
Vehicle Class Composition Identification Based Mean Speed Estimation Algorithm Using Single Magnetic Sensor

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Abstract: Magnetic vehicle detector is a rising traffic flow data collection technology in recent years. In the related research field, vehicle speed estimation based on single sensor is one of the hot spots. This paper introduced the magnetic vehicle detection technology. The distribution statistics of vehicle length on urban road network was then analyzed. Under certain reasonable assumptions, the vehicle class composition identification based mean speed estimation algorithm was put forward. In the algorithm, the OTSU method was used to classify vehicles into small vehicles and large vehicles. On urban road network small vehicles appeared mostly and the vehicle lengths distribution was centralized. According to the statistical characteristics, mean vehicle speed was calculated based on just small vehicles data in the algorithm. Finally, field experiment was conducted on road section in Beijing and the algorithm was verified on Matlab platform. It was concluded that, the algorithm was with high accuracy and stability. The accuracy of calculated mean vehicle speed exceeded 85%.

Keywords: Intelligent Transportation Systems, Magnetic Sensor, Mean Vehicle Speed Estimation, OTSU method

1 Introduction

Magnetic vehicle detector is based on magneto-resistive technology. Vehicles can be detected by the detectors through Wireless Sensor Network (WSN) placed on road surface, parking lots, etc. The new technology offers new solutions for real-time road traffic condition surveillance. The existing researches focus on dual-detectors^[1], that is to say, placing sensor node pair separated by some distance (e.g. 5 meters) on one lane. Traffic indices can be estimated by the sensor node pair with time and frequency synchronization. However, in actual wireless communication, time synchronization is hard to be realized precisely, which reduces the accuracy of estimated data. Consequently, it is necessary to research traffic indices estimation based on single magnetic sensor instead of dual-detectors, considering the aspects of data accuracy improving, cost control, resource conservation and workload reducing. Traffic volume, travel time (or occupancy) can be easily obtained from the field data of single sensor. This paper focuses on mean vehicle speed estimation based on single magnetic sensor.

At present, related literatures are about mean traffic speed estimation based on single inductance loop technology. Mean speed is estimated by traffic volume, occupancy and average

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valid vehicle length. Among the literatures, typical algorithms are g Factor^[2], Statistical Filtering^[3], Error Source Recognition^[4] and Pattern Recognition^[5], etc. Gong^[6] put forward speed estimation models respectively on free flow and non-free flow conditions, from the view of speed density model in typical traffic flow theory. Yu^[7] carried out simulation of the speed estimation algorithm based on frequency waveform of loop detectors.

In this paper, vehicle class statistics in urban traffic is studied firstly. Based on the statistical conclusion, the vehicle class composition identification based mean speed estimation algorithm is put forward. The new advanced algorithm can meet the requirements of high accuracy and less computational resources. In the following, magnetic vehicle detector technology is introduced. Then, detailed thinking and procedure of the algorithm is elaborated. In the end, the algorithm is tested and verified.

2 Magnetic Vehicle Detector Technology

Magnetic vehicle detector comprises magneto-resistive sensor, microprocessor, Flash and battery, etc. The voltage signal exported from magneto-resistive sensor is analog-to digital converted. The digital signal is stored in Flash temporarily and processed by microprocessor. The X, Y and Z axes components of geomagnetic field can be detected by different magneto-resistive sensors, which correspond to the direction of vehicle travel, the perpendicular direction of vehicle travel and the perpendicular direction of ground plane, as shown in Figure 1. Vehicle through or not can be detected by geomagnetic field change and disturbance.

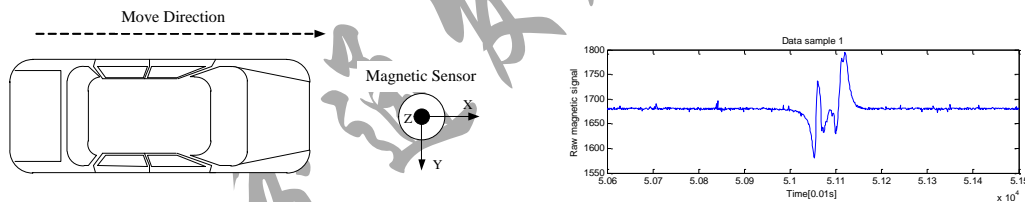


Fig. 1 Field Application of Magnetic Vehicle Detector

ATDA algorithm is selected in traffic indices calculation. At first, noise of the raw signal is filtered smoothly. As baseline threshold is calibrated real time, drifting of magnetic measurements resulted from natural conditions (e.g. sunlight) is eliminated mostly. Then, traffic volume and travel time (or occupancy) can be calculated through comparison between signal and threshold. Figure 2 is vehicle detection results sample.

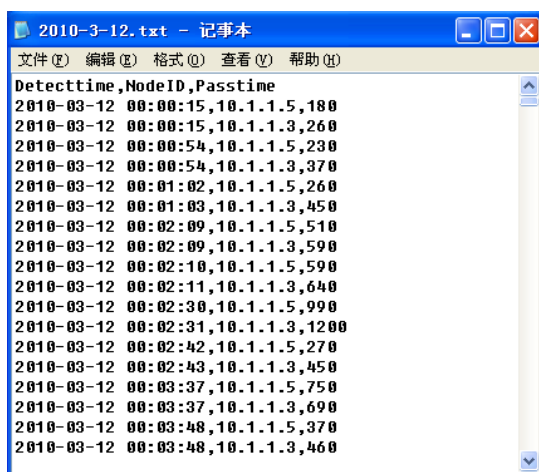


Fig. 2 Detection Results of Magnetic Vehicle Detector

3 Vehicle Class Composition Identification Based Mean Speed Estimation Algorithm

3.1 Vehicle Class Composition on Urban Road Network

Table 1. Vehicles Class Composition of Verification Line Survey in 2008

Vehicle class	Passenger car	Taxi cab	Bus		Big truck	Van	Shuttle
			Single	Articulated			
Proportion (%)	66.8%	13.8%	4.0%	3.4%	6.0%	3.1%	2.9%
Length (m)	[3.7, 5.1]	[4.4, 4.5]	[11, 16]			[6, 12]	

Table 1 shows vehicle class statistics according to Beijing Verification Line Survey in 2008^[8]. As the statistics, the proportion of passenger cars with 3.7 to 5.1 meters length is 66.8%. Mainstream models of taxi cabs in Beijing are Volkswagen Jetta and Hyundai Elantra with 4.4 to 4.5 meters length, and the proportion of taxi cabs is 13.8%. The length interval of vans, big trucks and shuttles is 6 to 12 meters, and the proportion of these three classes is 12.0%. In addition, the proportion of buses including single and articulated types with 11 to 16 meters length is about 7.4%.

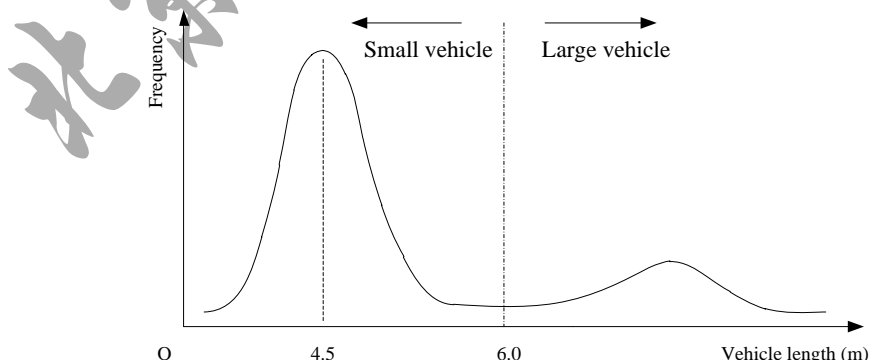


Fig. 3 Schematic Diagram of Vehicle Classification

For research convenience, vehicles are generally divided into small vehicles and large vehicles. Small vehicles mainly conclude passenger cars and taxi cabs. In the contrast, large vehicles mainly

conclude buses including single and articulated types, big trucks, vans and shuttles. Based on the above statistics, the length distribution of small vehicles is more concentrated than large vehicles from the perspective of probability distribution as shown in Figure 3. The intra-class variance of small vehicles length is smaller than that of the whole sample. Accordingly, in vehicle speed detection, to estimate vehicle length just based on small vehicles can preclude the calculation errors derived from large vehicles presence. Based on historical survey data, the estimated mean length of small vehicles can be set as 4.5 meters.

The symbols will be used in the following algorithm, which are:

- T : data collection time interval, $T = 30s$
- n : the number of time intervals in study period
- i : the No. of time interval
- $N(i)$: the number of detected vehicles during time interval i
- j : the No. of detected vehicles during time interval i , $j \in [1, N(i)]$
- \bar{L}_s : the estimated mean length of small vehicles
- $\bar{s}(i)$: the mean speed during time interval i

3.2 Mean Speed Estimation Algorithm

The vehicle class composition identification based mean speed estimation algorithm is based on the two assumptions.

Assumption (1): Vehicle speed is almost constant in study period. The study period contains n time interval T , where n is commonly equal to 10.

Assumption (2): During time interval T , while no small vehicle appears, the most amount of consecutively appeared large vehicles is N_{\max} .

Based on experimental statistics, the desirable value of N_{\max} is 5.

Set the minimum pass time among $N(i)$ vehicles during time interval i is t_{\min} , and the maximum pass time among $N(i)$ vehicles during the time interval i is t_{\max} , then,

$$t_{\min} = \min\{t_1(i), t_2(i), \dots, t_N(i)\}$$

$$t_{\max} = \max\{t_1(i), t_2(i), \dots, t_N(i)\}$$

According to *Assumption (1)*, vehicle lengths can be estimated and studied through vehicle pass times under almost constant speed. If $t_{\max} > \alpha \cdot t_{\min}$, it can be concluded roughly that both large vehicles and small vehicles exist in the samples. Based on experimental statistics, the desirable value of α can be set as 2.0. With the consideration of all kinds of vehicle class composition, the speed calculation is classified into 4 modes, as shown in Figure 4. As the sample data features in different quadrants, the mean vehicle speed is the calculated by different algorithms.

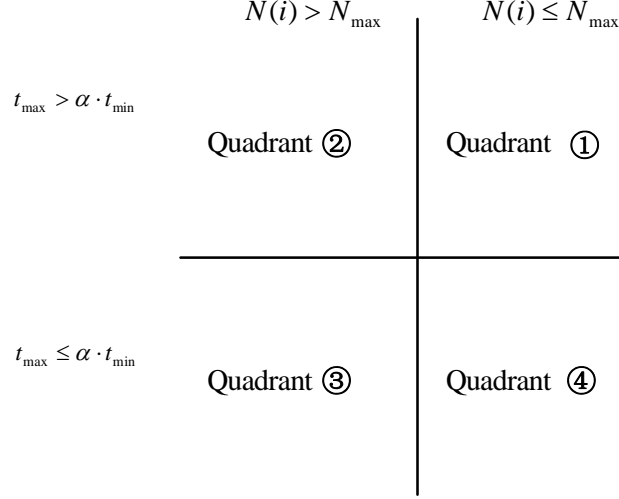


Fig. 4 Schematic Diagram of Vehicle Class Composition

3.2.1 Quadrant 1 and Quadrant 2

When $t_{\max} > \alpha \cdot t_{\min}$, it can be concluded directly that both small vehicles and large vehicles exist in the samples, regardless of the comparison result of $N(i)$ and N_{\max} . OTSU method^[9] is a typical adaptive threshold determination method, which was put forward by Nobuyuki in 1979. In this paper, OTSU method is used to distinguish small vehicles from large vehicles precisely. Then, mean vehicle speed can be calculated based on the mean pass time and mean vehicle length of small vehicles. This algorithm can reduce the estimation errors caused by the randomness of large vehicle amount. The algorithm is described as follows:

(1) Based on single magnetic sensor data with interval i , do data traversal of j and calculate the vehicle pass time threshold $t_j(i)$. Then, identify the vehicles which are less than or equal to $t_j(i)$ as small vehicles, and those which are greater than $t_j(i)$ as large vehicles.

(2) Denote the numbers of small vehicles and large vehicles as $N_S(i)$ and $N_L(i)$. Then,

$$N_S(i) + N_L(i) = N(i)$$

Denote the proportions of small vehicles and large vehicles of total as ω_S and ω_L . Then,

$$\omega_S = \frac{N_S(i)}{N(i)}, \quad \omega_L = \frac{N_L(i)}{N(i)}, \quad \omega_S + \omega_L = 1$$

(3) Denote the mean pass time of small vehicles and large vehicles as $\bar{t}_S(i)$ and $\bar{t}_L(i)$.

Denote the total mean pass time as μ . Then,

$$\mu = \omega_S \cdot \bar{t}_S(i) + \omega_L \cdot \bar{t}_L(i) \quad (1)$$

Then, the intra-class variance of the pass time $t_j(i)$ ($j = 1, 2, \dots, N(i)$) is calculated as:

$$g_j = \omega_S (\bar{t}_S(i) - \mu)^2 + \omega_L (\bar{t}_L(i) - \mu)^2 \quad (2)$$

Introduce Formula (1) into Formula (2), then:

$$g_j = \omega_S \omega_L (\bar{t}_S(i) - \bar{t}_L(i))^2 \quad (3)$$

(4) Do data traversal of j again and obtain the maximum g_j as,

$$g_{\max} = \max\{g_1, g_2, \dots, g_N\}$$

g_{\max} corresponds to $t_m(i)$. Set $t_m(i)$ as the final threshold value distinguishing small vehicles and large vehicles, that is,

$\forall t_j(i) \leq t_m(i)$, identify vehicle j as small vehicle.

$\forall t_j(i) > t_m(i)$, identify vehicle j as big vehicle.

(5) Finally, mean vehicle speed $\bar{s}(i)$ is calculated based on the pass time of small vehicles, as:

$$\bar{t}_S(i) = \frac{1}{N_S(i)} \sum_{j=1}^{N_S(i)} t_j(i)$$

$$\bar{s}(i) = \frac{\bar{L}_S}{\bar{t}_S(i)}$$

Where,

$\bar{t}_S(i)$ denotes the mean pass time of small vehicles.

3.2.2 Quadrant 3

If $t_{\max} \leq \alpha \cdot t_{\min}$, only one class exists in the passing vehicles. Furthermore $N(i) > N_{\max}$, under the Assumption (2), the passing vehicles cannot be all large vehicles. Consequently, all the passing vehicles are identified as small vehicles. The mean travel speed is calculated as:

$$\bar{t}(i) = \frac{1}{N(i)} \sum_{j=1}^{N(i)} t_j(i)$$

$$\bar{s}(i) = \frac{\bar{L}_S}{\bar{t}(i)}$$

3.2.3 Quadrant 4

If $t_{\max} \leq \alpha \cdot t_{\min}$, only one class exists in the passing vehicles. Furthermore $N(i) \leq N_{\max}$, there are two possible conditions. One possible is that the passing vehicles are all large vehicles. And the other possible is that the passing vehicles are small vehicles. The mean vehicle speed is calculated as follows.

(1) Firstly introduce the mean travel speed result $\bar{s}(i-1)$ of the above interval $i-1$.

(2) Make an assumption that the $N(i)$ vehicles are all small vehicles. Then, the mean travel speed $\bar{s}'(i)$ can be calculated by the algorithm of Quadrant 3.

(3) If the Euclidean distance between $\bar{s}'(i)$ and $\bar{s}(i-1)$ is less than a certain range, the above assumption establishes. Otherwise, the assumption does not hold. That is to say, the passing vehicles are all large vehicles. Then, under the *Assumption (1)*, the speed values between current interval and the above interval keep unchanged, that is:

$$\begin{cases} \bar{s}(i) = \bar{s}'(i), & |\bar{s}'(i) - \bar{s}(i-1)| \leq \beta \cdot \bar{s}(i-1) \\ \bar{s}(i) = \bar{s}(i-1), & |\bar{s}'(i) - \bar{s}(i-1)| > \beta \cdot \bar{s}(i-1) \end{cases}$$

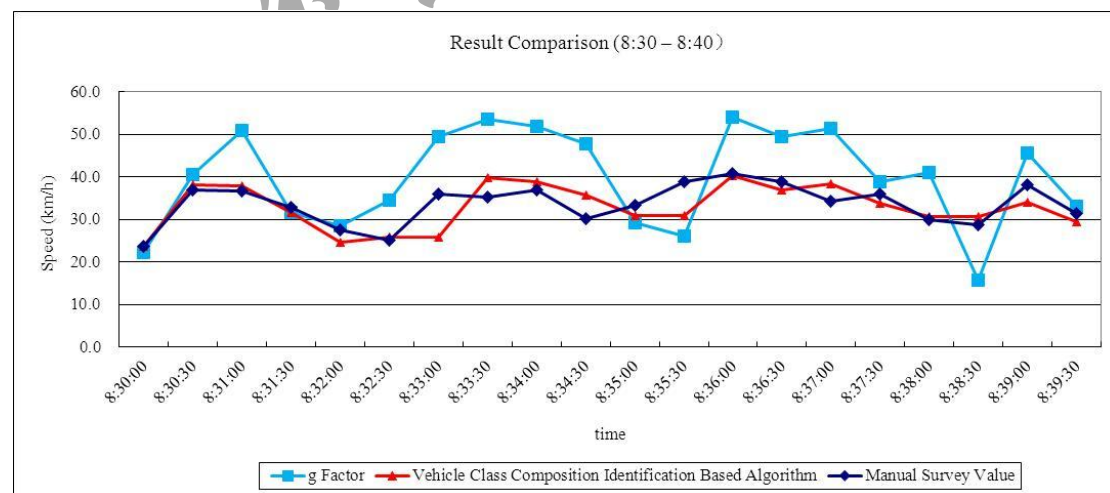
Where,

β can be set as 0.1.

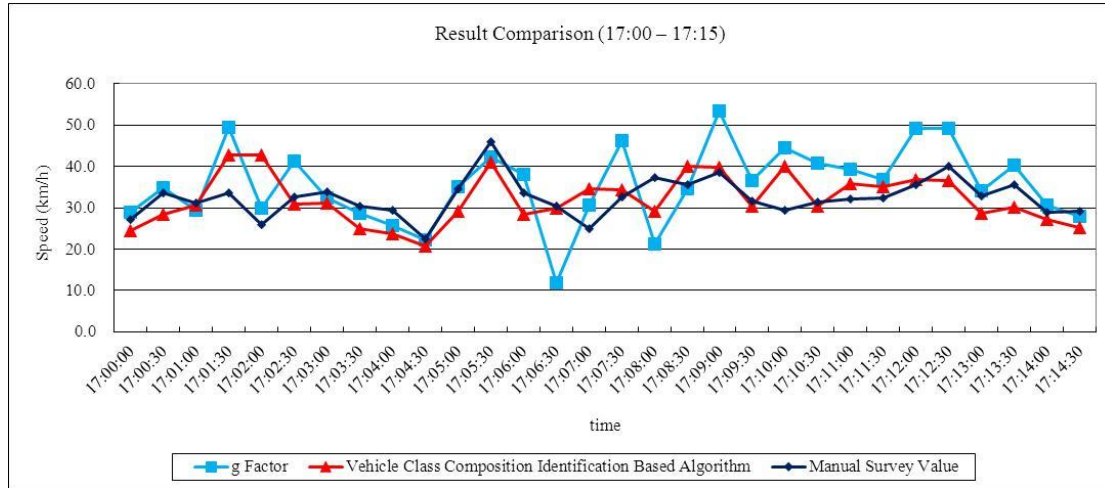
4 Experiment and Validation

Field test was conducted on side road of Lianshi Road (as urban expressway) in Beijing. Magnetic vehicle detectors were embedded into the road section. Two field data sets were collected, 8:30 to 8:40 and 17:00 to 17:15 on Apr. 12, 2010. Meanwhile, manual survey was done in the same time. The mean vehicle speed on the test road was recorded, with 30 seconds as interval.

In this paper, the vehicle class composition identification based mean speed estimation algorithm put forward in this paper and the typical g Factor algorithm were both selected in mean vehicle speed estimation on Matlab. In the calculation of g Factor algorithm, the parameter g was set as 2.40 according to the WSDOT system. In Figure 5, the sequence results of mean vehicle speed are compared among the two algorithms and the manual survey. In this experiment, the manual survey result is considered as true value. It is indicated that, the mean relative error during 8:30 to 8:40 is 8.3% and that during 17:00 to 17:15 is 14.1%. While the corresponding statistical indices of the g Factor algorithm are 28.0% and 19.5%.



(a) 8:30 - 8:40



(b) 17:00 – 17:15

Fig. 5 Mean Vehicle Speed Results Comparisons

5 Conclusions

In this paper, with the background of magnetic vehicle detector technology, the vehicle class composition identification based mean speed estimation algorithm is put forward. As the sample features in different quadrants, the mean vehicle speed is the calculated by different algorithms. The new algorithm uses the OTSU method to distinguish small vehicles and large vehicles. And, mean vehicle speed is calculated just based on small vehicles. Based on the statistics result that small vehicles are more than large vehicles and the length distribution of small vehicles is more concentrated than that of large vehicles on urban road network, the new algorithm can preclude the calculation errors derived from big vehicles presence.

As demonstrated from the field experiment and validation, the vehicle class composition identification based mean speed estimation algorithm is stable. The accuracy of estimated mean vehicle speed based on the new algorithm exceeds 85%. So, the algorithm can be put into practical application. In the future study, the new algorithm will be improved at efficiency and accuracy aspects. In addition, the conditions of traffic congestion and night traffic will be considered more in the algorithm.

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