Vehicle Detection and Classification for Low-Speed Congested Traffic With Anisotropic Magnetoresistive Sensor

Bo Yang and Yiqun Lei

***Abstract*— A vehicle detection and classification system has been developed based on a low-cost triaxial anisotropic magnetoresistive sensor. Considering the characteristics of vehicle magnetic detection signals, especially the signals for low-speed congested traffic in large cities, a novel fixed threshold state machine algorithm based on signal variance is proposed to detect vehicles within a single lane and segment the vehicle signals effectively according to the time information of vehicles entering and leaving the sensor monitoring area. In our experiments, five signal features are extracted, including the signal duration, signal energy, average energy of the signal, ratio of positive and negative energy of *x*-axis signal, and ratio of positive and negative energy of *y*-axis signal. Furthermore, the detected vehicles are classified into motorcycles, two-box cars, saloon cars, buses, and Sport Utility Vehicle commercial vehicles based on a classification tree model. The experimental results have shown that the detection accuracy of the proposed algorithm can reach up to 99.05% and the average classification accuracy is 93.66%, which verify the effectiveness of our algorithm for low-speed congested traffic.**

***Index Terms*— Anisotropic magnetoresistive sensor (AMR), low-speed congested traffic, vehicle detection, vehicle classification.**

I. Introduction

Vehicle detection and classification technologies play an important role in the Intelligent Transportation Systems (ITS). Most conventional traffic surveillance systems use inductive loop detectors and video cameras [1], [2]. For maximizing the benefits from these detection technologies, there must be a large scale deployment of traffic surveillance on all the major streets and freeways. As intrusive sensors, however, the installation and maintenance of the inductive loop detectors lead to a relative high cost. The video camera is also expensive for a large-scale deployment, and they are greatly affected by the environmental factors, such as shadow, snow and rain [3].

Magnetoresistive sensor has recently been utilized for vehicle surveillance owing to its advantages of easy installation, low cost, small size, strong anti-jamming capability [4], [5], etc. Scholars worldwide have investigated the application of magnetic sensor and wireless sensor network for vehicle detection and classification. They offer a very attractive alternative to inductive loops and video cameras. Currently, the most commonly used vehicle detection algorithms based on magnetic sensor are fixed threshold algorithm, the state machine algorithm and adaptive threshold algorithm [6]. Sing Y. C. et al. [7] proposed an efficient vehicle detection algorithm, Adaptive Threshold Detection Algorithm (ATDA), based on 3-axis Anisotropic Magnetoresistive (AMR) sensor with high precision of 99%. However the classification scheme was not good enough and overall detection rate was below 60%. Wireless sensor network based on AMR can detect and track moving vehicles to obtain more traffic information [8], [9]. Many classification algorithms using AMR sensors were proposed, including the Hill-Patterns algorithm, the Average-Bar algorithm, the BP Neural Network algorithm and the Support Vector Machine, etc. Most of them have conducted experimental tests and comprehensive study in normal driving situation and achieved good results. For example, a vehicle detection and classification system was proposed based on a wireless sensor network using the adaptive threshold algorithm and intelligent neuron classifier giving the promising classification rate at 90% [10].

However, little attention has been given to the vehicle detection and classification for low-speed congested traffic, which is prevalent in big cities. When vehicles driving at a low speed on a congested road, there will be serious waveform distortion in sensor signal output, and because vehicles are close to each other, the front and rear of the vehicle signals will interfere mutually. All these factors will have a negative impact on the vehicle detection and classification. Traffic surveillance for low speed congested vehicles will be a new direction for future research.

This paper focuses on the investigation of anisotropic magnetic sensor to detect the vehicle in a slow-moving and congested traffic zone. A simple and effective vehicle detection and classification system is developed based on low-cost three-axis AMR sensors. The characteristics of the vehicle magnetic detection signals are particularly analyzed and processed. A novel fixed threshold state machine algorithm is proposed based on variance weighting to detect vehicles within a single lane. The signal features are extracted accurately and the vehicles are classified by using a classification tree model.

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The authors are with the School of Automation Science and Electrical Engineering, Beihang University, Beijing 100191, China (e-mail: boyang@buaa.edu.cn; leiyiqun@foxmail.com).

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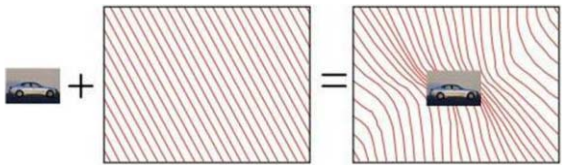


Fig. 1. The disturbance of of Earth's magnetic flux lines by a moving vehicle.

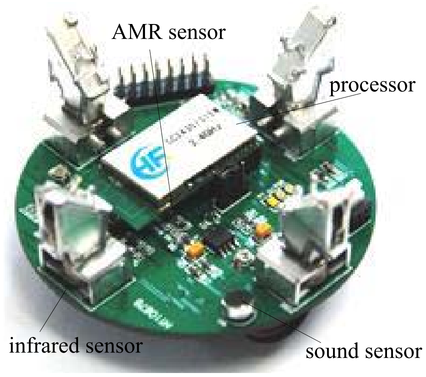


Fig. 2. Sensor node.

The experimental result has shown that the proposed algorithms can effectively detect the vehicles in the slow-moving and congested traffic zone and the accuracy of classification is improved correspondingly.

This paper is organized as follows. Section II introduces the foundation of vehicle detection using AMR sensor. Section III describes the principle of our novel signal variance based fixed threshold state machine algorithm. The algorithm for vehicle classification is given in Section IV. Section V presents the experimental results of vehicle detection and vehicle classification for low-speed congested traffic. Finally, Section VI contains some conclusions.

II. Foundation of Vehicle Detection Using AMR Sensor

The geomagnetic field provides a uniform magnetic field over a wide area and the magnetic sensor can detect the disturbances of the Earth's field caused by a large ferrous object like a vehicle. The disturbance depends on the ferrous material, its size and orientation (Figure 1).

The magnetic sensor is made of a nickel-iron (Permalloy) thin film deposited on a silicon wafer and patterned as a resistive strip. Typically, four resistors are connected in a Wheatstone bridge configuration to generate a differential output voltage [11].

Fig. 2 shows the sensor node we designed, which is composed of a CC2430 processor and an AMR sensor, etc. The AMR sensor we used is Honeywell triaxial HMC5883L, a fully digital sensor with built-in multiplexed ADC. The sensor has 12 bits ADC coupled with low noise AMR sensors and achieves 5 milli-gauss resolution in ±8 Gauss Fields. There are also 4 infrared sensors and a sound sensor in the sensor node to complete other measurement tasks. Only the AMR sensor is used in our experiment for the vehicle detection and classification with low power consumption. The average current drain of the sensor node is only about 100 μA at work. The AMR sensor senses disturbance of the Earth's magnetic field caused by a moving vehicle. This sensor can achieve magnetic field measurement for X, Y, and Z axis simultaneously with high accuracy and efficiency. Choosing a triaxial AMR sensor can obtain comprehensive information of magnetic field with high accuracy.

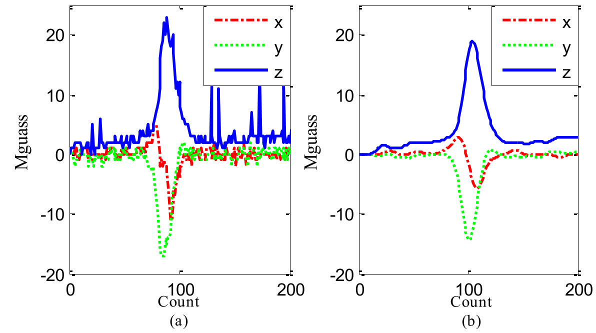


Fig. 3. Magnetic signals of a two-box vehicle: (a) original signal and (b) signal after filtering.

III. Vehicle Detection

When a vehicle passes over an AMR sensor, the sensor will detect the dipole moments of various parts of the vehicle, and the related field variation will reveal a very detailed magnetic signature of the vehicle. Figures 3(a) shows a 3-axis magnetometer output for a two-box vehicle passing directly over it. The three curves represent the X, Y, and Z-axis of the variation in the geomagnetic field respectively for the moving vehicle.

In order to facilitate the analysis for signals of the vehicle, a series of equally spaced sampling points are used to represent the three axis magnetic signals of vehicle. The sample rate of sensor is 75 Sa/s, so the horizontal axis is in Counts, and the vertical axis is in milli-gauss, which we mark as Mgauss in the following figures.

$$\begin{cases} X &= \{X(1), X(2), X(3), \ldots, X(n)\} \\ Y &= \{Y(1), Y(2), Y(3), \ldots, Y(n)\} \\ Z &= \{Z(1), Z(2), Z(3), \ldots, Z(n)\} \end{cases} \tag{1}$$

To get a smoother sensor signal, we use a digital filtering algorithm to eliminate noise. The filter combines fast Fourier transform and median filter, which can not only filter out background random noise well but also be able to suppress the big impulse noise. The filtering result are listed as follows and shown in Figure 3(b).

$$\begin{cases} filtered\_X(k) &= fftfilt(hn, medfilt1(X(k), N)) \\ filtered\_Y(k) &= fftfilt(hn, medfilt1(Y(k), N)) \\ filtered\_Z(k) &= fftfilt(hn, medfilt1(Z(k), N)) \end{cases} \tag{2}$$

where *hn* is the ideal low-pass filter window function and *N* is median filtering parameter.

The function *medfilt1* implements one-dimensional median filtering and the function *fftfilt* is a frequency domain filtering technique works on FIR filter using the efficient

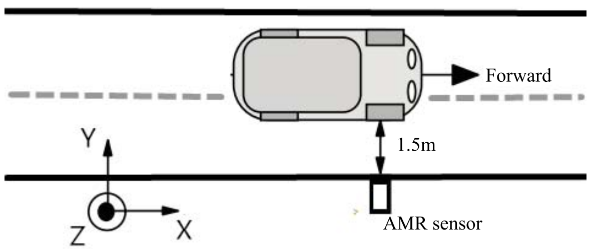


Fig. 4. Sensor installation diagram.

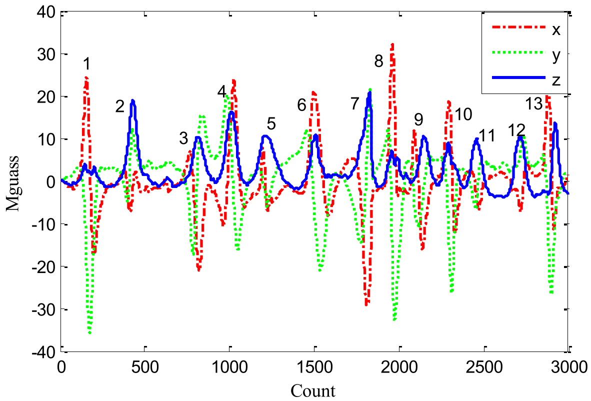


Fig. 5. Original magnetic signals of vehicles.

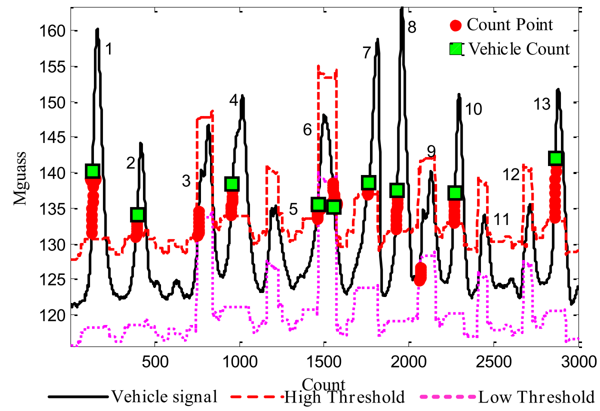


Fig. 6. Adaptive threshold detection algorithm [10].

FFT-based method of overlap-add. {*filtered_X(k)*, *filtered_Y(k)*, *filtered_Z(k)*} are 3-axis vehicle magnetic signals after the filtering processing.

The vehicle density in most developed cities is centralized and huge, which cause a small amount of amplitude attenuation of output magnetic signal as the vehicles are driving at slow speed. Signals of adjacent vehicles will interfere with each other as two vehicles are crawling bumper to bumper. Furthermore, the output magnetic signal of sensor will drift when environment temperature changes [12]. All these factors will have a serious impact on the detection and segmentation of the vehicle signals.

An experiment is performed to analyze the signal characteristics of the vehicles. An AMR sensor node is placed on the side of lane and is about 1.5 m away from the vehicle. The system layout is illustrated in Fig. 4. X-axis is the direction parallel to the moving vehicle. Y-axis is the direction perpendicular to the direction of moving vehicle. Z-axis is the direction perpendicular to the ground.

Fig. 5 shows the sensor signal of 13 vehicles driving at about 10km/h. There is a slight drift in background signal over time.

We define $F(k)$ as the magnetic field intensity of measured signal.

$$F(k) = \sqrt{X(k)^2 + Y(k)^2 + Z(k)^2} \tag{3}$$

A new variance-based multi-state machine adaptive threshold detection algorithm was proposed in Ref. [10]. The algorithm calculated the real-time data fluctuation using historical data variance and then predicted average signal threshold in future. This algorithm is an efficient vehicle detection algorithm with high precision of 97% when the vehicle is driving normally. But for the vehicles crawling bumper to bumper with low speed in congested urban traffic, the detection result is not satisfactory.

Fig. 6 shows that the geomagnetic disturbances will be weakened when the vehicle is traveling at a low speed, i.e. the 5th, 11th, 12th vehicles in the figure. On the one hand, the interval between two vehicles is so short that the variance of the history signal does not reduce and the adaptive threshold increases, on the other hand, the amplitude of signal is small due to low-speed. Therefore, the algorithm cannot detect all these vehicles correctly. In addition, the adaptive threshold algorithm is not conducive to accurately determine the time information of vehicles entering and leaving the monitored area, which will increase the difficulty of effectively separating the vehicle signal.

In order to detect the low-speed congested vehicles, this paper presents an effective fixed threshold state machine algorithm based on the signal variance weighting. Firstly, we calculate the variance of magnetic field intensity signal, and then multiply it by the original signal value as a weighting factor. This operation can retain the characteristics of the magnetic field intensity signal; meanwhile it can also suppress the signal drift by the property of signal variance. The algorithm is given by

$$Processed\_F(k) = filtered\_F(k) \times variance\_F(k) \tag{4}$$

where $filtered\_F(k)$ is the filtered magnetic field intensity signal and $variance\_F(k)$ is the variance of the magnetic field intensity signal.

$$filtered\_F(k) = fftfilt(hn, medfilt1(F(k), N)) \tag{5}$$

In this paper, the variance of the signal value is calculated by the forward and backward 15 points. In the absence of a passing vehicle, the variance of signal will still be very low. The vehicle signals become more significant and easier to identify because of the obvious increase of the signal variance when the vehicle is passing.

When the vehicle is driving at a low speed and the vehicle-to-vehicle distance is relative small, the reference value will generate a large deviation due to the signal interference between certain vehicles. To improve the stability of the proposed algorithm, a state machine is introduced to judge

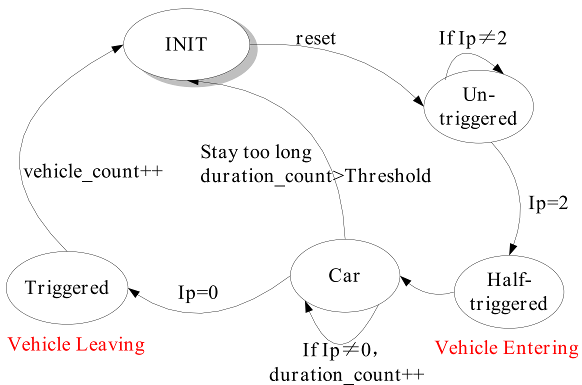


Fig. 7. Scheme of state machine algorithm.

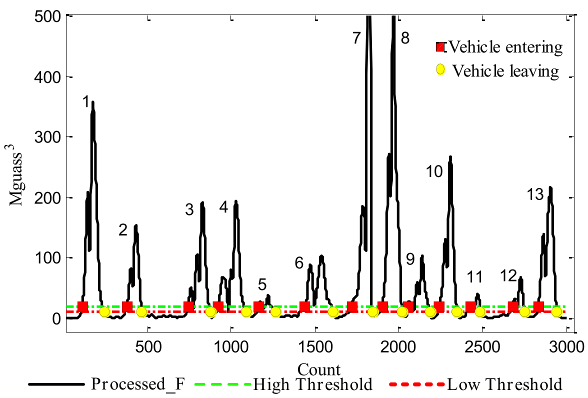


Fig. 8. The effect of vehicle identification.

the vehicles using two thresholds {*H-value, L-value*}which divided the input signal to three cases.

The vehicle detection algorithm uses the deviation of processed_F(k) from a baseline to drive a state machine, which makes the vehicle counting decisions (Fig. 7). The input of the decision state machine is defined as

$$Ip = \begin{cases} 0, & if \quad processed\_F(k) \leqslant \text{L-value} \\ 2, & if \quad processed\_F(k) \geqslant \text{H-value} \\ 1, & otherwise \end{cases} \tag{6}$$

where {*H-value, L-value*} are the high threshold and the low threshold.

At the initial state, reset all parameter to the initial value and the state machine to an Un-triggered state. *Duration_count* denotes the duration of vehicle signal and *vehicle_count* is the number of vehicles. If Ip changes to 2 (*processed_F(k)* ≥ *H-value*), the state machine will turn to a Half-triggered state and we consider the vehicle may enter the sensor monitoring area.

Normally, processed_F(k) increases first and then decreases. If it has exceeded the L-value for a long time, the algorithm will return to INIT. Otherwise, Ip will turn to 0, and the state machine will turn to a Triggered state. Then, we consider the vehicle is leaving the sensor monitoring area. Let the vehicle_count plus 1 and return to INIT waiting for another vehicle arriving.

The vehicle detection result is shown in Fig. 8. The variance of the signal can effectively prevent the reference value from drifting caused by the mutual interference between two adjacent vehicles. The processed signal can be distinguished more clearly even though the vehicles are driving bumper to bumper. It can be concluded that our algorithm has higher detection rate both for low speed and congested vehicles.

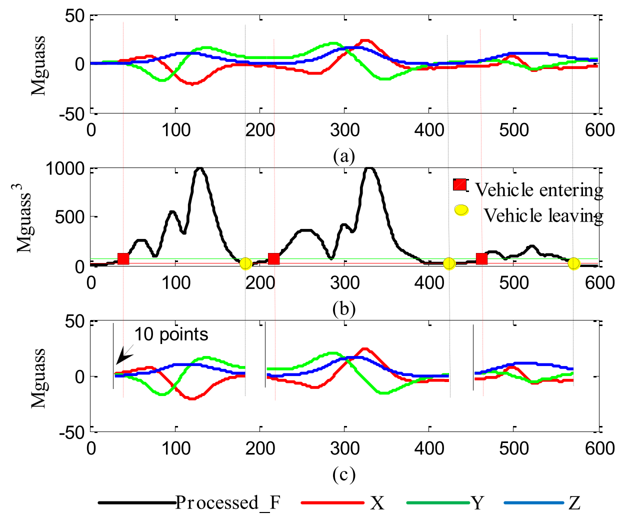


Fig. 9. Vehicle signal segmentation. (a) Original vehicle signal. (b) Vehicle identification. (c) Vehicle signal segmentation.

IV. Vehicle Classification

We perform a simple classification based on a hierarchical tree methodology as in Ref. [13], which uses the above vehicle information to classify the vehicles into five types: Motorcycle, Two-box, Saloon, Bus and Sport Utility Vehicle (SUV).

A. Signal Segmentation

The first step of vehicle classification is to extract the vehicle signal from sensor signal. The selection of entering and leaving points of vehicles will have a great influence on vehicle classification. We assume the vehicle entering if the signal is just above H-value, and the vehicle leaving if lower than L-value in the above-mentioned detection algorithm. Then we segment the vehicle signals effectively according to the time information of vehicles entering and leaving the sensor monitoring area. There is slight loss about signal interception portions due to the high threshold, so that we compensate the time when the vehicle enters the sensor detection zone. In this paper, we extend 10 forward measuring points of the signal expansion to solve this problem (Figure 9).

Fig. 10 shows a schematic view of signal segmentation for above 13 vehicles in Section III. This result illustrates that vehicle X-axis signal and Y-axis signal have significant characteristics compared with Z-axis signal. The Z-axis signal is a single peak wave because the geomagnetic disturbances are consistent in this direction when vehicle passes over the AMR sensor.

B. Feature Extraction

In order to identify the vehicle type, some quantitative indices are required to extract the features of the magnetic signal. These indices should have high correlations with the signal waveform and can be easily computed. As above

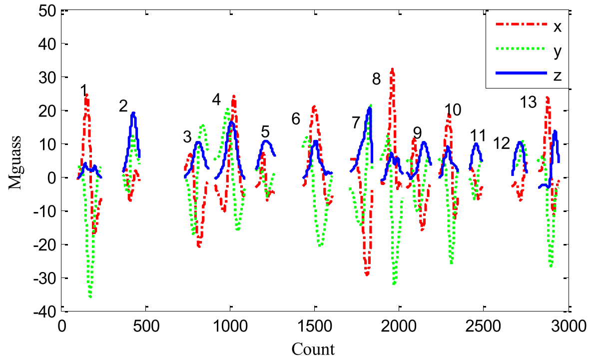


Fig. 10. The effect of vehicle signal segmentation.

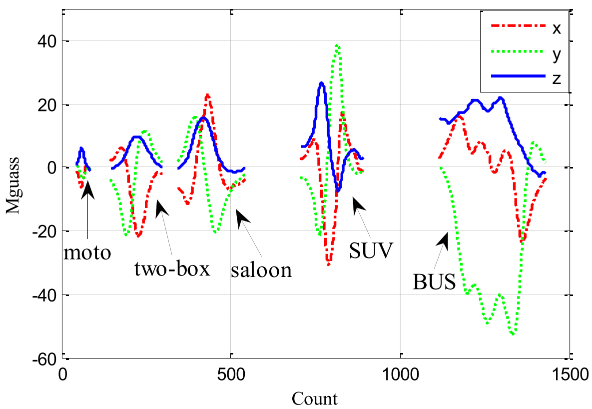


Fig. 11. Magnetic signals generated by different types of vehicles.

mentioned, the Z-axis signal characteristic of the vehicle has less influence in classification process. Thus, only X-axis and Y-axis vehicle signals are analyzed in the following process of feature extraction.

There are five types of vehicles to be analyzed. Each type of vehicle signal has its own unique characteristics due to the different structure of vehicle. In this paper, we will extract features through the time-domain waveform structure after data analysis. It should be noted that, the same type of vehicle signal waveform may be slightly different due to the impact of vehicle speed, vehicle equipment and other factors. But this does not have much impact for identifying the characteristics of vehicle signal. These five types vehicles signal characteristics are shown in Fig. 11.

We define that L is the vehicle signal duration; E and EV are the signal energy and the average energy of the signal.

$$E = \sum (X^2(k) + Y^2(k) + Z^2(k)) \tag{7}$$

$$EV = \frac{E}{L} \tag{8}$$

VX is the ratio of positive and negative energy of X-axis signal; VY is the ratio of positive and negative energy of Y-axis signal.

$$VX = \frac{\sum\limits_{X(k)>0} X^2(k)}{\sum\limits_{X(k)<0} X^2(k)} \quad VY = \frac{\sum\limits_{Y(k)>0} Y^2(k)}{\sum\limits_{Y(k)<0} Y^2(k)} \tag{9}$$

TABLE I

DIFFERENT TYPES OF VEHICLES SIGNAL CHARACTERISTICS

	Moto	*Two-box*	*Saloon*	*SUV*	*Bus*
					
L	53~102	65~129	73~139	109~154	243~445
E	125~331	1879~3421	3988~5534	>94650	---
EV	1.6~3.2	17.5~38.9	42.1~70.1	>720	---
VX	---	0.04~0.57	1.07~20.9	---	---
VY	---	0.23~0.65	0.78~3.21	---	---

A total of 100 vehicle signals (20 vehicles for each type) were collected for analysis of their characteristics under the same test condition. The speed of vehicles in our experiment is about 10km/h $\sim$ 30km/h. The analysis result is shown in Table I.

The number of vehicle sampling points is defined as the vehicle signal duration. The bus signals are sampled at about 200 to 400 points with a sampling frequency of 75 Hz, while sampling points of other types are generally between 50 and 100 and can even exceed 150 in particularly low speeds. The average speeds of vehicle we concerned in experiments are in a limited range (10 $\sim$ 15km/h for the low-speed congested traffic and 30 $\sim$ 40km/h for the normal traffic). Within this speed range, even if a bus drives faster and other vehicles drive slower, the signal duration of the bus is still significantly longer than others. Therefore, we can distinguish the bus from the other smaller cars by using the signal duration L.

The volume of vehicles is reflected in vehicle signal energy so that we can distinguish the motorcycles and SUV commercial vehicle according to the signal energy E and EV. In order to increase the stability of the proposed algorithm, the average energy of vehicle signal EV is extracted as an auxiliary characteristic value for vehicle classification.

Two-box car and saloon car are relatively similar in terms of signal length and energy, but the structure of the vehicle signal has more obvious characteristics. The value of X-axis signal of two-box car is essentially negative while value of X-axis signal of saloon car is positive. The ratio of positive and negative energy of X-axis signal is extracted as a characteristic for identification. In order to increase the stability of the proposed algorithm, the ratio of positive and negative energy of Y-axis signal is also extracted as an auxiliary characteristic to distinguish two-box car from saloon car.

C. Vehicle Classification Algorithm

The above features are used here to construct the hierarchical classification tree for classifying vehicles. The specific classification process is based on hierarchical tree shown in Fig. 12.

Vehicle Classification Algorithm

①if($L \geq L_0$); {bus}count, else
② if($E \leq E_a$&&$EV \leq EV_a$); {moto}count, else
③ if($E \geq E_b$&&$EV \geq EV_b$); {suv}count, else
④ if($VX \leq VX_0$&&$VY \leq VY_0$); {two-box}count else
⑤ {saloon}count, return ① cycle until the end of all vehicles judgment

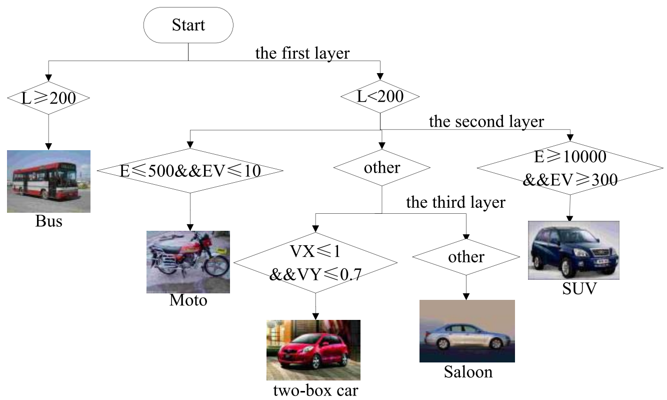


Fig. 12. Schematic of classification algorithm.

The classification tree model has three layers: the first layer of the classification criteria is the vehicle signal duration L; the second layer is the vehicle signal energy, including energy E and average energy EV; the third layer is the ratio of positive and negative energy of X-axis signal VX and Y-axis signal VY. The vehicle will be considered as a saloon car only when its characteristics do not meet any of the given conditions.

$\{L_0,\ E_a,\ EV_a,\ E_b,\ EV_b,\ VX_0,\ VY_0\}$ is a set of fixed threshold algorithm parameters. The thresholds are chosen as follows: $L_0 = 200$, Ea = 500, EVa = 10, Eb = 10000, EVb = 300, $VX_0 = 1$, $VY_0 = 0.7$. Various types of vehicles can be distinguished effectively using the vehicle classification algorithm. The advantage of this algorithm has small amount of calculation and high classification accuracy.

V. Experimental Results and Analysis

In this paper, the congested traffic condition is our main concern. The experimental test is performed for normal traffic and low speed congested traffic respectively at temperature about 21 ∼ 25 °C. The vehicle speed we tested is about 30 ∼ 40km/h for normal traffic, and 10 ∼ 15 km/h for low-speed congested traffic respectively. The sensor node is placed 7 cm above the ground and about 1.5 m away from the vehicle (Figure 13).

We focus on the vehicle detection and classification on a single lane in experiments. The AMR magnetic sensors work well for normal curbside sensing ranges of one to five feet (about 1.5m), while the width of lane is about 3.5m in the urban road of Beijing and the width of the vehicle is more than 2m in normal conditions, so the effect caused by the other lanes could be neglected.

Vehicle detection results are listed in Table II. For normal traffic, there are 147 vehicles being detected and all vehicles

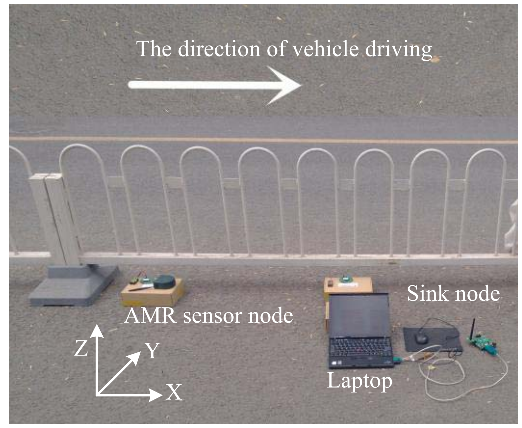


Fig. 13. Experimental scene.

TABLE II
RESULTS OF VEHICLE DETECTION

Normal traffic (30 ∼40km/h)			*Low-speed congested traffic (10 ∼15km/h)*		
Observed Vehicles	Detected Vehicles	Correct%	Observed Vehicles	Detected Vehicles	Correct %
147	147	100	105	106	99.05

TABLE III
RESULTS OF VEHICLE CLASSIFICATION

Class	*Normal traffic (30 ∼40km/h)*			*Low-speed congested traffic (10 ∼15km/h)*		
	Test Results	Actual results	Correct %	Test Results	Actual results	Correct %
Motorcycle	20	20	100	-	-	-
Two-box	31	30	96.7	53	49	92.45
Saloon	45	44	97.78	31	32	96.87
SUV	28	30	93.33	22	24	91.67
Bus	23	23	100	-	-	-

are identified correctly. For low-speed congested traffic, there are 105 vehicles being observed. But one of the vehicles is not detected as it approaching another one too close. Two vehicles are misjudged as four due to the low speed. Therefore, the total number of vehicle detection result is 106 and the detection accuracy is still over 99% for low speed congested traffic.

Vehicle classification results are listed in Table III.

The vehicles are tested on the main and side roads because the motorcycles and the buses cannot drive in the same lane. Most vehicles on the congested roads are small cars and SUV vehicles. During the rush hours, bus lanes are travel lanes restricted to buses. Therefore, the classification process in low-speed driving is given only for these three types of vehicles.

The classification accuracy is over 90% for low-speed congested traffic. Although it is slightly lower than the accuracy for normal traffic due to the amplitude attenuation of vehicle signal and the interference between adjacent vehicles, it is still good and promising.

VI. Conclusion

This paper presents the vehicle detection and classification methods for low-speed congested traffic with anisotropic magnetoresistive sensor. A novel fixed threshold state machine algorithm based on signal variance is proposed to detect low-speed congested vehicles within a single lane. Five signal features are extracted to classify the detected vehicles into five types using the model classification algorithm based on hierarchical tree methodology. The experimental results obtained from the low-speed congested traffic have shown that the proposed algorithm has a high detection and classification accuracy.

The average speeds of vehicle we concern in the experiments are in a limited range (10 $\sim$ 15km/h for the low-speed congested traffic and 30 $\sim$ 40km/h for the normal traffic). Once the vehicle speed change exceeds the range, it should be introduced as a correction factor for the signal characteristics, which will be investigated in our future research.

REFERENCES

[1] R. Wang, L. Zhang, K. Xiao, R. Sun, and L. Cui, "EasiSee: Real-time vehicle classification and counting via low-cost collaborative sensing," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 1, pp. 414–424, Feb. 2014.

[2] Y. Iwasaki, S. Kawata, and T. Nakamiya, "Robust vehicle detection even in poor visibility conditions using infrared thermal images and its application to road traffic flow monitoring," *Meas. Sci. Technol.*, vol. 22, no. 8, p. 085501, Aug. 2011.

[3] E. Sifuentes, O. Casas, and R. Pallas-Areny, "Wireless magnetic sensor node for vehicle detection with optical wake-up," *IEEE Sensors J.*, vol. 11, no. 8, pp. 1669–1676, Aug. 2011.

[4] S. Taghvaeeyan and R. Rajamani, "The development of vehicle position estimation algorithms based on the use of AMR sensors," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 4, pp. 1845–1854, Dec. 2012.

[5] M. H. Kang, B. W. Choi, K. C. Koh, J. H. Lee, and G. T. Park, "Experimental study of a vehicle detector with an AMR sensor," *Sens. Actuators A, Phys.*, vol. 118, no 2, pp. 278–284, Feb. 2005.

[6] P. Ni, L. Le, and W. Yu, "Review of vehicle detection algorithms based on magnetoresistive sensors," *Comput. Eng. Appl.*, vol. 45, no. 19, pp. 245–248, 2009.

[7] S. Y. Cheung, S. Coleri, B. Dundar, S. Ganesh, C.-W. Tan, and P. Varaiya, "Traffic measurement and vehicle classification with single magnetic sensor," *J. Transp. Res. Board*, vol. 1917, no. 1, pp. 173–181, Dec. 2005.

[8] B.-G. Lee and J.-H. Kim, "Algorithm for finding the moving direction of a vehicle using magnetic sensor," in *Proc. IEEE Symp. CICA*, Apr. 2011, pp. 74–79.

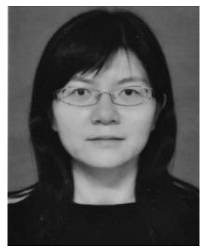
[9] S. Marshall, "Vehicle detection using a magnetic field sensor," *IEEE Trans. Veh. Technol.*, vol. 27, no. 2, pp. 65–68, May 1978.

[10] B. Yang and W. Nin, "Vehicle detection and classification algorithm based on anisotropic magnetoresistive sensor," *Chin. J. Sci. Instrum.*, vol. 34, no. 3, pp. 537–544, Mar. 2013.

[11] X. S. Li, R. Q. Kang, Y. X. Liu, Z. H. Wang, and X. Y. Shu, "High accuracy AMR magnetometer and its application to vehicle detection," *Adv. Mater. Res.*, vols. 443–444, pp. 150–155, Jan. 2012.

[12] P. Ripka, M. Butta, and A. Platil, "Temperature stability of AMR sensors," *Sensor Lett.*, vol. 11, no. 1, pp. 74–77, Jan. 2013.

[13] S. Kaewkamnerd, R. Pongthornseri, J. Chinrungrueng, and T. Silawan, "Automatic vehicle classification using wireless magnetic sensor," in *Proc. IEEE Int. Workshop IDAACS*, Sep. 2009, pp. 420–424.



Bo Yang was born in Sichuan, China, in 1972. She received the B.S. and M.S. degrees from Beihang University, Beijing, China, in 1993 and 1996, respectively, and the Ph.D. degree from the University of Paderborn, Paderborn, Germany, in 2004, all in electrical engineering.

She has been with the School of Automation Science and Electrical Engineering, Beihang University, since 2004, where she is currently an Associate Professor. Her main research interests include intelligent measurement and control.

Yiqun Lei was born in Shaanxi, China, in 1991. She received the B.S. degree in automation science and electric engineering from Beihang University, Beijing, China, in 2013, where she is currently pursuing the M.S. degree at the School of Automation Science and Electrical Engineering. Her research interest includes wireless sensor networks.