Roadside Sensor based Vehicle Counting in Complex Traffic Environment

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***Abstract*—The 5G networks are expected to support autonomous driving to enhance driving experience and travel efficiency. Toward this goal, the valuable data generated by the complex and dynamic transportation system need to be collected. In this paper, we propose a roadside sensor-based vehicle counting scheme for collecting traffic flow information in complex traffic environment. In the scheme, the roadside sensor can sense the magnetic data, where the magnetic flux magnitude will be changed if a vehicle passes though the sense coverage of the sensor. Based on this, we first analyze the change of the magnetic signals in the complex traffic environment and process the magnetic signals collected by the roadside sensor. Then, an integrated algorithm is designed to detect and count the traffic flow by considering the features of the collected signals. After this, we carry out experiments to evaluate the performance of the proposed vehicle counting scheme and analyze the vehicle counting error. According to the features of the error, we further design the error compensation strategy to correct the experiment results. Experimental verification results show that the vehicle counting accuracy before and after the error compensation in the complex traffic environment are 97.07% and 98.5%, respectively.**

***Index Terms*—Autonomous driving, roadside sensor, traffic surveillance, intelligent transportation system, vehicle counting.**

I. Introduction

With the rapid development and deployment of 5G networks, autonomous driving has attracted worldwide attention to change the way people drive [1]. For example, Baidu has produced the driverless minibus, called Apollo, in 2018. To achieve autonomous driving and enhance travel efficiency, a large amount of traffic data, such as humidity, traffic lights and traffic flow, need to be collected by the base stations in 5G networks [2]–[4]. The data provided by base stations can be collected by the sensors deployed along roads. With different types, roadside sensors can provide various data for vehicles to make real-time driving decisions with the target of having a safe and comfortable travel.

As a typical application of autonomous driving in 5G networks, path planning can provide vehicles with the optimal driving path according to the road congestion information. The accuracy of the congestion information therefore directly affects driving decisions of vehicles. To obtain the congestion information, the number of vehicles in each road needs to be counted accurately. Consequently, the vehicle counting technology becomes an important issue which needs to be solved to facilitate the autonomous driving in 5G networks.

Conforming to this trend, a number of works have been carried out to study the problem of vehicle counting. Based on the regression analysis, Liang *et al*. [5] propose a novel algorithm to count and classify highway vehicles based on videos. Similar to [5], many works have been studied to enhance the vehicle counting performance by using video or image information [6]–[11]. However, the video camera is costly for a large-scale deployment. On the other hand, the environment factors (e.g., shadow and rain) have a large effect on the performance of the vehicle counting [12]. Different from vehicle counting schemes based on video, there are many works have focused on the roadside sensors. By analyzing the magnetic field model, Taghvaeeyan *et al*. [13] develop an algorithm to improve the vehicle counting accuracy by reducing errors created by the vehicles driving in the nonadjacent lane. Balid *et al*. [14] present an intelligent vehicle counting system with the adoption of magnetic sensors. In this scheme, the sensors are deployed in the middle of the road. Consequently, the installation and maintenance of the sensors may cause a high cost. Based on signal variance, Yang *et al*. [15] propose a vehicle detection method with anisotropic magnetoresistive sensor. However, the scene considered in this work is congested traffic condition, where the vehicles have low driving speed.

Unlike the above researches, we focus on the complex traffic environment to achieve vehicle counting based on roadside sensors. Compared with the conventional environment, the complex traffic has the following features: 1) the vehicles driving in the lanes have more types; 2) the velocity of vehicles changes with a larger range; 3) the traffic flow has a larger range. The roadside sensor used in our work can collect the magnetic data, where the magnetic flux magnitude will be changed if a vehicle passes though the sense coverage of the sensor. In this way, we first analyze the change of the magnetic signals in the complex traffic environment and process the signals collected by the roadside sensor. Then, we design an integrated algorithm to detect and count the traffic flow by considering the features of the collected signals. After this,

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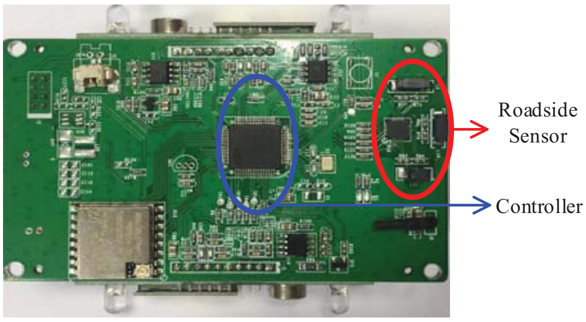

Fig. 1. Roadside sensor.

experiments are carried out to evaluate the performance of the proposed vehicle counting scheme and analyze the vehicle counting error. Based on the features of the error, the error compensation strategy is designed to correct the experiment results. Experimental verification results show that the vehicle counting accuracy before and after the error compensation in the complex traffic environment are 97.07% and 98.5%, respectively.

The rest of this paper is organized as follows. The description of our vehicle counting system is introduced in Section II. In Section III, we present the designed vehicle counting scheme. Section IV evaluates the proposal by experiments, followed by the conclusion in Section V.

II. System Model

In this section, we introduce the system of the vehicle counting scheme, which consists of roadside sensor, controller and data receiver

- **Roadside sensor:** As shown in Fig. 1, the roadside sensor is RM3100, which is charged by the controller of the chip. The sensor is deployed along roadside and can collect the magnetic signal of three axes (i.e., X, Y and Z). Specifically, X-axis and Y-axis stand for the directions parallel to the direction of vehicle and perpendicular to the direction of vehicle, respectively. Different from X-axis and Y-axis, Z-axis is the direction perpendicular to the road surface. The magnetic flux lines will be changed if a vehicle passes though the sense coverage of the roadside sensor.
- **Controller:** The controller is integrated on the chip, which is used to control the roadside sensor and process the data collected by the sensor. After obtaining the number of vehicles, the controller then sends the vehicle counting result to the data receiver.
- **Data receiver:** The data receiver can be regraded as a based station to integrate the vehicle counting results collected by a group of roadside sensors to manage the traffic on the road. Based on the results, the receiver can make traffic scheduling commands to plan the traffic flow. The data transmission between the controller on the chip and the data receiver is based on the LORA wireless serial port module.

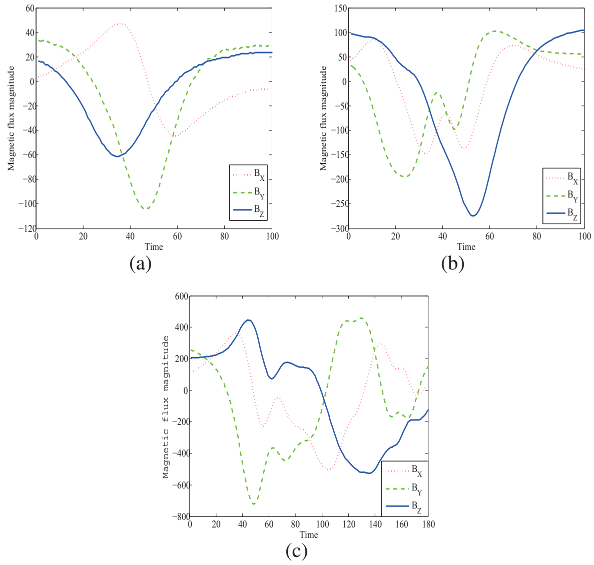

Fig. 2. Signals of three axes. (a) Saloon. (b) SUV. (c) Bus.

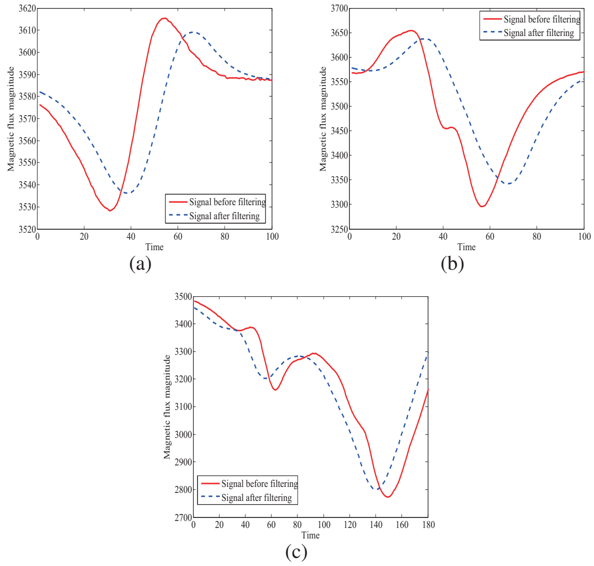

Fig. 3. Signal after data fusion. (a) Saloon. (b) SUV. (c) Bus.

III. Vehicle Counting Scheme

In this section we present the vehicle counting scheme proposed in this paper.

A. Data Fusion

The magnetic signals of X-axis, Y-axis and Z-axis collected by the roadside sensor are shown in Fig. 2, where Fig. 2(a), Fig. 2(b) and Fig. 2(c) are the magnetic signals of a saloon, SUV and bus, respectively. From this figure, we can see that the signals of the three axes have different features. In addition, vehicles with different types generate different magnetic signals. In order to make full use of the information

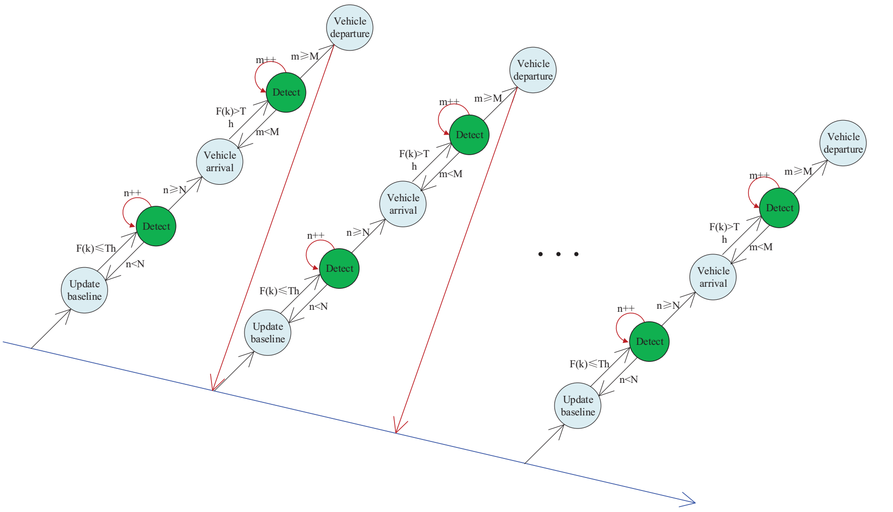

Fig. 4. Vehicle counting flow chart.

of the three axes, the data output from the three axes for the k-th time can be fused by

$$F(k) = \sqrt{F_X(k)^2 + F_Y(k)^2 + F_Z(k)^2}, \tag{1}$$

where $F_X(k)$, $F_Y(k)$ and $F_Z(k)$ are the data output by X-axis, Y-axis and Z-axis, respectively. The signal after data fusion can be seen in Fig. 3.

B. Data Filtering

As can be seen from Fig. 3, the signal has a lot of interference before processing. The interference may make the false detection and counting of vehicles. Therefore, the signal needs to be processed before being used for vehicle counting. For the data collected by the roadside sensor, it is first fused by using (1) and then processed by uing the median filtering method. Specifically, we define a data set to determine the value of the collected data. We remove the maximum and minimum values of the data in the set and average the remaining data to obtain the filtered data, shown as

$$\overline{F(k)} = \frac{1}{L-2}\left(\sum_{k=1}^{L} F(k) - F_{\min} - F_{\max}\right), \tag{2}$$

where L is the length of the data set. $F_{\min}$ and $F_{\max}$ are the maximum and minimum values, respectively. The signals before filtering and after filtering are shown in Fig. 3.

C. Vehicle Counting

In the vehicle counting scheme, we need to address two problems. First, by considering the drift of the magnetic baseline caused by the traffic environments, how to design an adaptive method to update the baseline of the magnetic flux magnitude. Second, how to accurately determine the arrival and departure of a vehicle. To address these problems, we design a two-phase vehicle counting algorithm. The first phase is charge of updating the baseline, where the baseline stands for the situation that there is no vehicle in the detection coverage of the roadside sensor. The second phase is the process to count vehicles by judging vehicle arrival and vehicle departure.

- **Baseline update:** We define a data set, denoted as $R = \{1, ..., r, ..., R\}$, to determine the magnetic baseline. The initial value of the baseline is determined by the case that there is no vehicles in the sense coverage of the roadside sensor. It is calculated by

$$F_{\text{baseline}} = \frac{1}{R}\sum_{r=1}^{R} F(r). \tag{3}$$

Based on the initial value, we resort to the moving average method to update the baseline. In other words, if there is no vehicle in the coverage of the roadside sensor, the collected data will be added to the set and used for updating the baseline. As such, the baseline can be adaptively changed with the environment.

- **Vehicle arrival:** Based on the magnetic baseline, we define a vehicle detection threshold, denoted as Th. The threshold is used to judge whether a vehicle enters in the detection coverage of the roadside sensor or not. It can be calculated by

$$Th = F_{\text{baseline}} - \lambda, \tag{4}$$

where λ is determined by the traffic conditions.
If a data collected by the roadside sensor is larger than the threshold, it will be used to update the baseline. Otherwise, the algorithm moves to the first state of the second phase, namely, the vehicle arrival detection state. The remaining states of this phase are vehicle arrival, vehicle departure detection and vehicle departure, respectively. To avoid the false detection caused by the interference, we set a counter N. If N consecutive data are no larger than the threshold, the algorithm will decide that there arrivals

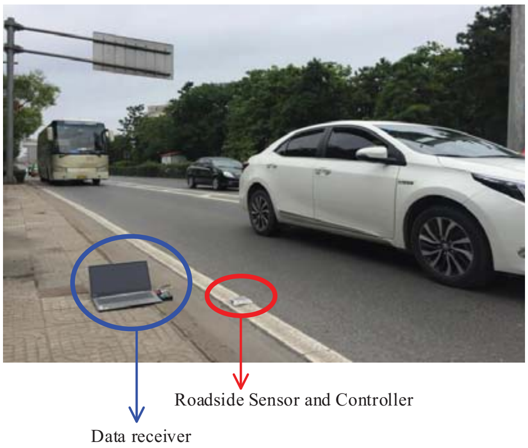

Fig. 5. Experimental scene.

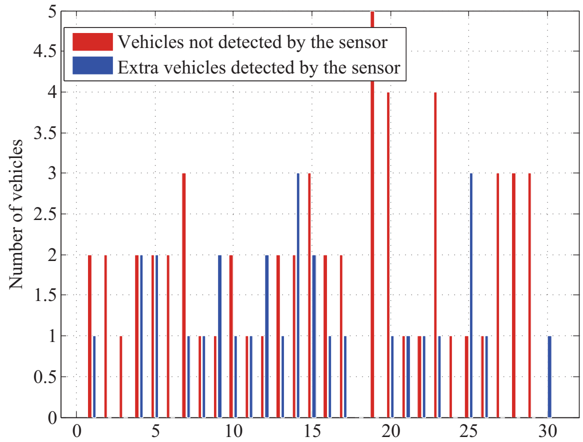

Fig. 6. The distributions of the vehicles not detected and the extra vehicles counted by the sensor in each group.

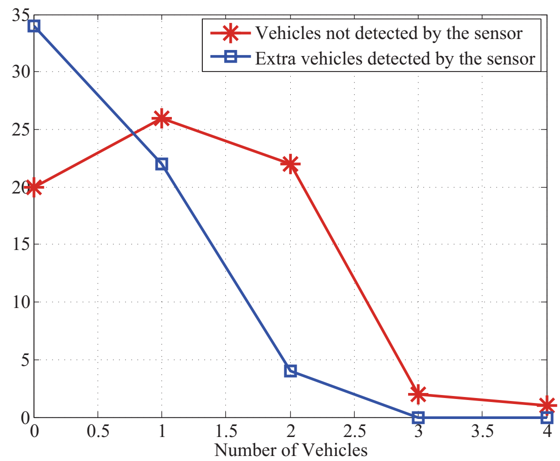

Fig. 7. The number of vehicles not detected and the number of extra vehicles counted by the system.

a vehicle. Otherwise, the change in the intensity of the magnetic flux is caused by the disturbance so that the magnetic flux magnitude is smaller than the threshold. If this situation occurs, the system will return to the first phase of the algorithm and update the baseline.

- **Vehicle departure:** After judging that a vehicle has entered in the coverage of the roadside sensor, it is necessary to further judge the departure of the vehicle. We draw on the method by which the vehicle enters in the sense coverage of the roadside sensor. If the collected data is larger than the threshold for the first time, the system will move to the detection state. If the number of data that are consecutively larger than the threshold is less than M, the fluctuation of magnetic flux magnitude is considered to be caused by interference. That is to say, the vehicle does not leave the sense coverage of the sensor. Otherwise, it is determined that the vehicle departure process is finished. The system moves from the detection state to the vehicle departure state. After the vehicle leaves, i.e., the process of counting this vehicle is finished, the system moves to the baseline update state.

The vehicle counting flow chart proposed in this paper is detailed in Fig. 4.

IV. Experiment Results

In this section, we carry out experiments to evaluate the proposed vehicle counting scheme.

A. Experimental Scenario

We select an urban road on the second ring of Xi'an to deploy the experimental scene. As shown in Fig. 5, we focus on the vehicle counting on a single lane. The roadside sensor and the controller are integrated on the chip. The data receiver in the experiment is a laptop. The vehicle speed on the selected road ranges from 10 km/h to 70 km/h. The traffic flow changes from 5 veh/min to 40 veh/min. In addition, there are many types of vehicles on the road, including two-box vehicle, saloon, SUV, lorry vehicle and bus. The width of the selected urban road is about 3.5 m. The values of N, M, R and L are set to be 12, 30, 200 and 20, respectively. The value used to determine the threshold, λ, is 60 in the experiments.

B. Experimental Results

In this subsection, we detail the experiment results of the proposed vehicle counting scheme. We did two sets of experiments on the same road segment. The result of the first experiment is used to analyze the detection error. Based on the results of the first experiment, we perform statistical analysis on the error compensation of the vehicle counting results. After this, we verify the error compensation results in the second set of experiments.

In the first experiment, we tested 30 groups, where the number of vehicles in each group is 100. The distributions of the vehicles not detected and the extra vehicles counted by the sensor in each group are shown in Fig. 6. From this figure,

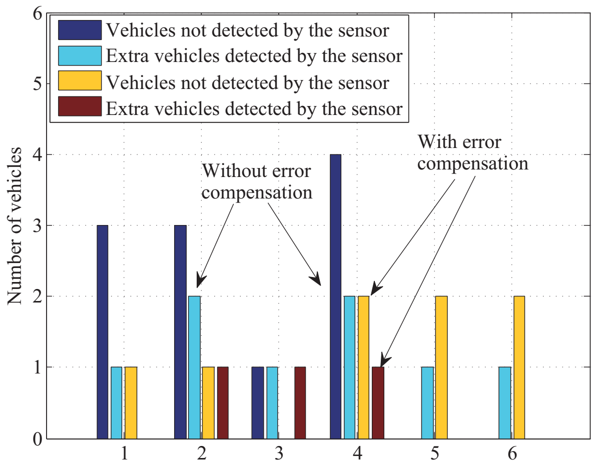

Fig. 8. Vehicle counting results.

we can see that the number of vehicles not detected is more than the extra vehicles counted by the sensor. As can be seen in Fig. 7, the number of vehicles not detected by the sensor is 58 and the probability that a vehicle is not detected by the sensor is 1.93%. In contrast, the number of extra vehicles that are counted by the system is 30, where the probability that the system counts an extra vehicle is 1%. In this experiment, the vehicle counting accuracy is 97.07%. Through the experiment, as shown in the figure, we can see that for every 100 vehicles, 2 vehicles are not detected and 1 extra vehicle is counted by the system. Therefore, we use this information as a priori knowledge to compensate the vehicle counting results.

For the second experiment, we tested 6 groups, where the number of vehicles in each group is 100. The vehicle counting results before the error compensation and after the compensation are shown in Fig. 8. Obviously, the number of vehicles not detected and the extra vehicles detected by the system are reduced by using the error compensation. In addition, with the error compensation, the counting accuracy of the vehicles in the selected urban road is 98.5%.

V. Conclusion

In this paper, we have proposed a vehicle counting scheme based on roadside sensors in complex traffic environment. In the scheme, the change of the magnetic signals in the complex traffic environment is first analyzed. Then, the signals collected by the roadside sensor are processed to facilitate the vehicle counting. After this, we have designed an integrated algorithm with two phases to detect and count the traffic flow by considering the features of the collected signals. Experiments have been carried out to evaluate the performance of the proposed vehicle counting scheme and analyze the vehicle counting error. Based on the analysis of the error, we have designed the error compensation strategy to correct the experiment results. The results have shown that the vehicle counting accuracy before and after the error compensation in the complex traffic environment are 97.07% and 98.5%, respectively.

For the future work, we plan to study the vehicle speed in the complex traffic environment based on the roadside sensor. In addition, the vehicle detection and counting in multi-lane scenario will be considered.

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