A Novel Cost-Effective IoT-Based Traffic Flow Detection Scheme for Smart Roads

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***Abstract*—Autonomous driving is expected to be realized in the future with the development of information and communication technology (ICT). However, the reliability of autonomous vehicles (AVs) in complex environments needs major improvement. To facilitate the autonomous driving, high-precision and low-cost traffic flow detection is essential for driving decision and traffic surveillance, and has drawn increasing attention from both academia and industry. In this paper, we propose a novel cost-effective IoT-based traffic flow detection scheme with particular focuses on vehicle counting and speed measurement. To this end, microwave Doppler radar sensors with a unit price of $2.3 are utilized to collect the traffic data of passing vehicles on the road. Then, a multi-threshold detection algorithm is proposed to extract features for vehicle counting and speed measurement. After this, experiments are carried out in different scenarios to evaluate the proposed traffic flow detection scheme. The results validate the high-precision detection with average 98.3% vehicle counting accuracy and 95.8% speed measurement accuracy.**

***Index Terms*—Autonomous driving, traffic surveillance, internet of things, vehicle counting, speed measurement.**

I. Introduction

The development of information and communication technology (ICT) is expected to enable fully autonomous driving in the future [1]. For example, produced by Tesla, a vehicle called Modle S has realized automatically steering, acceleration and braking in the lane. However, fully autonomous driving has not yet been achieved, the reasons are as follows. On the one hand, without the support of road-side communication and sensing autonomous vehicles (AVs) can not achieve global sensing requirements for safe driving. On the other hand, the roads are not smart enough to provide sufficient assistance information to facilitate the autonomous driving. The reliability of AVs in complex environments where the traffic flow, the speed and the types of vehicles change greatly needs major improvement. There is still a long journey for autonomous vehicles to achieve true Level 5 autonomy [2].

The smart roads require real-time and accurate road traffic information (i.e., number and speed of vehicles in each road), which is essential for driving decision and traffic surveillance. Consequently, the vehicle counting and speed measurement, especially in complex environments, become important issues to provide reliable information for autonomous driving. In order to obtain the information, a number of studies have been published about traffic flow detection. For one thing, the rapid development of image processing technology has greatly promoted the development of traffic flow detection scheme based on video. For another, sensor technology and information processing technology are also in rapid innovation, which make the sensor-based scheme one of the mainstream solutions of traffic flow detection. Liang *et al.* proposed a novel algorithm called HCR (Hierarchical Classification Based Regression) to classify and count highway vehicles based on video [3]. Similarly, more video-based works have been carried out to improve the accuracy of vehicle counting and speed measurement [4]-[9]. Though detection accuracy of the video-based scheme is high, the video camera is costly for a large-scale deployment. In the sensor-based schemes, Taghvaeeyan *et al.* [10] proposed a scheme based on the collaboration of multiple magnetic sensors to obtain the number and speed of vehicles in the adjacent lane. However, an additional magnetic sensor is required to reduce the errors caused by vehicles in the nonadjacent lane. Based on continuous wave Doppler radar, Misans *et al.* [11] used zero-crossing algorithm and the least squares method to estimate the vehicle speed, but they only simulated with Matlab/Simulink software. Nguyen *et al.* [12] and Jeng *et al.* [13] processed data from microwave radar in the frequency domain. However, they only considered vehicles with speeds less than 50km/h and the former achieved the accuracy only more than 80%. Fang *et al.* [14] designed a low-cost vehicle detection and classification system utilizing time-frequency analysis based on a microwave radar, but the accuracy of vehicle counting is only above 95%.

Compared with the video cameras, microwave Doppler radar sensors are much cheaper and smaller, suitable for a large-scale deployment. In addition, unlike magnetic sensors, the performance of microwave Doppler radar sensors is unaffected by geographical changes. Although many studies have been carried out to realize traffic flow detection utilizing spot sensers, there are still many work to do to balance the detection accuracy and the cost. In particular, schemes based on microwave Doppler radar sensors generally achieve traffic flow detection by extracting Doppler frequency, which is largely affected by the performance of microwave Doppler radar sensors, making it difficult to reduce the cost while ensuring high detection accuracy. Consequently, in this paper we utilize microwave Doppler radar sensors to collect the traffic data with the number and speed information of vehicles on the road. Then, by the multi-threshold algorithm proposed in this paper, features for traffic flow detection are extracted and analyzed. After this, experiments are carried out to evaluate the performance of the proposed traffic flow detection scheme.

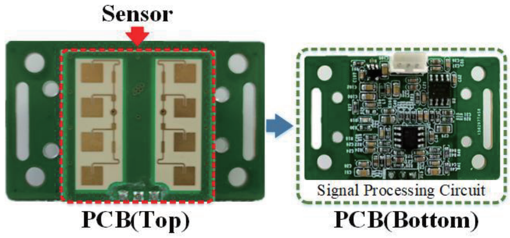


Fig. 1: Physical board of the traffic flow detection system.

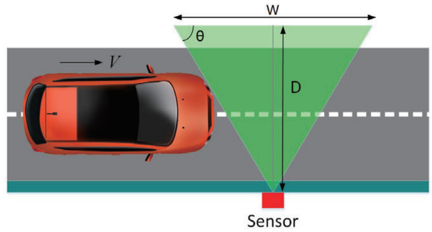


Fig. 2: Sensor configuration for data collection.

The remainder of this paper is organized as follows. Section II presents the structure of the proposed traffic flow detection system. In section III, the vehicle counting scheme is described. The speed measurement scheme is described in section IV. Section V presents the experimental results of vehicle counting and speed measurement, followed by the conclusion in section VI.

II. System Model

In this section, we describe the traffic flow detection system, which consists of collector, signal amplifier and controller. The physical board is shown in Fig. 1.

- **Collector:** As shown in Fig. 1, The CDM324 microwave Doppler radar sensors are utilized in the system as data collectors. This 24 GHz sensor costs only about \$2.3, and the radius of effective detection area is 6 m. The signal is transmitted at a fixed frequency by the microwave Doppler radar sensor. When reflected by the moving vehicle, the frequency of the received signal will be changed, which can be calculated as

$$f_r = f_t\left(\frac{1+v/c}{1-v/c}\right) = f_t\left(\frac{c+v}{c-v}\right) \tag{1}$$

where f_r is the receiving frequency. f_t is the transmitting frequency. v is the relative velocity of the moving object. c is the speed of light. And the Doppler frequency

$$f_d = f_r - f_t = 2v \cdot \frac{f_t}{c-v} \tag{2}$$

Since $v \ll c$, Eq. (2) can be rewritten as

$$f_d \approx 2v \cdot \frac{f_t}{c} \tag{3}$$

As shown in Fig. 2, we assume that the speed of a vehicle is V, the maximum width and maximum distance of the microwave beam are W and D, the angle of the line between the vehicle and the sensor and the horizontal direction is θ, the Doppler frequency

$$f_d(t) = 2V\cos\theta(t) \cdot \frac{f_t}{c} \tag{4}$$

where $\theta(t)$ can be calculated as

$$\theta(t) = \begin{cases} \arctan(\frac{D}{W/2-Vt}), Vt \le \frac{W}{2} \\ \pi - \arctan(\frac{D}{W/2-Vt}), Vt > \frac{W}{2} \end{cases} \tag{5}$$

The received signal can be written as

$$s(t) = A(t) \cdot \sin(2\pi f_d(t) \cdot t) \tag{6}$$

where $A(t)$ is the amplitude of the received signal, $s(t)$ changes when vehicles pass by. Then, the received signal will be collected by the signal amplifier.

- **Signal amplifier:** The original signal levels are low when the microwave Doppler radar sensors are placed on the side of the road, it is necessary to use higher amplification before extracting features for vehicle counting and speed measurement.
- **Controller:** After analogue-to-digital conversion, the signal can be processed by the controller, which is integrated on the STM32F103RC ARM chip. Each chip costs about \$1.7. After obtaining the signal from the amplifier, signal preprocessing and feature extraction are carried out by the controller, vehicle counting and speed measurement algorithms are utilized to realize traffic flow detection.

III. Vehicle Counting Scheme

In this section, we introduct the proposed vehicle counting scheme in detail.

A. Data Collection

Fig. 2 shows the configuration of the vehicle counting system. A single microwave Doppler radar sensor is placed on the side of the road and 50 cm above the ground to collect the signal. The detection area of the sensor is a sector with a radius of 6 m, which is enough to detect the vehicle in an entire lane. When a moving vehicle enters the microwave beam, the received signal $s(t)$ changes until the vehicle leaves the microwave beam. The sensor signal to be processed by the controller is shown in Fig. 3(a).

B. Signal Preprocessing

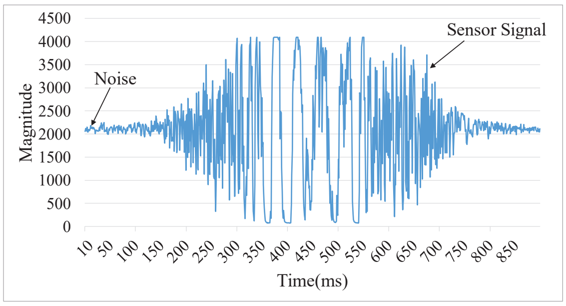
The amplitude of the sensor signal is distributed above and below the baseline, which is not conducive to feature extraction. The signal features of the vehicle passing by are reflected by the variation of the amplitude relative to the baseline, so we preprocess the sensor signal by

$$y(k) = |x(k) - \beta| \tag{7}$$

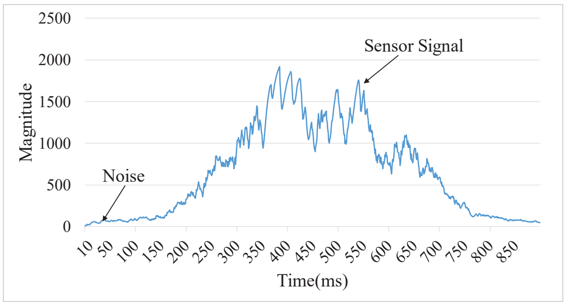
where $y(k)$ is the k-th amplitude relative to the baseline. $x(k)$ is the k-th amplitude of the signal before preprocessing. β is the value of the baseline.

Then, a low-pass filter is used to reduce the interference of noise on the signal.

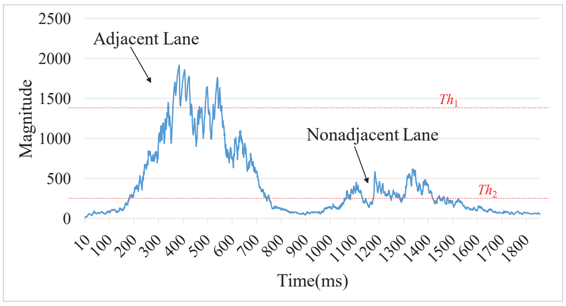
$$w(k+1) = \alpha y(k+1) + (1-\alpha)w(k) \tag{8}$$



(a) Before preprocessing



(b) After preprocessing



(c) Different lanes

Fig. 3: The sensor signal.

where $w(k)$ is the k-th amplitude of the signal after preprocessing. α is the filter coefficient. The signal after preprocessing is shown in Fig. 3(b).

C. Feature Extraction

In order to distinguish between sensor signals and noise, a sliding window is defined. We assume that the window has a length L, starting at the n-th amplitude, where $w(n) \geq Th$.

$$\bar{w} = \frac{1}{L} \sum_{k=n}^{n+L-1} w(k) \tag{9}$$

$$w_k = w(k), w(k) \geq Th \tag{10}$$

where $\bar{w}$, w_k and Th are defined as the average energy, the satisfactory value, and the threshold of the satisfactory value respectively. Besides, N is defined as the number of the satisfactory value among the sliding window. We define $\bar{w}$ and N as two features to count vehicles.

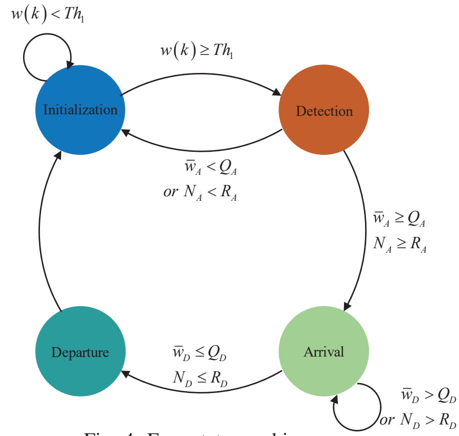


Fig. 4: Four-state machine process.

D. Four-state Machine

As shown in Fig. 4, a four-state machine algorithm is proposed to realize vehicle counting according to the sensor signal after preprocessing. Multiple thresholds are defined, including L, Th, Q and R, where Q and R are used to determine whether the vehicle has reached or left the sensor beam.

- **Initialization:** In order to avoid vehicles in nonadjacent lane causing errors in detection, Th is set to be Th_1. As shown in Fig. 3(c), Th_1 is over the maximum amplitude of the sensor signal collected from the nonadjacent lane. The controller continuously obtains $w(k)$. In case $w(k)$ is less than Th_1, initialization state is maintained, the controller keeps comparing $w(k)$ and Th_1. Otherwise, the state is updated.
- **Detection:** Eq. (9) and (10) are used to calculate $\bar{w}$ and N, where L and Th are set to be L_1 and Th_1. In this state, the results are denoted as $\bar{w}_A$ and N_A, Q and R are set to be Q_A and R_A. If $\bar{w}_A$ and N_A are over the thresholds, a vehicle is supposed to be arrived, the state is updated, otherwise the state is reverted back to the previous state.
- **Arrival:** For the vehicle has already arrived, the next step is to determine the departure of the vehicle. Similar to the previous state, $\bar{w}_D$ and N_D are calculated based on Eq. (9) and (10), where L and Th are set to be L_2 and Th_2. As shown in Fig. 3(c), Th_2 is over the maximum amplitude of the noise. By comparing them with the thresholds Q_D and R_D, whether a vehicle has left the sensor beam is determined, and the state is determined to be kept or updated.
- **Departure:** After the departure of a vehicle, the total number of vehicles increases by one. The system refreshes to the initialization state to restart the vehicle counting.

E. Define Optimal Thresholds

To define the optimal thresholds, we preliminarily determine the approximate range of each threshold based on the waveforms of dozens of vehicles passing by the sensor. Then

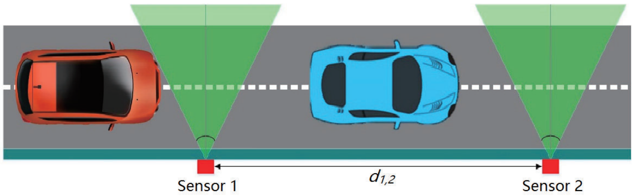


Fig. 5: Sensor configuration for speed measurement.

we assume event A is the actual observation, event B is the detection result. $A = 1$ denotes the passing of a vehicle, $A = 0$ denotes no vehicle passes, $B = 1$ denotes the detection result is that a vehicle passes, $B = 0$ denotes the detection result is that no vehicle passes. The probability of misdetection can be denoted as

$$\begin{aligned} P_r\left(A \neq B\right) = P_r\left(B = 0 \mid A = 1\right) P_r\left(A = 1\right) \\ + P_r\left(B = 1 \mid A = 0\right) P_r\left(A = 0\right) \end{aligned} \tag{11}$$

where $P_r\left(A = 1\right)$ and $P_r\left(A = 0\right)$ are prior probabilities, which are determined by traffic flow and vehicle speed, $P_r\left(B = 0 \mid A = 1\right)$ is the probability of a vehicle passing by without detection, $P_r\left(B = 1 \mid A = 0\right)$ is the probability of detecting a vehicle when no vehicle is passing. For example, assuming that the average length of a vehicle is 4 meters, and the average interval between vehicles is 6 meters, we can figure out that $P_r\left(A = 1\right) = 0.4$, and $P_r\left(A = 0\right) = 0.6$.

We detected about 10,000 vehicles with multiple sets of thresholds on different roads to define the optimal thresholds corresponding to the smallest $P_r\left(A \neq B\right)$. The type and speed of vehicles and the traffic flow vary greatly to ensure the universal of the optimal thresholds.

IV. Speed Measurement Scheme

To measure individual vehicle speed, a speed measurement scheme is proposed in this section.

A. *Scheme Design*

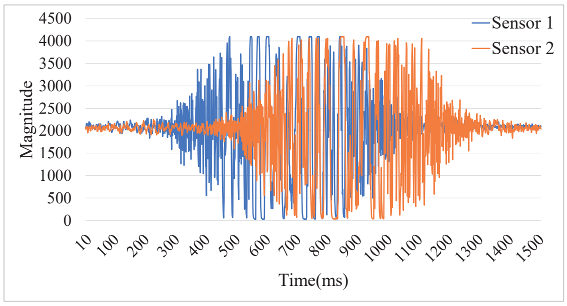
For large-scale deployment, we proposed a speed measurement scheme using two low-cost microwave Doppler radar sensors. The configuration of the speed measurement system is shown in Fig. 5. Based on the distance between two sensors and the time interval required for a vehicle to pass by, the vehicle speed can be calculated as

$$V = \frac{d_{1,2}}{\Delta t_{1,2}} \tag{12}$$

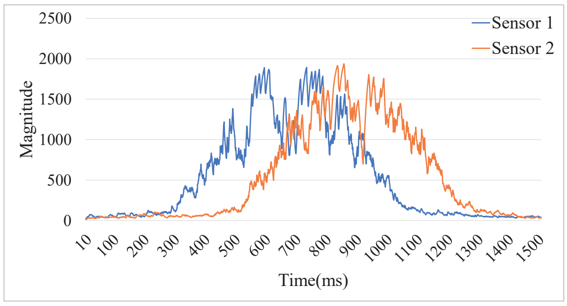
where $d_{1,2}$ is the distance between sensor 1 and sensor 2, set to be less than the length of a vehicle. $\Delta t_{1,2}$ is the time interval required for a vehicle to pass by sensor 1 and sensor 2. To calculate $\Delta t_{1,2}$, $t_{1,A}$, $t_{2,A}$, $t_{1,D}$ and $t_{2,D}$ are defined, denoting the timestamps. Eq. (12) can be rewritten as

$$V = \frac{d_{1,2}}{\left(\left(t_{2,A} - t_{1,A}\right) + \left(t_{2,D} - t_{1,D}\right)\right)/2} \tag{13}$$

different from the exact timestamps, $t_{1,A}$ and $t_{2,A}$ are the customized timestamps that a vehicle enters the microwave beam of sensor 1 and sensor 2. $t_{1,D}$ and $t_{2,D}$ are the customized timestamps that a vehicle leaves the microwave beam of sensor 1 and sensor 2. There is no need to focus on judging the exact timestamps that a vehicle enters and leaves the microwave beam, we only need to calculate the time interval required for a vehicle to pass by sensor 1 and sensor 2. The signals collected by two sensors are shown in Fig. 6.



(a) Before preprocessing



(b) After preprocessing

Fig. 6: Signals collected by two sensors.

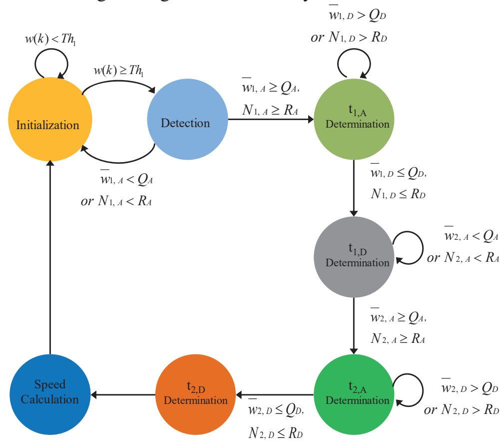


Fig. 7: Speed measurement flow chart.

B. *Speed Measurement*

Similar to the vehicle counting scheme, the signals are collected by two sensors, and preprocessed according to Eq. (7) and (8). Then $t_{1,A}$, $t_{2,A}$, $t_{1,D}$ and $t_{2,D}$ are determined by the proposed speed measurement scheme, based on the average energy and the number of the satisfactory value. The flow chart is shown in Fig. 7.

- **Initialization:** When the system is in initialization state, only noise is collected and no vehicles pass by. The

(a) (b)

Fig. 8: Experimental scenario.

TABLE I: Parameters setup

Par.	Value	Description
f_s	2 kHz	Sampling frequency
$d_{1,2}$	10 m	Distance between two sensors
L_1	100	Length of sliding window
L_2	50	
Th_1	1450	Threshold of satisfactory value
Th_2	450	
Q_A	600	Amplitude threshold
Q_D	300	
R_A	4	Threshold of satisfactory points
R_D	2	

detection will not be triggered until $w(k)$ of the signal collected by sensor 1 is over Th_1.

- **Detection:** Whether a vehicle has reached the microwave beam of sensor 1 is determined in this state. In order to eliminate $w(k)$ changes caused by noise, $\bar{w}$ and N are calculated based on Eq. (9) and (10), the results are denoted as $\bar{w}_{1,A}$ and $N_{1,A}$. If the results are both over the thresholds, a vehicle is determined to have reached the microwave beam of sensor 1. Otherwise the system returns to the initialization state.
- **Timestamps Determination:** In this state, the vehicle has reached the microwave beam of sensor 1, the timestamp is recorded as $t_{1,A}$. If the distance between sensor 1 and sensor 2 is set to be more than the length of a vehicle, a vehicle will leave the microwave beam of sensor 1 before reaching the microwave beam of sensor 2. Then it is determined whether the vehicle has left the microwave beam of sensor 1. After determining $t_{1,A}$, $\bar{w}$ and N are calculated, the results are denoted as $\bar{w}_{1,D}$ and $N_{1,D}$. If $\bar{w}_{1,D}$ or $N_{1,D}$ is less than the thresholds, a vehicle is determined to have left the microwave beam of sensor 1, $t_{1,D}$ is determined. Similarly, $t_{2,A}$ and $t_{2,D}$ are determined successively.
- **Speed Calculation:** Two time intervals are determined based on $t_{1,A}$, $t_{2,A}$, $t_{1,D}$ and $t_{2,D}$. To reduce the timing error, we take the average of these two time intervals as $\Delta t_{1,2}$. Then Eq. (13) is used to calculate the speed of the vehicle passing by. After the calculation, the speed measurement process of a vehicle is finished, the system moves to the initialization state.

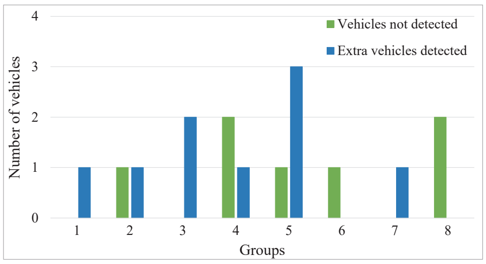


Fig. 9: Distributions of vehicles not detected and extra vehicles detected.

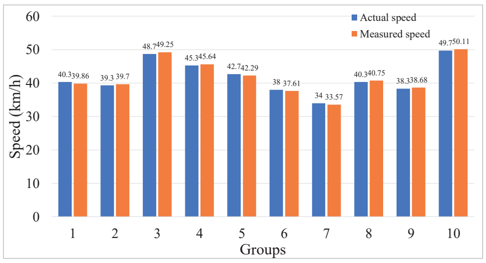


Fig. 10: Average speed comparison in each group.

V. Performance Evaluation

Experiments are carried out in this section to evaluate the proposed traffic flow detection scheme.

A. Experimental Setup

As shown in Fig. 8, two different roads are selected to conduct the experiments in the urban area of Xi'an. Baisha road has three lanes in the same direction, the second ring road has two lanes in different directions. The width of a single lane is 3.5 m. We focus on the vehicle counting and speed measurement on a single lane. There are many types of vehicles on the both roads, including saloon, SUV, street sprinkler, street sweeper truck, station transport wagon, single-decker bus and double-decker bus. The speed of those vehicles varies from 20 km/h to 80 km/h. The traffic flow ranges from 5 veh/min to 40 veh/min, and the average traffic flow on the second ring road is about twice that of Baisha road. Two microwave sensors and an ARM chip are utilized in the traffic flow detection system as data collectors and controller. Vehicle counting and speed measurement schemes are realized based on the date from one single sensor and tow sensors. The sampling frequency of the traffic flow detection system is set to be 2 kHz. $d_{1,2}$ is set to be 10 m. Th_1, L_1, Q_A and R_A are set to be 1450, 100, 600 and 4 to detect the arrival of a vehicle, Th_2, L_2,Q_D and R_D are set to be 450, 50, 300 and 2 to detect the departure of a vehicle.

B. Experimental Results

1) Vehicle Counting: We conducted 8 groups of tests, each with 120 vehicles. The distributions of vehicles not detected and extra vehicles detected in each group are shown in Fig. 9. The number of vehicles not detected is less than 2 in each group, and the number of extra vehicles detected is no more than 3 in each group. The counting accuracy ranges from 96.7% to 99.2%. Overall, there are 7 vehicles not detected and

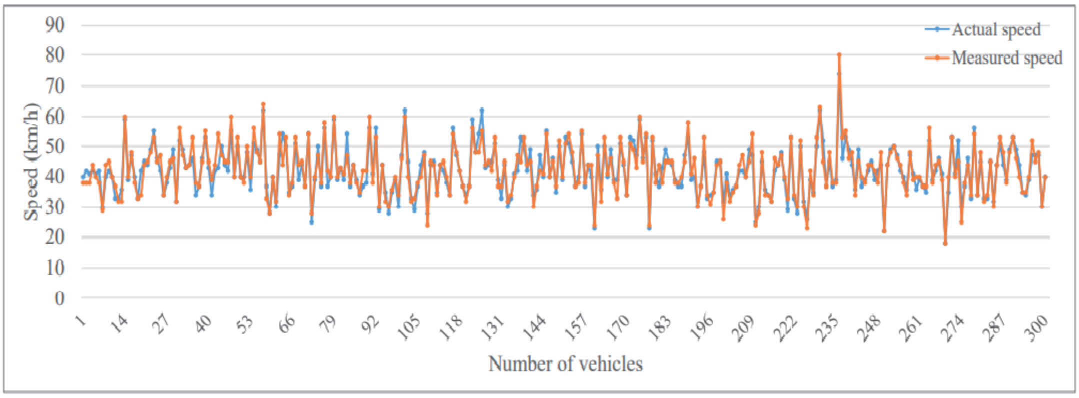


Fig. 11: Speed comparison of each vehicle.

9 extra vehicles detected out of 960 vehicles, which causes a 1.7% error. In this experiment, the vehicle counting accuracy is 98.3%.

2) Speed measurement: The speed measurement results of Bushnell 101921 speedometer are taken as the actual speed of vehicles. We totally measured the speed of 300 vehicles in 10 groups, each with 30 vehicles. The comparison between measured speed and actual speed is shown in Fig. 10 and 11. The speed of vehicles ranges from 18 km/h to 74 km/h, concentrated between 30 km/h to 60 km/h. The mean absolute errors are 1.91 km/h, 1.71 km/h, 2.37 km/h and 3.02 km/h when actual speed is below 30 km/h, between 30 km/h and 40 km/h, between 40 km/h and 50 km/h, and over 50km/h. We adopt the mean absolute percentage error to evaluate the performance, which shows that the accuracy of the proposed speed measurement scheme is 95.8%.

VI. Conclusion

In this paper, we proposed a high-precision traffic flow detection scheme in complex traffic environment based on low-cost microwave Doppler radar sensors, costs only about $7. The CDM324 microwave Doppler radar sensors are utilized to collect the traffic data with traffic flow and vehicle speed information. Then, we have extracted the average energy and the number of the satisfactory value as features and designed a multi-threshold algorithm to realize vehicle counting and speed measurement. To evaluate the performance of the proposed scheme, we have conducted experiments in different scenarios where the traffic flow, the speed and the types of vehicles change greatly. Experimental results have shown a 98.3% vehicle counting accuracy and a 95.8% speed measurement accuracy.

Acknowledgment

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