A Traffic-Network-Model-Based Algorithm for Short-Term Prediction of Urban Traffic Flow

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Abstract—In the research field of Intelligent Transportation Systems (ITS), traffic flow prediction is a key technology for traffic guidance and advanced control strategy. Accuracy and immediacy are the main requirements for prediction methods. This paper presents a short-term prediction algorithm of traffic flow rate based on the macroscopic urban road network model. Classified into different typical elements, a traffic road network can be expressed as a matrix. Taking crosses and their links as basic research objects, the proposed prediction method can only use a few real traffic parameters obtained from loop detectors to realize accurate short-term prediction of traffic flow rate. This method can also be adaptable to different kinds of road network. In case study, the real traffic system is simulated with the microscopic traffic simulation platform (CORSIM). In the given simulation environment of road network, the experiment results illustrate that the proposed prediction algorithm can accurately predict flow rate in short term.

Keywords—short-term prediction; urban traffic flow; traffic network model; CORSIM; loop detector

I. INTRODUCTION

With the rapid development of economy and society, road paving has not reached the requirement of increasing vehicles. Then, in most of big cities, traffic jams gradually become a serious problem that causes traffic confusion and environment pollution. Intelligent Transportation Systems (ITS) have been a scientific resort to relieve this problem. As a key technology of ITS, short-term prediction of traffic flow is always a hot research point. For different uses, the predicted objects involve traffic flow rate, average speed, travel time, etc. This paper selects the traffic flow rate on the links of urban traffic network as the predicted object.

During the recent decades, the research on traffic flow prediction has made much progress, and many methods have been put forward to solve this problem. Typically, there are AutoRegressive Integrated Moving Average (ARIMA)[1][2], Kalman Filter[3], Neural Network based[4][5], Support Vector Machine[6][7], etc. However, these methods pay much attention on the model in terms of time domain and frequency domain, and seldom considered the relation between links of road network. For freeway networks, these methods can obtain enough accuracy in prediction, as there are not many disturbances to traffic flow. However, in complicated urban traffic network, traffic flow is disturbed by many factors, such as adaptive control signals of traffic lights, pedestrians, bicycles, and traffic accidents. When traffic flow changes too frequently, and is not smooth any more, the traditional methods based on time series analysis cannot satisfy the accuracy requirement of traffic flow prediction in engineering practice.

In order to make better use of the spatial information between links, Shu et al.[8] proposed a prediction model that closely bases on the network structure. This method achieved good results in the comparing experiments with the microscopic traffic simulation platform (CORSIM). However, there are too many parameters to be determined in their prediction model; furthermore most of them, e.g. link content and lengths of waiting queues, are difficult to obtain by traffic detectors (e.g., loop detectors, GPS probe vehicles) in actual road network.

In this paper, we improve the prediction algorithm proposed in [8] to make it be able to use the information provided by loop detectors. By this means, it could become possible to apply the short-term prediction model of traffic flow based on the traffic network model into engineering practice.

II. ROAD NETWORK MODEL

A. Basic Element of Urban Traffic Network

In order to understand the mechanism of an urban traffic network, we need firstly define the network element and the relation between one element and its four adjacent ones. To give an example, two adjacent elements are listed in Fig. 1. Coordinate \((i, j)\) and \((i, j+1)\) indicate their positions, where \(i\) represents the row number and \(j\) represents the column number.

![Figure 1. Two adjacent network elements](image)
Fig. 1 shows two horizontal adjacent elements—$E(i, j)$ and $E(i, j+1)$, both of which are crossing. A vehicle in these links can go through, turn left, or turn right, according to a turning rate. For instance, the element $E(i, j)$ has four links, and a vehicle is running on the west link $E_W(i, j)$. When the vehicle turns right on the crossing, it will be on the link $E_S(i, j)$. Link $E_E(i, j)$ and link $E_W(i, j+1)$ indicate the same road, which connects elements $E(i, j)$ and $E(i, j+1)$, but in reverse direction. The coordinates point out the crossings into which vehicles in the link will run.

B. Urban Traffic Network Model

Based on the traffic network elements described in last subsection, the urban traffic network model can be constructed as follows.

In real traffic, roads usually connect to each other and form like a grid. No matter large or small, the grid only consists of two main parts: joint and link. Links are made up of 2 or 4 lanes or more, but always two directions, whereas joints can be classified according to the number of links running in. In Fig. 2, the network is a 5×5 grid, and the black circles indicate the nodes and 9 joint nodes. The sourcing node means the interface which contains direction information. Node 2, Node 4, Node 7, and Node 9 are T-shape, which also connects 4 links and the T-shape which connects 3 links. In this figure, node 2, 4, 7, and 9 are T-shape, which also contains direction information. Node 2, Node 4, Node 7, and Node 9 is defined by $T_S$ (south), $T_E$ (east), $T_N$ (north), and $T_W$ (west), respectively. The sourcing node is defined with the direction in the same way. According to the rule mentioned above, the urban traffic network shown in Fig. 2 can be described by a 5×5 matrix in (1).

\[
\begin{pmatrix}
0 & S_s & 0 & S_s & 0 \\
S_E & C & T_S & C & S_w \\
0 & T_E & C & S_s & S_w \\
S_E & T_S & C & T_w & 0 \\
0 & 0 & S_N & S_N & 0
\end{pmatrix}
\]

(1)

The traffic network element is described using the following variables:

- $i$: line number of the cross;
- $j$: column number of the cross;
- $T$: sampling time interval;
- $T_p$: prediction time period, usually set 5min;
- $D \in \{W, N, E, S\}$: orientation of the link (i.e., west, north, east, south);
- $t \in \{s, l, r\}$: turning direction of the traffic flow (i.e., straight, left, right);
- $V_{avg,D}(i, j, k)$: average speed of the vehicles in the link in the past prediction period;
- $V_D(i, j)$: predefined congested speed in the link;
- $F_D(i, j, n)$: average traffic flow rate in the $n$th $T_p$ period;
- $C_D(i, j)$: capacity of the link expressed by vehicle numbers;
- $N_D(i, j)$: number of lanes of the link;
- $L_{veh}$: average length of the vehicles;
- $S_D(i, j)$: saturated flow rate of the link;
- $\gamma_D(i, j, k)$: ratio of the vehicles turning $t$ at the stop line of the link at time $k$;
- $D_{De}(i, j, k)$: number of the vehicles that depart from the link turning $t$ at time $k$;
- $D_{in,D}(i, j, k)$: number of the vehicles that enter the link at time $k$;
- $D_{in,De}(i, j, k)$: number of the vehicles that enter the link which is the destination when turning $t$ at time $k$;
- $D_{out,D}(i, j, k)$: number of the vehicles that depart from the link at time $k$;
- $W_D(i, j, k)$: number of the vehicles waiting in the link at time $k$;
- $W_{t,t}(i, j, k)$: number of the vehicles that wait in the link intending to turn $t$ at time $k$;
- $Q_D(i, j, k)$: number of the vehicles arriving at the tail of the waiting queue in the link at time $k$;
- $Q_{t,t}(i, j, k)$: number of the vehicles arriving at the tail of the waiting queue in the link at time $k$, and the waiting queue is going to turn $t$;
- $f_D(i, j, k)$: available free space in the link at time $k$ expressed by the number of vehicles;
- $f_{De,dl}(i, j, k)$: free space in the downstream link of the departure vehicles turning $t$ in the link at time $k$;
- $g_{De}(i, j, k)$: signal symbol for the vehicles turning $t$ in the link (1 when the signal is green, 0 when the signal is red);
- $Cog_{De}(i, j, k)$: a BOOL symbol to indicate whether the link turning $t$ is congested.

![Figure 2. Road network topology](image-url)
III. PROPOSED SHORT-TERM PREDICTION ALGORITHM

The prediction object of this algorithm is Average Traffic Flow Rate, which is defined by (2).

\[ F_{p}(i, j, n) = \sum_{t = t_0}^{t_{n}} D_{out,D}(i, j, k) \times \frac{60}{T_f} \]  
(2)

Traffic flow rate in a link can be described by the number of the vehicles running out of this link. It is updated every prediction period, i.e., \( T_p \), which is shown as (3).

\[ D_{out,D}(i, j, k) = D_{Dh}(i, j, k) + D_{Dj}(i, j, k) + D_{Dp}(i, j, k) \]  
(3)

Before the vehicles run into the cross or T-shape, they may choose different directions according to their destination and the signal display. \( D_{Dh}(i, j, k) \), the number of the vehicles going out at one direction, will be determined by the vehicles waiting at the stop line since last period and the arriving ones in this period. It is also restricted by the traffic state of the link that it will go into and the signal display. Although the precise traffic state of the downstream link like link content is difficult to obtain in the engineering practice, we can estimate it by use of the average speed that we obtain from the data of loop detectors. The calculation method is given in (4) and (5).

\[ D_{Di}(i, j, k) = \begin{cases} 0, & \text{if } g_{Di}(i, j, k) = 0 \text{ or } Cog_{Di}(i, j, k) = 0 \\ \min \{ W_{Di}(i, j, k) + Q_{Di}(i, j, k), S_D(i, j, k) \times T \}, & \text{else} \end{cases} \]  
(4)

\[ Cog_{Di}(i, j, k) = 1, \text{ if } V_{avg,D}(i, j, k / T) < V_D(i, j, k) \]  
(5)

When the average speed of the traffic flow in the downstream link is below \( V_D(i, j, k) \), which is predefined usually between 0.1~0.2 of the free flow speed, the traffic flow is treated as congested. The saturated output rate \( S_D(i, j) \) is another restriction, which is related to cross specific features; \( (i_D, j_D) \) represents the downstream link of the traffic flow; \( T \) is the sampling time interval; \( \lfloor \cdot \rfloor \) denotes the operation of reserving integer.

In (4), \( W_{Di}(i, j, k) \) can be computed by (6).

\[ W_{Di}(i, j, k + 1) = W_{Di}(i, j, k) + Q_{Di}(i, j, k) - D_{Di}(i, j, k) \]  
(6)

When the sampling time interval is large, the decimal part is relatively small so that the latter part of (6) can be neglected.

At the stop line of the crossing, vehicles usually join different waiting queue according to their turning directions. Therefore, \( Q_{Di}(i, j, k) \) can be computed by (7).

\[ Q_{Di}(i, j, k) = V_{Di}(i, j, k) \times Q_{Di}(i, j, k) \]  
(7)

where \( Q_D(i, j, k) \), the number of the vehicles arriving at the tail of the waiting queue, is mainly determined by \( \beta_D(i, j, k) \), the integer part of the time it takes when running from entering to tails. Then we can have

\[ Q_D(i, j, k) = \frac{((T - \alpha_D(i, j, k)) / T) \times D_{sd}(i, j, k) - \beta_D(i, j, k) - \sigma_i)}{T} + \frac{((\alpha_D(i, j, k)) / T) \times D_{sd}(i, j, k) - \beta_D(i, j, k) - 1 - \sigma_i}{T} \]  
(8)

where \( \alpha_D(i, j, k) \) and \( \beta_D(i, j, k) \) are the fractional and integral part of the time that the vehicles spend on travelling from the entrance of the link to the tail of the waiting queue at the stop line. They can be computed by (9) and (10). \( \sigma_i \) is the constant parameter that represents the time during which the vehicles go through the joint.

\[ a_D(i, j, k) = \text{mod} \left[ \frac{C_D(i, j) - W_D(i, j, k) \times L_D(i, j)}{N_D(i, j) \times V_{avg,D}(i, j, k - 1) \times T} \right] \]  
(9)

\[ \beta_D(i, j, k) = \text{floor} \left[ \frac{C_D(i, j) - W_D(i, j, k) \times L_D(i, j)}{N_D(i, j) \times V_{avg,D}(i, j, k - 1) \times T} \right] \]  
(10)

In (5), the dynamic value of \( V_{avg,D}(i, j, k, j) \) can be obtained from the data of loop detectors by the estimate method in [9].

IV. SIMULATION EXPERIMENTS

CORSIM is an authoritative software of microscopic traffic simulation, which is exploited by the FHWA [10]. In this section, we take CORSIM as the experiment environment to verify the proposed prediction algorithm, i.e., to use the proposed algorithm to predict the traffic flow of CORSIM every 5 minutes. The urban traffic network shown in figure 1 was taken as the experiment network. In this road network, the length of each link was 1200m, and each link had 3 lanes per direction. For the turning percentage of the vehicles at each cross or T-shape, we selected the pre-defined values in CORSIM. The saturation flow rate of every link was set 2000 veh/h. We set one loop detector at the middle of each link to detect the traffic state of the link. Then, the prediction results of link 7-8 under different traffic inputs are shown figure 3, 4, and 5. In these figures, the real line is the real flow rate of CORSIM, and the dashed is the prediction result of the proposed algorithm.

Fig. 3 shows the result under the condition that the input flow rate at every sourcing node is 1000veh/h. When input flow rate is 2000 veh/h, the result is shown in figure 4. Figure 5 shows the result under changing input flow rate: 1000 veh/h from beginning, 2000 veh/h from 20min, and 3000 veh/h from 40min to end.
The average values and standard deviations of the prediction errors are listed in Table I.

<table>
<thead>
<tr>
<th>Figure No.</th>
<th>ARE</th>
<th>EMSD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fig. 3</td>
<td>8.26%</td>
<td>10.70</td>
</tr>
<tr>
<td>Fig. 4</td>
<td>12.44%</td>
<td>12.73</td>
</tr>
<tr>
<td>Fig. 5</td>
<td>17.24%</td>
<td>13.54</td>
</tr>
</tbody>
</table>

ARE: Average Relative Error, EMSD: Error Mean Square Deviation

From the experiment results, we can see that the curves of the prediction results can follow the CORSIM curves well. The prediction accuracy of the proposed algorithm can be larger than 80%, even if the input traffic flow exceeds the saturation flow of the links, or there are sudden changes in the input of traffic flow.

V. CONCLUSION

In this paper, a traffic-network-model-based algorithm is presented to realize short-term prediction of the traffic flow rate. This algorithm is more adaptive for the practical application than the former algorithm based on the traffic network model, as it can directly make use of the detection data provided by loop detectors. Compared with the real traffic flow rate of the road network in CORSIM, the prediction accuracy of the proposed algorithm can reach a desirable level. The experiment results imply that the proposed algorithm is promising for the future practical application.

REFERENCES