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Research on Traffic Flow Mathematical Model in Urban Traffic

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Abstract

In this paper, we take the urban road network as the object, a further study on the method of traffic signal self organization under the condition of traffic state identification and local congestion. In the urban road traffic state identification study, according to the need of traffic signal control, respectively from qualitative and quantitative point of view, the urban road traffic state is defined. In order to be able to obtain real-time traffic data as the foundation, design urban road traffic state evaluation index system. Based on the current mainstream micro traffic simulation software VB and VISSIM as the tool to build the experimental platform, and set up the UTC-CI (Urban Traffic Control for Congested Intersections) experimental environment, the above method is verified by simulation. The results show that the traffic state identification method and the related signal control method have the expected effect in reducing congestion duration.

Keywords*: Urban Road Traffic, Traffic Flow, Mathematical Model, UTC-CI*

1. Introduction

So far, very few algorithms have been developed to diagnose the traffic state of transportation signal control system [1-5]; but too many have been proposed to recognize the traffic state of such systems as traffic event management system and traffic information distribution system which are based on the collected data by the detector in transportation signal control system [6-10]. Those methods are being improved and becoming perfect, which provides many referential ideas for the traffic state discerning method here. In this study, compared with identification of cross-road traffic states, the discrimination of road segment traffic states becomes more important, because traffic congestion on crossing roads is primarily manifested by the state of each entrance lane, which is much directional; moreover, for the traffic dispersion, the effect in some particular flow directions is rather highlighted.

For the purpose of traffic signal control system, regarding some road sections with fixed type detectors, we'll design respectively single-section traffic state recognition algorithm and double-section one based on the location of deployed detectors; with regards to road sections without fix-type detectors but with GPS floating cars the travel time on such sections can be obtained, we'll design the discrimination algorithm based on the estimated value of average journey speed. Besides, based on the discriminative results of segment traffic states, we'll design the algorithm to identify cross-road traffic state.

2. Road Segment Traffic State Recognition Algorithm Based on Single-Section Detector Data

Single-section detectors are deployed on road segment generally in these two manners:

(1) Deployed on the upper course of the segment;

(2) Deployed near parking lines. At present, of the mature signal control systems based on detector data, only SCATS system deploys the detector around parking lines.

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With the data acquired at the layout position of detectors, what can be only identified is whether the traffic flow approximates the saturation flow rate of the section. In this case, the traffic state can be divided into non-saturation and over-saturation state, without further partition of the traffic state on the road section. Hence from the perspective of recognizing congested traffic flow and self-organizing signal control, we think it's more reasonable to install single-section detectors on the upper course of the section if it has to be, because traffic data acquired at that position can reflect more subtly traffic states on the section.

When designing the traffic state recognition algorithm based on single-section detector data, we consider only detectors installed on the upper course, not including the situation near parking lines. Then, with traffic data got by those detectors, we design an automatic identification algorithm for section traffic state based on neural network techniques.

2.1. Selection of Traffic State Indictors

We use induction coil type fixed detectors. Such kind of detector can provide lots of traffic parametric data like traffic flow (q), speed (v) and occupancy rate (o).

Traffic flow (q), renamed traffic volume or flow, means the actual vehicles going through the detector in unit time.

Traffic speed (v) refers to the distance that vehicles travel in unit time. Traffic speed has many kinds in conceptual sense since road traffic flow is a complicated system consisted of various types of vehicles.

Occupancy rate (o) includes space and time occupancy. What the induction coil type detector gets is time occupancy, which means in certain observed time, the ratio between the total time of traffic detector occupied by vehicles and the observed time length, as calculated in the following equation:

$$o = \sum \nabla t_i / t \qquad (1)$$

Time occupancy to a certain degree represents the state of running traffic flow. When the traffic flow is small, vehicles passing the detector in unit time are fewer and time occupancy is lower due to fast speed. With increasing traffic flow, more vehicles pass the detector in unit time and the speed slows down. The detector is occupied longer by vehicles; thus the time occupancy increases. When there's traffic congestion, traffic flow passing the detector may descend; but time occupancy still keeps a higher level because of decelerating speed.

In the case of traffic jam, induction coil type detector captures the change of traffic parameters in its position, as shown in Figure 1, where, axis X is sampling cycle. To display data of each parameter in the same window, we processed original data and normalized them.

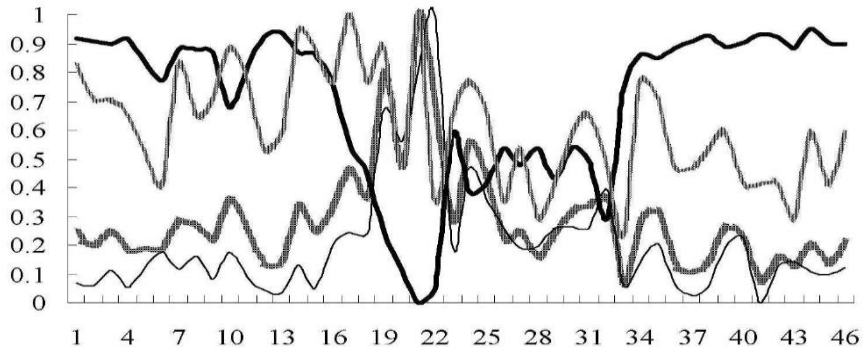


Figure 1. Traffic Data State Distribution Map

From Figure 1, we see in the course of congestion occurring, lasting and dispersing, the occupancy and speed data gathered by such a detector are more sensitive to congested time and degree; while the volume reacts bad. However, the average occupancy based on the combined occupancy and flow by a single vehicle has good responsiveness. Accordingly, to choose traffic state indictors, we convert the combination of flow and occupancy to single vehicle occupancy mean; and use occupancy and speed to form traffic state feature vector $x = (y_1, y_2, y_3)^T$.

The indexes of feature vector are respectively:

$$y_1(t) = occut(t) \tag{2}$$

$$y_2(t) = \frac{occu(t)}{q(t)} \tag{3}$$

$$y_3(t) = speed(t) \tag{4}$$

2.2. Design of Road Section Traffic State Discrimination Algorithm

When traffic data at some point are possibly obtained, we can establish the mapping relationship between such data and the traffic state assessed by using road segment service level as evaluating indictor to recognize traffic states on road section. That mapping relationship is one typical non-linear function relation. Artificial neural network techniques were found better performance in solving this problem. BP neural network is a kind of network node in the ANN (artificial neural network).

So we choose BP neural network to build the mapping relationship between traffic parameters and states at the collecting position as to eventually realize the identification of road segment traffic states.

The discrimination algorithm for road segment traffic states based on BP neural network is carried out in these steps:

(1) Follow the specified sampling time interval t to obtain in a manual observation manner the average travel speed data in representative time range on designated road and traffic data at certain position on the segment, such as flow, speed, occupancy;
(2) Based on average travel speed data, utilize service level analysis method to figure out the traffic state evaluation result time sequence in each time frame on the segment, “1” for smooth, “2” for “blocked”, “3” for “congested”;
(3) Calculate traffic state feature vector $y_1(t)$, $y_2(t)$ and $y_3(t)$ in each period and normalize them to [0-1];
(4) Use $y_1(t)$, $y_2(t)$ and $y_3(t)$ as input variables of BP neural network and figures about traffic state in (2) as output variables to train BP neural network; after successful training, save the network;
(5) Acquire the current data of induction coil as per designated time interval and make normalized conversion of them;
(6) Input time interval feature vectors to the well-trained neural network in (4);
(7) The output of neural network is the current traffic state, which should be passed to traffic signal control system.
(8) Set $t = t + 1$, in (5)

3. Road Segment State Recognition Algorithm Based on Double-section Detector Data

On urban roads, to know accurately traffic condition as to improve the effect of traffic signal control, generally a couple detectors are laid out respectively on the upper and around parking line of some important cross-road segments to realize double-section observation of traffic data.

For the convenience of introduction, we name the detector near parking line as D_1 and the other on upper section as D_2, as described in details as follows:

(1) Follow the specified time interval t to get vehicle number N_1^t passing D_1 and vehicle number N_2^t passing D_2;

(2) Compute the queuing length of the section in t and that the rest vehicle number on road section is $Q^t = Q^{t-1} + N_2^t - N_1^t$;

(3) Discriminate traffic states on the segment according to the confirmed evaluation criteria;

(4) Output the result of identifying traffic state and send to traffic signal control system.

(5) Set $t = t + 1$, in (1)

4. Crossing Road Traffic State Discrimination Algorithm

In the urban road net, cross-roads are of a variety due to plentiful road sections and different road grades. The traffic state at the crossing is determined by that of its road sections. But, for road sections of different grades, the traffic state affects the intersection differently. When discriminating traffic state at the crossing, we should consider the traffic state of its own road segments and the static grade of such segments, *i.e.*, recognizing the traffic state by considering combined both.

We carry out following steps to fulfill the discrimination of traffic state at the intersection:

(1) Obtain the discriminative result of road segment traffic state at the time interval t;
(2) Get grade information M of each road segment; $M \in (A, B, C)$, Where ,A is the main road, B is a secondary road, C is a branch;
(3) Based on the importance degree of each road segment, allocate one initial weight to each segment; $\omega_M^i, i \in (1, 2, 3)$, ω_M^i is the weight value of grade M section;
(4) Sum up the weight of different grade road segments with different degree of congestion
(5) The traffic state to which the sum of maximum weights corresponds is the traffic state at the crossing. Set $t = t + 1$, in (1)

5. Experiment Design and Discussion

For the proposed method for recognizing urban road traffic state, the premise is identification of road segment traffic state. The judgment of traffic state at the crossing is based on that of road segment, which is further statistics and analysis of the discriminative result of road section traffic state. So we take the discrimination of traffic state on road segments for instance to validate the proposed new algorithm.

5.1. Design of Simulation Experiment on Traffic State Discrimination on Road Sections

We use the intersection between Ziyou Road and Yatai Street in Changchun city as research object. It is shown in Figure 2. It is a crossed junction with eight lanes in two directions, in the fixed timing signal controlling way with signal time length 180 seconds.

We make use of data acquired through artificial traffic survey in two consecutive weeks to execute fundamental parameter calibration on VISSIM simulation software. In the meantime, delay data are got as well at the location, so as to find out if the traffic state result got here through the mapping method mentioned above is in line with the actual evaluated service level. The flow input approach in the simulation road net is presented in Table 1. Traffic flow is composed of heavy vehicles and light vehicles, which takes respectively 8% and 92%. Of them, 10% vehicles turn left, 20% turning right and 70% going straight. Signal timing at the intersection is shown in Table 2 and Figure 3.

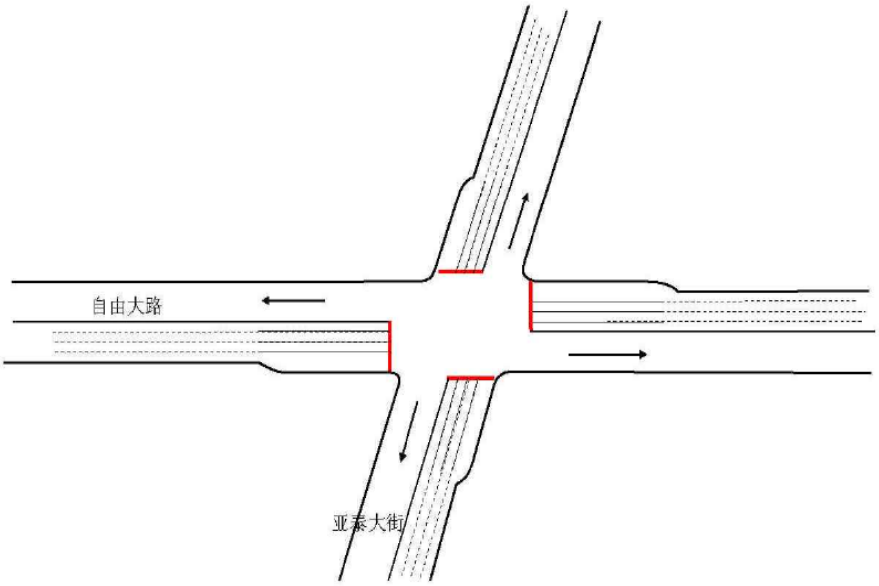


Figure 2. Free Road-Yatai Street Intersection

Table 1. Traffic Input Scheme in Simulation Network

Flowinput position / Time slot(s)	East	North	South	West
0-1800	1350	1400	1320	1540
1801-3600	1440	1600	1400	1650
3601-5400	1620	1800	1510	1740
5401-7200	1760	1900	1640	1850
7201-9000	1940	2110	1720	1940
9001-10800	2010	2230	1850	2160
10801-12600	2150	2350	1750	2050
12601-14400	1940	2180	1660	1930
14401-16200	1850	1920	1630	1820
16201-18000	1680	1830	1520	1730
18001-19800	1530	1740	1410	1630
9801-21600	1420	1620	1300	1550

Table 2. Signal Lamp Group

SG1	SG2	SG3
		
SG4	SG5	SG6
		

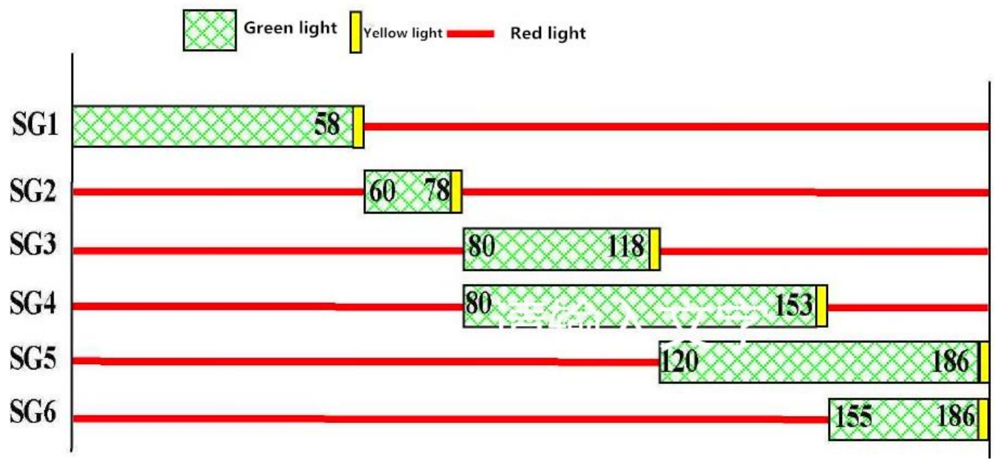


Figure 3. Intersection Signal Timing Scheme

In the upper location of each lane in west-east direction, we install traffic sensors to gather traffic flow parameter data on the upper section of the road segment.

When designing the experimental program, to show the influence of traffic signal timing at the crossing, we set time to three intervals like 120s, 188s and 300s to analyze the traffic state, which is respectively shorter/equal/longer than signal cycle. In UTC-CI testing environment, make simulation test on each program. During the simulation, set 11 random seeds. For each seed, the simulation time is 21500s. Traffic data generated by the first ten seeds constitute the training sample set X, which is used to train BP neural network; traffic data produced by the 11^{th} seed are applied for real-time discriminative test, *i.e.*, testing sample set Y.

At present, parametric data provided by VISSIM like occupancy, speed and volume can be obtained only after the simulation. Those data can be used to train off-line BP neural network, but infeasible for online recognition of traffic state. To build the testing scenario for online discrimination of traffic state, we employ VC program language. We control VISSIM running with COM interface. With CON, VISSIM can acquire detector real-time data during the simulation, which are input to the well-trained BP neural network to judge the current traffic state. Figure 4 gives the module of discriminating real-time traffic state in the demonstration system compiled here.

5.2. Analysis of Experimental Results about Traffic State Discrimination on Road Segments

In the experimental environment created here, we used the algorithm in [11] (algorithm 1) and the proposed method (algorithm 2) to identify the traffic state of west-east road segment at the crossing through three testing programs. Figure 5-7 illustrates the discriminative result of each program, where axis X is time and Y is degree of congestion; 1 for "smooth", 2 for "blocked" and 3 for "congested".

From Figure 5-7, we note compared with that by algorithm 2, algorithm 1 got much fluctuating results of identification and the congestion lasted a long time. The finding is not consistent with the observed traffic situation both during the actual investigation and during the simulation. That may be because flow indicators don't change too much in the whole process of congestion occurrence, continuation, and dispersion. Algorithm 1 regards flow as one of traffic state feature indictors, and it doesn't make normalized treatment of data's order of magnitudes, impairing the congestion feature represented by other parameters during the traffic jam. Data in some non-congestion areas are classified to congested areas and thus the duration of congestion becomes longer. Algorithm 2 converts the combination of flow and occupancy into single vehicle occupancy mean, which is more susceptible to the duration and degree of congestion.

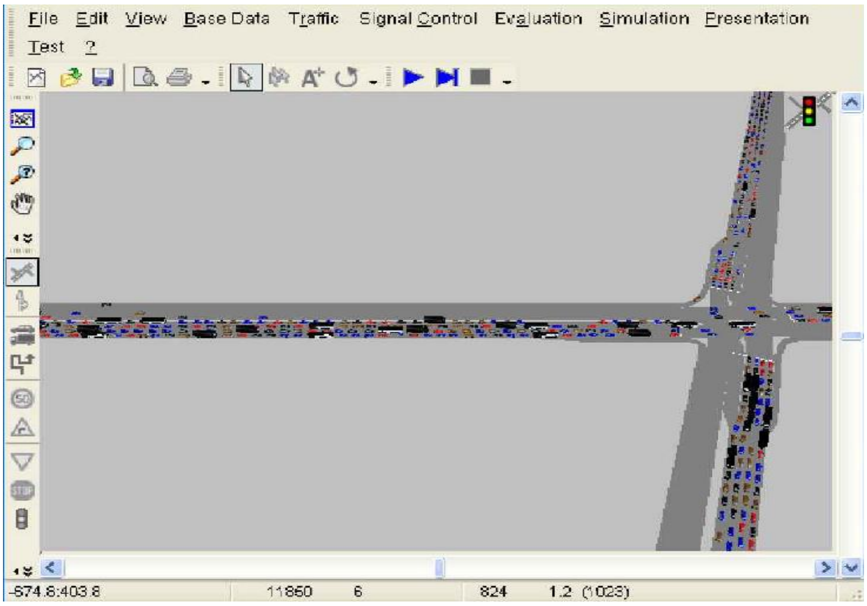
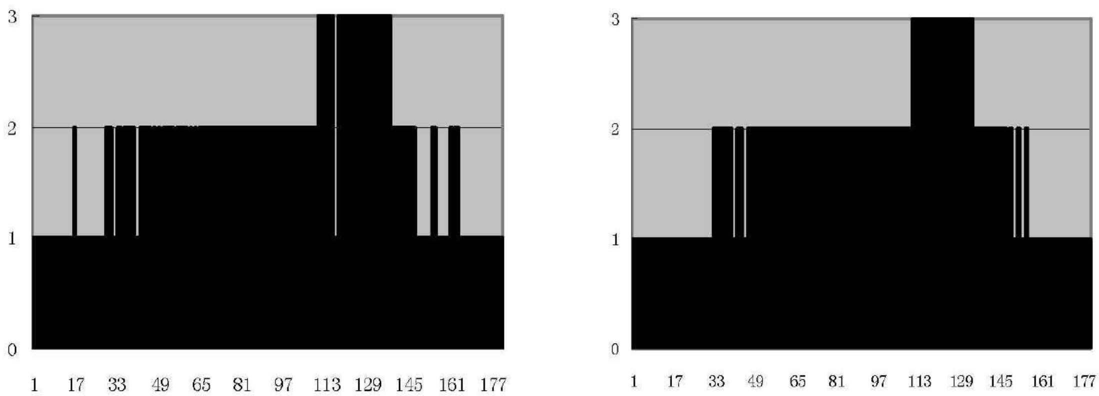
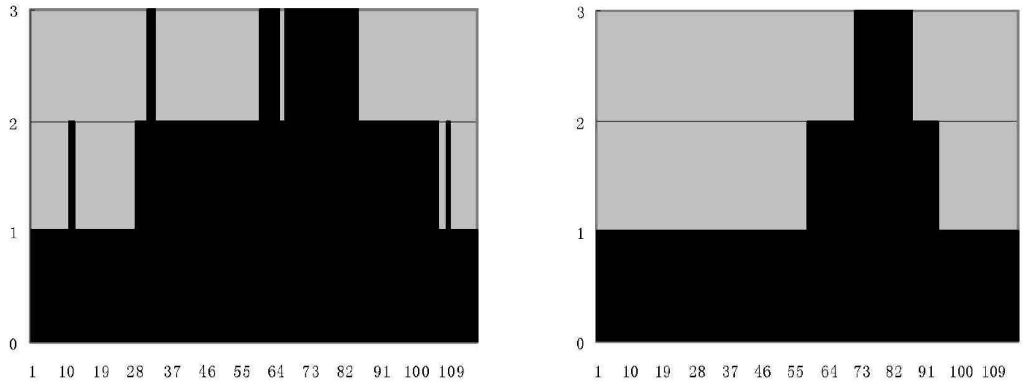


Figure 4. Traffic State Real Time Program



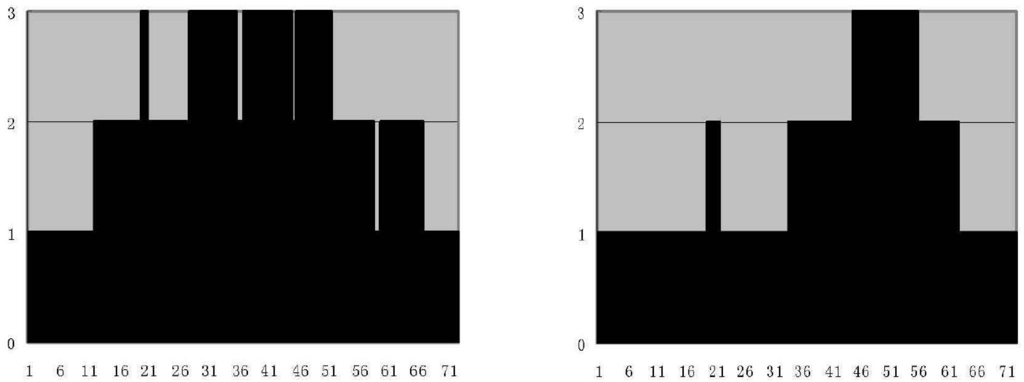
(a) Algorithm1 Discriminant Results (b)Algorithm 2 Discriminant Results

Figure 5. 120 Second Time Interval Discriminant Results



(a) Algorithm1 Discriminant Results (b)Algorithm 2 Discriminant Results

Figure 6. 188 Second Time Interval Discriminant Results



(a) Algorithm1 Discriminant Results (b)Algorithm 2 Discriminant Results

Figure 7. 300 Second Time Interval Discriminant Results

Besides, from Figure 5-7, we find when the time interval is shorter than cross-road signal cycle length, traffic state discriminating result is much volatile; when the interval is longer than the signal cycle length, the discriminative result is stable; when the time interval is the same long as the signal cycle length, the discrimination of traffic state reaches the best result. However, in practical use, the signal cycle length differs at different intersection, especially in the self-adaptive signal control condition, signal cycle length at each crossing is not fixed, it's impossible to regard signal cycle length as the time interval to judge traffic state. So we suggest the time interval for analyzing traffic state should be longer than the biggest signal cycle length of signal intersection.

In order to compare the traffic state discriminating effect of algorithm 1 and 2, we take the evaluation result based on service level as standard and compare their results about testing sample set Y. For comparison, we use experimental results got at the interval 300s as benchmark. During the simulation for 21500s, it outputs totally 72 discriminant results. Then according to formula (1), we can estimate misjudgment rate of each method.

$$a^* = \frac{n_1^* + n_2^* + n_3^*}{N} \times 100\% \tag{5}$$

From Table 3 and Formula5, misjudgment rate of algorithm1 is 9.7%, misjudgment rate of algorithm2 is 5.5%.

It can be considered that the performance of the proposed algorithm is superior to the contrast algorithm, and the accuracy of the traffic state is higher, which can meet the need of traffic signal control system.

Table 3. Performance Comparison of Traffic State Identification Algorithm

Discriminant traffic condition	Smooth	Block	Crowded
	40	15	17
Number of false / Discriminant algorithm	n_1^*	n_2^*	n_3^*
Algorithm1	3	2	2
Algorithm2	3	0	1

6. Conclusion

To meet the requirements of traffic signal control system for real-time discrimination of traffic state, road GPS segment traffic state discriminative method based on single-section detector data and double-section detector data were designed, with the advantage of traffic data collected by induction coil type detectors installed on some road sections. By depending on road segment traffic state recognition result, the method for judging traffic state at the crossing was designed. Lastly, in UTC-CI experimental environment, simulation tests were made to verify those methods and comparison was done between them and existing peer methods. Results prove that the proposed discriminating algorithm can improve the real-time judgment of urban road traffic state and the accuracy of such discrimination fulfills the need of traffic signal control system.

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