight and deviation used to get the minimal total error, it need to train Fusion model. The weight is trained by Newton method, which is a fast optimal method based on quadratic's Taylor series. Newton method is defined as

\[ x_{k+1} = x_k - A_k^{-1} g_k \]  

Where \( x_{k+1} \) is \( k+1 \) th weight or deviation; \( x_k \) is previous weight or deviation; \( g_k \) is coefficient of variable; \( A_k^{-1} \) is Hessian matrix which is obtain from error performance function in the current weights and threshold value.

It is supposed that the performance function \( f(x) \) is secondary differentiable real function which is from optimized problem \( \min f(x)(x \in R^n) \). The basic idea of Newton method is that with a quadratic function locally approximate \( f(x) \) at first, and then find minimum of approximated function. The Hessian function can be expressed as:

\[ A_k^{-1} = \nabla^2 f(x) = 2J^T(x)J(x) + 2S(x) \]  

where \( J(x) \) is Jacobean matrix

\[ S(x) = \sum_{i=1}^{N} v_i(x) \nabla^2 v_i(x) \]  

Where \( v_i(x) \) is error vector. When \( S(x) \) very small, Hessian matrix is approximately expressed as

\[ A_k^{-1} \approx \nabla^2 f(x) \equiv 2J^T(x)J(x) \]  

Suppose that \( f(x) \) is the form of (12), gradient can be expressed as follows.

\[ \nabla f(x) = 2J^T(x)v(x) \]  

Where \( J(x) \) is:

\[
J(x) = \begin{bmatrix}
\frac{\partial v_1(x)}{\partial x_1} & \frac{\partial v_1(x)}{\partial x_2} & \cdots & \frac{\partial v_1(x)}{\partial x_n} \\
\frac{\partial v_2(x)}{\partial x_1} & \frac{\partial v_2(x)}{\partial x_2} & \cdots & \frac{\partial v_2(x)}{\partial x_n} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial v_N(x)}{\partial x_1} & \frac{\partial v_N(x)}{\partial x_2} & \cdots & \frac{\partial v_N(x)}{\partial x_n}
\end{bmatrix}
\]  

Make second derivative to formula (17), the \( k, j \) th element of result is that

\[
\left[ \nabla^2 f(x) \right]_{k,j} = \frac{\partial^2 f(x)}{\partial x_k \partial x_j} = 2 \sum_{i=1}^{N} \left[ \frac{\partial v_i(x)}{\partial x_k} \frac{\partial v_i(x)}{\partial x_j} + v_i(x) \frac{\partial^2 v_i(x)}{\partial x_k \partial x_j} \right]
\]

So Newton method is expressed as:

\[ x_{k+1} = x_k - \left[ J^T(x_k)J(x_k) \right]^{-1} J^T(x_k)v(x_k) \]  

The Newton method has fast convergence speed and always can be found minimum of quadratic function in one step, so it can be used to train weight and deviation of Fusion model. When data of probe vehicle and data of loop vehicle detector are fused, the fusion result can reduce training time and reduce the consumption of computer resource with this method. It also can guarantee real-time performance of fusion algorithm.
EXPERIMENTS AND DISCUSSION

A. Data Source

The experimental data is collected by employing a traffic simulation software VISSIM3.6, according to the road model presented by Fig. 2. Urban road model of unidirectional three-lane carriage way with intersections is constituted in the software. VISSIM simulate the traffic characteristic of urban road at rush hours. Traffic volume is ranged from 800 veh/h to 1150 veh/h, and proportion of probe vehicles is ranged from 10% to 15% of the total vehicles of the simulation model. The collecting interval is set at 5 min. 360 groups of data have been obtained by running the simulation software.

B. Data Preprocessing

As precise as the data stimulated by VISSIM3.6, additional noise is demanded to be considered. For the data of loop vehicle detectors, missing data, error data and abnormal data should be considered according to the causation of the false data, so the data screening and data recover methods are used to identify these data further. The threshold value of speed is set at 80km/h. The arithmetical mean algorithm is finally used to obtain mean speed of the loop detectors.

For probe vehicles, a matching procedure is needed to search the data belonging to links measured, and these data are classified according to the collection interval. Mean speed of each segment can be also calculated by the arithmetical mean algorithm according to the urban road model that is shown in Fig. 2.

C. Data Fusion Processing

360 groups data of probe vehicles and loop vehicle detectors are acquired after data preprocessing. They are imported into the Space-matching-based fusion model to estimate link mean speed, respectively, and 12 of the results are shown in TABLE II.

<table>
<thead>
<tr>
<th>No.</th>
<th>Segments speed(km/h)</th>
<th>Speed(km/h)</th>
<th>1st</th>
<th>2nd</th>
<th>…</th>
<th>7th</th>
<th>GPS</th>
<th>Loop</th>
<th>True</th>
<th>Fusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>58.2</td>
<td>51.6</td>
<td>11.7</td>
<td>40.3</td>
<td>46.6</td>
<td>38.9</td>
<td>38.9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>58.6</td>
<td>56.0</td>
<td>17.2</td>
<td>51.0</td>
<td>50.2</td>
<td>48.6</td>
<td>48.5</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>60.5</td>
<td>58.8</td>
<td>10.3</td>
<td>45.8</td>
<td>47.8</td>
<td>42.0</td>
<td>42.2</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>4</td>
<td>61.8</td>
<td>56.1</td>
<td>29.2</td>
<td>55.5</td>
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<td>46.2</td>
<td></td>
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</tr>
<tr>
<td>5</td>
<td>54.3</td>
<td>51.9</td>
<td>16.0</td>
<td>45.8</td>
<td>49.8</td>
<td>45.7</td>
<td>46.6</td>
<td></td>
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<tr>
<td>6</td>
<td>56.5</td>
<td>57.8</td>
<td>19.8</td>
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<td>7</td>
<td>54.7</td>
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<td>48.7</td>
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<td>8</td>
<td>56.6</td>
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<td>12.0</td>
<td>42.5</td>
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<td>48.5</td>
<td>43.1</td>
<td>37.4</td>
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</tr>
</tbody>
</table>

In this paper, the whole link is divided into 7 segments according to its length. As shown in TABLE II, the mean speed data of segment 1, 2 and 7 collected by probe vehicles are listed. Speed data of “GPS” and “Loop” are collected by probe vehicles and loop detectors. Speed data of “True” are the actual link mean speed calculated by link travel time of all vehicles. Speed data of “Fusion” are estimated link mean speed calculated by the fusion model.

Figure 3. Speed parameter curves of probe vehicle, loop vehicle detector, fusion method and actual value

Some of the results plotted are shown in Fig. 3. It is clear that curve of the fusion method is closer to that of actual value than curve plotted by speed data from probe vehicles and loop vehicle detectors, respectively.

The data accuracy of the probe vehicles, loop vehicle detectors and fusion method are listed in TABLE III.

<table>
<thead>
<tr>
<th>No.</th>
<th>Data accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Probe vehicle</td>
<td>90.4%</td>
</tr>
<tr>
<td>Loop detector</td>
<td>87.7%</td>
</tr>
<tr>
<td>Fusion model</td>
<td>96.9%</td>
</tr>
</tbody>
</table>

As shown in TABEL III, the speed accuracy of the probe vehicles is 90.4% calculates by 360 groups data, while the speed accuracy of the loop detectors is 87.7%. The estimation model presented in this paper improves the speed accuracy obviously.

D. Results Analysis

From results acquired above, it is perceived that data precision of probe vehicle is higher than that of loop vehicle detector. The reason is that the number of speed data of one probe vehicle is much more, and these speed data are collected from different location of the link, while loop vehicle detectors are coded near the downstream of the link, possessing a lower precision of link mean speed, resulting from its sampling from single road point. The space-matching fusion model presented in this paper, improves the accuracy of the link mean speed. Compared to the probe vehicles and loop vehicle detectors, the precision of the link mean speed has been brought on 6.5% than the former and 9.2% than the later.
VIII. CONCLUSION

Traffic flow data are the basis on which ITS is capable of supervising and controlling of road network. The data quality has direct impact on the reliability of traffic information. In this paper, a space-matching fusion model is presented to improve the accuracy of the estimated arterial speed, according to the fact that probe vehicle data and loop vehicle detector data are strongly complementary in space. In this fusion model, an urban road model is proposed which divided road into several equal length segments. Then the loop vehicle detector data are matched to each segment according to the adjustment coefficient. Finally, a weighted fusion model is used to calculate link mean speed by each segment data, in the model Newton method is used as training method to get the weights. Through experiment analysis, it can be found that the fusion model can improve the accuracy of the arterial speed, and the speed estimation method is efficiently. Consequently, fusion model based on space matching consisted with the data sources of loop vehicle detectors and probe vehicles is practicable. This fusion model is reliable by using the simulation data, but it should be applied to practice further.

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REFERENCES


