**Vehicle Classification Based on Pulse Coherent Radar**

**Abstract:** The technology of traffic information collection is the basis of Intelligent transport system. However, it’s a challenge to effectively perform the road vehicle classification, due to the dynamical traffic environment and various types of vehicle on the road. In this paper, we proposed a real time approach of road vehicle classification based on the new Pulse Coherent Radar. We deploy the radar in the middle of road lane and intercept the vehicle data when a vehicle passes over the radar. Then extract the feature of vehicle chassis outline and height from the intercepted vehicle data to fit a Random Forest model. According to the input data of feature, the model output the type of vehicle, which include car, SUV, bus and middle truck. In the experiment, we collected the sufficient vehicle data in the actual road environment, and the average accuracy of our approach is 94.03%.

**Key words:** Internet of Things, intelligent transportation system, vehicle classification, pulse coherent radar, random forest.

**I. INTRODUCTION**

Intelligent transport system (ITS) is an effective approach to solve the problems such as traffic congestion and difficult parking. The system is based on real-time traffic information detection technology. Based on the traffic information obtained accurately, ITS can provide a variety of services for traffic management departments and residents, which include path planning [1]-[3], autonomous driving [4]-[7].

The sensors used in the current real-time traffic detection technology mainly include magnetic sensors and cameras. Magnetic sensors have low cost and power consumption, and have a long-life cycle, but they are susceptible to magnetic interference from vehicles in adjacent lanes or urban rail transit [8]. Compared with magnetic sensors, the camera can obtain more information, such as the license plate number. But the camera is susceptible to weather and light interference, and the outdoor video detection technology requires the deployment of power lines and communication lines causing the high installation and maintenance costs. At present, the research of radar sensors in the field of intelligent transportation is mostly based on lidar and millimeter-wave radar, and mainly focuses on the field of autonomous driving [9]-[11]. Lidar and millimeter-wave radar have long detection distances and high accuracy, but they are not suitable for traffic detection in terms of power consumption, size and cost.

The Pulse Coherent Radar, PCR used in this article is a new type of millimeter-wave radar working in the 60GHZ frequency band. It combines the advantages of low power consumption of pulse radar and high accuracy of phase radar [12], with an area of only 29 . And it is not interfered by magnetic field and light.

When road vehicle passes above the PCR, the data generated by PCR can reflect the height and profile characteristics of the vehicle chassis, which could be used for vehicle classification. To this end, we propose a road vehicle classification approach by deploying PCR in the middle of road lane. In particular, we first design the method to effectively intercept the PCR data when vehicle passes over the PCR. Then we convert each intercepted vehicle data collected in the real road environment into a feature vector of vehicle chassis outline and height. Then we use all the feature vectors to fit a Random forest model. The model divides the road vehicle into four types: car, SUV, bus and middle-truck. The contributions of this paper are two-fold:

1. we propose a vehicle classification approach base on the new pulse coherent radar. Design the effective method to intercept the vehicle data and extract the features of vehicle chassis outline and height. And use the Random forest model to divide the vehicle type into four categories.
2. Collect sufficient vehicle data in the actual environment. Based on the collected data, we evaluated the proposed approach, which shows the average accuracy is 94.02%.

The rest of the paper is organized as follows. Section II provides related work. Section III introduces the radar PCR and describes the classification task based on PCR. Section IV details the proposed approach of vehicle detection and classification in detail. Section V evaluates the approach based on the data collected in actual environment, followed by conclusion and future work in Section VI.

**II. RELATED WORK**

There have been many studies on vehicle classification based on different sensors, mainly include magnetic sensor and camera.

In [13], a group of magnetic sensors are placed along the roadside for vehicle detection and classification, where vehicles are classified into four groups by estimating their magnetic length. In [14], a single three-axis magnetic sensor is deployed along the roadside. The magnetic field data of each vehicle is converted into 2-dimensional images and the vehicle is categorized into 7 types by a 2-dimensional convolution neural network (CNN). In [15], the authors extract the features of relative vehicle length, total waveform energy, and “peak-valley graph”, then use hierarchical decision tree algorithm to perform vehicle classification, which is suitable for embedded systems because of the small amount of calculation.

With the development of artificial intelligence, the research of vehicle classification based on camera increasingly focuses on deep learning algorithms include Faster R-CNN [16]-[17], SSD [18] and YOLO [19]-[21]. In [22], the authors present a novel method for vehicle detection based on the MobileNet which is integrated into Faster R-CNN structure. The method improves the detection accuracy and saves computation resources compared with Faster R-CNN. In [23], the authors propose a real-time system to enhance the accuracy level on detection and classification of vehicles for a multi-view surveillance video using an optimized YOLOv2 deep learning algorithm.

Although there have been many studies of vehicle classification based on magnetic sensor or camera. It’s always difficult to solve the interference problems of magnetic sensor and camera. And the previous radars lidar and millimeter-wave radar are not suitable for traffic information collection because of the power consumption, size and cost. Therefore, there is the important value of vehicle classification research based on the new radar PCR, which is not interfered by magnetic field, sunlight and weather and has the advantages of low power consumption, small size and low cost.

**III. PROBLEM DESCRIPTION**

Deploy PCR in the middle of the roadway and assume the vehicle is driving in a lane. When road vehicle passes over the PCR, the data generated by PCR can reflect the outline and height of the vehicle chassis for vehicle classification.

The PCR model A111, which is used in our scenario, provides Envelope mode that supports high precision ranging. And the A111 working in Envelope mode performs one measurement by transmitting a sequence radar pulses and measuring the received pulses energy in different time intervals. The Envelope data generated from the *t*-th measurement is shown as

|  |  |
| --- | --- |
| , | (1) |

where is a set of *n* real valued samples, *t* refers to that the data are collected at the *t*-th time, **refers to an amplitude representing** the received energy from a specific distance calculated by

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| --- | --- |
| , | (2) |

where is the fixed range resolution which is approximately equal to 0.48 mm, is the closest distance that radar can detect. In addition, there is

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| --- | --- |
| , | (3) |

where is the range length of the radar detection. Formula 3 indicates the number of samples *n* is determined by the parameter .

When there are two objects near the radar as shown in Figure 1(a), we get the Envelope data generated from one measurement with of 10 cm and of 40 cm shown in Figure 1(b), where we can see there are two peaks at the sample counts of 200 and 416. Then we calculate and are approximately equal to 20 cm and 30 cm respectively according to Formula 2. Therefore, we estimate that there are two objects at 20 cm and 30 cm from the radar.

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| --- | --- |
|  |  |
| (a) Measurement scene | (b) Envelope data |
| Fig. 1 Envelope data generated by one measurement | |

Our goal is to obtain vehicle type when the vehicle passes over the radar, and our problem is divided into two parts.

The first part is vehicle detection to get the times of measurement when the vehicle is driving towards and away from the radar which is called “start-end times” in this paper. The first part is described as follows

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| --- | --- |
| , | (4) |

where the input data are the Envelope data collected between -th time and-th time measurements.The output data are the measurement times of the *i*-th vehicle driving towards and away from the radar between the -th and -th measurements, respectively.

The second part is vehicle classification to obtain the vehicle type according to the Envelope data intercepted by each pair of start-end times

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| --- | --- |
| , | (5) |

where is the type of the *i*-th vehicle **divided into four types .**

**IV. ALGORITHM DESIGN**

A. OVERVIEW

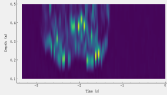
The overview of the approach we proposed is shown in Figure 2. The original data are collected from the radar PCR, which is deployed in the middle of road lane. Then the module of vehicle detection effectively intercepts the data when vehicle passes over the radar. Then the intercepted vehicle data are adjusted to a fixed size. Then we extract the feature vector of vehicle chassis outline and height from the resized vehicle data. With the input data of feature vector, the trained Random Forest model output the result of vehicle type.

Vehicle

Detection



Original data



Feature Extract

Feature vector

Random Forest Model

Vehicle type

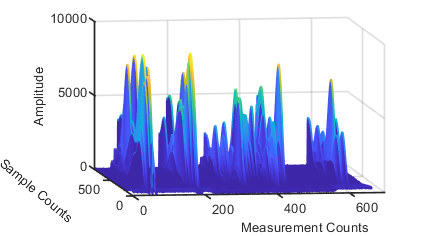
Resize

Intercepted vehicle data

Fig. 2 Approach overview

B. VEHICLE DETECTION

Figure 3 shows the series of Envelope data when car, SUV, bus and middle-truck pass over the radar in turn. The Envelope data generated from one measurement has too much samples with the number *n*, which are redundant for vehicle detection because the Envelope data changes quite obviously when the vehicle passes over the radar as shown in Figure 3.



**SUV**

**Car**

**Bus**

**Middle-truck**

Fig. 3 Envelope data of vehicle passing over the radar

Therefore, we firstly fuse the data by averaging the Envelope data generated from one measurement, expressed as

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| --- | --- |
| , | (6) |

where is the averaged Envelope data generated from the *t*-th time measurement.

Our algorithm of vehicle detection is divided into 2 steps: 1) Preliminarily divide the averaged data into 2 categories: there is vehicle or no vehicle. 2) Filter the result of step 1 by Mathematical Morphology [8].

**Step 1: divide the averaged data into 2 categories**

Figure 4 shows the averaged data calculated from the Envelope data in Figure 3. The when the vehicle passes the radar is much larger than the when no vehicle passes by. Therefore, we simply use a threshold to distinguish whether there is a vehicle passing over the radar. In details, we have

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| --- | --- |
|  | （7） |

where refers to the dynamical threshold changed by *t*, indicates there is no vehicle at the *t*-th time measurement and indicates there is a vehicle passing over the radar at the *t*-th time measurement.



Fig. 4 Averaged data of vehicle passing over the radar

The baseline of the averaged data will change with the environmental factors such as weather and temperature on the road. Therefore, we update the threshold in real time with the baseline which is tracked dynamically by Exponential Weighted Average method. In particularly, we have

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| --- | --- |
| , | (8) |

where is the baseline. is the coefficient to adjust the threshold. The is updated by

|  |  |
| --- | --- |
|  | （9） |

where is the weighting factor to update the baseline when .

**Step 2: filtering by Mathematical Morphology**

The averaged data fluctuate greatly when vehicle passed over the radar, and sometimes it is below the threshold. In addition, complex environment on the road makes the Envelope data contain individual noise. Therefore, the result from the first step generally has some glitches, which appear as gully and spikes shown in Figure 5.



Fig. 5 Result of step 1

Our method to eliminate those glitches is based on two operations: corrosion and expansion, which are the basic operations of Mathematical Morphology [8].

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| --- | --- |
| , | (10) |

|  |  |
| --- | --- |
| , | (11) |

where is the structural parameter, is the length of . and are the results obtained by respectively corroding and expanding with the structural . In our scenario, we set

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| , | (12) |

Then the open and close operation are realized by combining the two operations of corrosion and expansion.

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| --- | --- |
| , | (15) |

|  |  |
| --- | --- |
| , | (16) |

where and refer to open and close operation respectively.

The close operation can fill the gully, and the open operation can remove the spikes. To calculate the start-end times, we first perform the close operation to fill the gully, then perform the open operation to remove the spikes, which is called close-open operation expressed as

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| --- | --- |
| , | (17) |

where is the filtered result of performing close-open operation on . The filtered result is shown in Figure 6.

Based on the filtered result, we can precisely obtain the start-end times of different vehicles.

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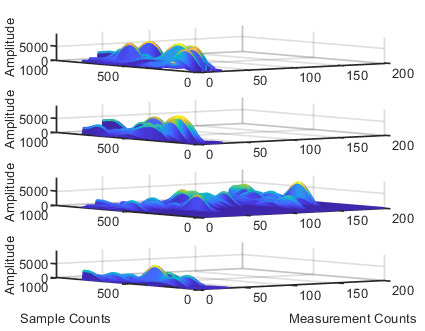
Fig. 6 Filtered result

C. VEHICLE CLASSIFICATION

After performing the vehicle detection, intercept the Envelope data by the start-end times and each intercepted data is called a **vehicle sample**. After obtaining the vehicle sample, the algorithm of vehicle classification is divided into 3 steps: 1) Resize; 2) Feature extract; 3) Random forest model [25] for vehicle classification.

**Step 1: Resize**

The obtained vehicle samples for car, SUV bus and middle-truck are shown in Figure 7, where the total numbers of measurement in different vehicle samples are different because of the different vehicle speeds and lengths. The Random forest model requires the size of input data consistent, therefore we resize different vehicle samples before feature extraction and classification.



**Car**

**SUV**

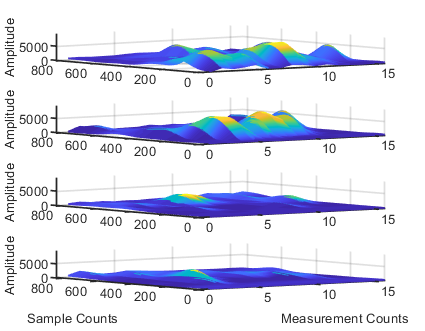
**Bus**

**Middle-truck**

Fig. 7 Vehicle samples

We call the total number of **samples** as the height of vehicle sample, and the total number of measurements as the width of vehicle sample. Because the height of each vehicle sample is fixed as *n*, therefore we just need to adjust the width of sample.

In particular, we perform Linear Interpolation [] on each row of the vehicle sample to fix the vehicle sample size to , where the value of is **determined as 16 by experiment in Section V.** Figure 8 shows the resized vehicle samples.



**Car**

**SUV**

**Bus**

**Middle-truck**

Fig. 8 Resized vehicle samples

**Step 2: Feature extract**

The algorithm of vehicle classification needs to run on embedded devices which is integrated with the PCR, and extracting the effective features helps to save the computing and storage resources of the embedded devices.

The Envelope data is collected during the fast moving of vehicle and the chassis of vehicle is uneven, therefore the Envelope data in the vehicle sample generally has multiple crests, shown in Figure 8, and the wave crest location in the Envelope data is related to the outline and height of the vehicle chassis. In our scheme, the features of vehicle chassis outline and vehicle chassis height are extracted for vehicle classification.

**Extraction of vehicle chassis outline**

One resized vehicle sample is expressed as

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| --- | --- |
| , | (17) |

where is the *j*-th Envelope data in the resized vehicle sample. In our scenario, we extract the wave crests from every Envelope data as the feature of vehicle chassis outline, which is expressed as

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| --- | --- |
| , | (17) |

where is the wave crests in the *j*-th Envelope data.

**Figure 9 shows the wave crest number distribution of one Envelope data in the resized vehicle sample set, where we can see only 3.4% of Envelope data has 4 or more wave crests. In order to save computing and storage resources, the number of crests extracted from the envelope data is fixed at 3. In particular,** we first sort the wave crests in descending order of the wave crest height, then only keep the first 3 sets of wave crests, and fill them with 0 if there are less than 3 sets. Therefore, the wave crests in one Envelope data are fixed as the 6-dimensional vector

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| --- | --- |
| , | (17) |

where refer to the *i*-th wave crest in the *j*-th Envelope data, is the index and is the -th sample amplitude in the *j*-th Envelope data.





Fig. 9 Distribution of the wave crests number of one Envelope data

Calculating the wave crest by the mathematical definition of maximum points will cause many missed selections and multiple selections, because the Envelope data collected in actual environment is discrete and the wave crest of the data can’t conform the mathematical definition of maximum points in many cases. For that, the calculation of the maximum points in one Envelope data is divided into 2 steps.

In the first step, we first perform mean filtering of the Envelope data to smooth Envelope data, then select some candidate points from all the sample points in the smoothed Envelope data. These candidate points meet a loose condition, which is that for the 9 points before the candidate point, the y of the candidate point is at least larger than one of them, and for the 9 points behind the candidate point, the y of the candidate point is also at least larger than one of them.

The significance of the first step is to avoid missing some wave crests by using a loose condition. And these candidate points should include all wave crests. Figure 10 shows the result of the first step.



Fig. 10 Candidate points selected from Envelope data

In the second step, we select the wave crests from these candidate points which are distributed over multiple regions shown in Figure 10. In particular we select the midpoints of each region formed by candidate points as the wave crests. Figure 11 shows the result of the second step. Our algorithm to extract the wave crests can effectively avoid the case of missed selection and multiple selection.

 Fig. 11 Wave crests selected from Envelope data

**Extraction of vehicle chassis height**

Although the height of vehicle chassis is an effective feature to distinguish different types of cars, it’s difficult to accurately compute the height of chassis because of the multiple crests in the Envelope data.

In our scheme, we firstly approximately calculate the height based on each piece of Envelope data in the resized vehicle sample

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| --- | --- |
|  | (6) |

where is the height calculated by the *j*-th Envelope data in the resized vehicle sample, is the sample count of the highest wave crest in the *j*-th Envelope data. Then average the heights

|  |  |
| --- | --- |
| , | (6) |

where is the feature of vehicle chassis height extracted from the vehicle sample.

**Step 3: Random forest model for vehicle classification**

After the feature extraction, we have obtained the features of vehicle chassis outline and height, which are expressed as a feature vector of size . In the third step, we categorize the feature vector into vehicle types based on the machine learning algorithm Random forest [26], which has the advantages of simple, fast and good generalization performance.

In our scenario, the Random forest model is trained by the feature vector set obtained from the whole vehicle samples collected in the actual environment. The model contains 100 decision trees, and each decision tree is trained in turn by a subset, **which is obtained by randomly selecting some samples and some features from the feature vector set.** After training, we obtain the Random forest model, which divides the road vehicle into 4 types: car, SUV, bus and middle-truck.

**V. EXPERIMENTS**

1. EXPERIMENTAL SETTING

Some parameters of PCR are important to the vehicle classification task and the configurations of these parameters are shown in Table 1.

The height of road vehicles chassis is generally between 15 cm and 40 cm. Therefore, we fix the parameters and to 10 cm and 40 cm. With this configuration and fixed range resolution, the dimension of Envelope data generated from one measurement is 826.

The PCR working in Envelope mode filters each Envelope data by an exponential smoothing filter, which reduce the response of Envelope data when vehicle passed over the radar. Therefore, we set the weight (average-fact) of the filter as 0 to forbidden it.

The road vehicle has different length and speed. If the measurement frequency of PCR is too low, it’s unable to detect the vehicle of moving too fast. Therefore, we set the measurement frequency as 25 HZ to ensure there are at least 5 measurements when a vehicle of length 4 m and speed 70 km/h passes over the radar.

Tab. 1 Experimental parameters

|  |  |  |
| --- | --- | --- |
| Parameter | Description | Value |
|  | the closest distance that PCR can detect | 0.1 |
|  | the length of the distance interval that PCR can detect | 0.4 |
|  | measurement frequency of PCR | 25 |
| average-fact | weight of the exponential smoothing filter | 0 |

In the experiment, the Envelope data has not changed when a vehicle passed by an adjacent lane. Therefore, PCR is completely immune to interference from vehicles in adjacent lanes. **In fact, even a motorcycles or tricycles passed by the PCR at a very close distance, the Envelope data still has no response**. Therefore, it’s difficult to distinguish motorcycles or tricycles. For that, our classification task doesn’t include distinguishing motorcycles or tricycles.

With the configurations of Table 1, We collect data on multiple roads in Dongguan, China. As shown in Figure 6, the detection node is deployed in the center of the lane, and the gateway node and the host computer are placed near the detection node and connected through a serial port, and the mobile phone is used to record the vehicle model. The gateway node receives the data of the detection node, and the host computer saves it locally. Finally, 1,281 vehicle data are obtained, including 315 cars, 324 SUVs, 342 buses, and 300 middle-trucks.

|  |
| --- |
|  |
| Fig. 12 Experimental scenario |

B. SELECTION OF VEHICLE DETECTION PARAMETERS

In this section, we configure the parameters , and in Formulas 8, 9 and 12 for the best performance of the vehicle detection algorithm, and the results are concluded in Table 2.

Tab. 2 Configuration of vehicle detection parameters

|  |  |  |
| --- | --- | --- |
| Parameter | Description | Value |
|  | the weight to update the baseline | 0.2 |
|  | the coefficient to adjust the threshold | 0.2 |
|  | the structural parameter length of close-open operation | 17 |

As shown in Figure 4, the averaged data changes acutely and sometimes fluctuates below the threshold especially when a bus passed over the radar. Therefore, there are some missed judgments based on the method shown in Formula 7. In order to avoid the baseline being incorrectly stretched by these data of missed judgments, we set as 0.2 to ensure the past values of baseline have the much larger weight 0.8 when updating the value of baseline.

The configurations of and are determined by the actual data. To confirm the best values of and , we set different and to calculate the accuracy of vehicle detection on the whole collected data, and the result is shown in Figure 13, where we conclude 0.2 and 17 are the best configurations. In addition, there is a correlation between and , which is that when  is bigger and the should be bigger too to get good performance in general. Because when is bigger, the threshold becomes bigger and there are less incorrect but more missed judgments, which causing wider gully in , then the should be bigger to fill the wider gully.

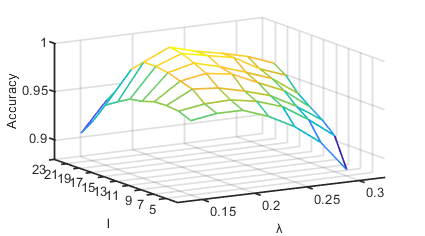


Fig. 13 Accuracy of vehicle detection with different l and

C. RESULTS OF VEHICLE CLASSIFICATION

1. COMPARISON ALGORITHM

The approach proposed in this article is called VCRF. Another method is implemented for comparison experiments:

VCSVM: the vehicle classification algorithm based on SVM []. What the difference between VCSVM and VCRF is that VCSVM use the feature vector **set** to fit a SVM model rather than a Random forest model in VCRF.

The 5-fold cross-validation method [20] is used to evaluate the two algorithms. The method is to randomly divide the feature vector set into 5 equal parts. Choose 4 of them for training, and choose the remaining 1 for testing. Each time a different aliquot is selected for training and testing, and it is executed 5 times in total. Accumulate each test result, and finally get the test result of the algorithm on the entire feature vector set.

1. PERFORMANCE INDICATORS

For a type of vehicles, we define the following concepts to calculate the performance indicators.

**True Positive TP**: the number of samples belonging to this type and classified as this type.

**False Negative FN**: the number of samples belonging to other type and classified as this type.

**False Positive FP**: the number of samples belonging to this type and classified as other type.

**True Negative TN**: the number of samples belonging to other type and classified as other type.

Then the performance indicators accuracy, precision and recall can be calculated by

|  |  |
| --- | --- |
|  | (10) |

3) SELECTION OF INTERPOLATIONS AND RESIZED VEHICLE SAMPLE WIDTH

The interpolation method and the resized vehicle sample width will affect the performance of vehicle classification approach. Figure 8 shows the average accuracy of vehicle classification with between 2 and 100, and interpolations including Nearest Neighbor Interpolation, Linear Interpolation and Cubic Interpolation [].

When m is less than 8, the accuracy of the three interpolation methods is lower, but the improvement is faster. When m is between 8 and 22, Cubic Interpolation and Linear Interpolation have better accuracy than Nearest Neighbor Interpolation. However, when m is greater than 22, the accuracy of Cubic Interpolation is reduced, while the accuracy of Linear interpolation is relatively stable, and is always greater than the accuracy of Nearest Neighbor Interpolation. Therefore, we choose Linear Interpolation to resize the vehicle sample. In addition, the larger m is, the more storage and computing resources are consumed, besides when m is greater than 16, the accuracy of linear interpolation changes slowly, therefore m is determined to be 16.



Fig. 14 Accuracy of vehicle classification with different m and interpolation methods

4) ACCURACY AND SPEED RESULTS

The detail classification results with the two algorithms are summarized in Table 3 and 4, respectively.

It can be seen from the Table 3 that car and SUV have lower accuracy, precision and recall compared with bus and middle-truck, which indicates that there are more incorrectly judgments between car and SUV, that’s because the chassis of car and SUV is more similar and more difficult to distinguish.

The bus has the highest accuracy, 99.30%. This is because the chassis of the bus is very different from other types of vehicles, furthermore the chassis of different buses are also very similar because the bus model in a city is relatively fixed.

It can be seen from the Table 4 that the comparison algorithm VCSVM has a bit lower accuracy than VCRF.

Tab. 3 Classification results with RF

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Car | SUV | Bus | Middle-Truck |
| Accuracy | 89.93% | 88.99% | 99.30% | 97.89% |
| Precision | 74.60% | 88.61% | 99.12% | 91.74% |
| Recall | 89.52% | 64.81% | 98.25% | 100% |

Tab. 4 Classification results with SVM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | Car | SUV | Bus | Middle-Truck |
| Accuracy | 88.52% | 87.82% | 98.59% | 96.96% |
| Precision | 73.73% | 81.82% | 98.21% | 89.91% |
| Recall | 82.86% | 66.67% | 96.49% | 98.00% |

Figure 14 shows the time required for the algorithms VCRF and VCSVM to classify different numbers of vehicle samples, where VCRF requires more time. Table 4 lists the speeds of the two algorithms to classify a single vehicle sample. The speed of VCRF can meet real-time requirements, although it is slightly lower than VCSVM.



Fig. 14 Classification efficiency comparison

Tab. 4 Classification speed

|  |  |
| --- | --- |
| Algorithm | Time required to classify one vehicle sample |
| VCRF | 51.6ms |
| VCSVM | 46.5ms |

**VI. CONCLUSION**

The road vehicle classification is the basis of ITS. In this paper, we have proposed a road vehicle classification approach based on the new radar sensor, PCR. In the approach, we first intercept the vehicle data effectively by a dynamical threshold and open-close operation, which can effectively deal with the individual noise in actual environment. **Then extract the features of vehicle chassis outline and height from the intercepted vehicle data, which is used as the input of a Random Forest model.** The model is trained by the features set calculated by all the **intercepted vehicle** data, and categorizes the vehicle into 4 types: car, SUV, bus and middle-truck. The experimental result has shown the averaging accuracy of our approach is 94.02%.

In the future works, we will realize the traffic information collection system based on the radar PCR, where the radar node will embed the vehicle classification approach from this paper and parking detection approach from [27].

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