**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, which is deployed in the middle of road lane. We first intercept the vehicle data when a vehicle passes over the radar. Then extract the maximum points feature 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%.

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

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 these 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 square millimeters. And it is not interfered by magnetic field and light.

When road vehicle passed 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, in this paper, 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 passed over the PCR. Then we convert each intercepted vehicle data collected in the real road environment into a feature vector of maximum points. Then we use all the feature vectors to fit a Random forest model. The model outputs the type of vehicle according the input data feature vector which is extracted by intercepted vehicle data. Our main contributions 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 feature of vehicle data. And use the Random forest model to divide the vehicle type into four categories.
2. . Collect large of road vehicle data of PCR in the real road environment. Based on the data, we evaluated three machine learning algorithms SVM[], Random forest[] and CNN[] and concluded that Random forest was the best fit for our problem.

**0 RELATED WORK**

There have been many research 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 focus 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 research 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 road 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.

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**1 PROBLEM DESCRIPTION**

Deploy PCR in the middle of the roadway and assume the vehicle is driving in a lane. When road vehicle passed above the PCR, the data generated by PCR can reflect the height and profile characteristics of the vehicle chassis for vehicle classification. **The model A111 of radar PCR is used in our scenario. A111 provides Envelope mode which supports high precision ranging to reflect the** **height and** **profile characteristics of the vehicle chassis.**

The **A111** operating 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 one measurement at the t-th time is shown as

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| , | (1) |

where is a set of *n* real valued samples, *t* refers to that the data are collected at the t-th time, *i* refers to sample index and **refers to an amplitude reflecting** the received energy from a specific distance which is expressed as

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

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where is the length of the interval that the radar can detect. Eq.3 indicate the number of samples *n* is determined by the parameter .

For example, when there are two objects near the radar as shown in Fig.1(a), we get the Envelope data generated from one measurement with of 10 cm and of 40 cm shown in Fig.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 20cm and 30cm respectively according to Eq.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 a vehicle passed over the radar. In particular, 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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where the input data are the Envelope data collected between *(t-s)*-th time and *t*-th time measurements.The output data are the measurement times of the *i*-th vehicle driving towards and away from the radar between the *(t-s)*-th and *t*-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 .

1. **ALGORITHM DESIGN**

A. OVERVIEW

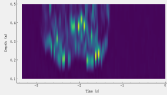
The overview of the approach we proposed is shown in Fig.2. The original data are collected from the radar PCR, which is deployed in the middle of road lane. Then the module of vehicle detection effectively intercepts the data when vehicle passed over the radar. Then the intercepted vehicle data are normalized and adjusted to the fixed size 70\*827. Then we extract the feature from the processed vehicle data. With the input data of feature, the trained Random Forest model output the result of vehicle type.

Vehicle

Detection



original data



Feature extract

Feature

Random Forest model

Vehicle type

Normalization and Resize

Intercepted vehicle data

Fig.2 Approach overview

B. VEHICLE DETECTION

Fig.3 shows the Envelope data of SUV and bus passing over the radar. 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 Fig.3.



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, shown 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 passing over the radar, according to a dynamic threshold. 2) Further calculate the start-end times through open-close operation of morphology.

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

Fig.4 shows the averaged data calculated from the Envelope data in Fig.3. The data when vehicles pass over the radar is much larger than the data when no vehicles pass 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 data when there is no vehicle will changes 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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where is the baseline. is the coefficient to adjust the threshold. The is updated by

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|  | （9） |

where is the weighting factor to update the baseline when S(t)=1.

**Step 2: calculation of the start-end times**

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 Fig.5. Those glitches are not conducive to the calculation of start-end times. To this end, we need to eliminate those glitches before calculate start-end times.



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[].

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

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

Therefore Eq.10 and 11 is simplified to Eq.13 and 14.

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| , | (9) |

|  |  |
| --- | --- |
| , | (9) |

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

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

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

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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| , | (12) |

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



Fig.6 Filtered result

After obtaining the filtered result, we calculate the difference sequence of CO\_S(t)

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| , | (12) |

Finally, record the subscripts equal to 1 corresponded to the start time and -1 corresponded to the end time in the difference sequence in turn, and use these subscripts as the start-end times of different vehicles.

We can see the parameter , and will affect the performance of the vehicle detection algorithm. There are some missed judgments based on the dynamical threshold method shown in Eq.7, because the changes acutely and sometimes fluctuates below the threshold especially when a bus passed over the radar. Therefore in order to avoid the baseline being incorrectly stretched by averaging these data of missed judgments, we set w 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 Envelope data we collected with the configuration of PCR in Tab.x, and the result is shown in Fig.x. where we conclude 0.3 and 25 are the best configurations.

In addition, we discovered when is bigger and the should be bigger too to get good performance in the experiment. The threshold becomes bigger when is bigger, then there are less incorrect but more missed judgments, which causing more and wider gully in S(t). Therefore the should be bigger to fill the wider gully.

C. VEHICLE CLASSIFICATION

The Envelope data when the vehicle passes over the radar are intercepted by the start-end times for vehicle classification. And the algorithm of vehicle classification is divided into 3 parts: 1) normalization and resize 2) Feature extract; 3) Random forest model[] for vehicle classification.

1. normalization and resize

The original value of Envelope data changes

The speed and length of road vehicles are different, which makes the length of vehicle data collected by radar different. We need to make the length of different vehicle data samples consistent for subsequent classification processing. To keep the information of vehicle data as far as possible, we use bicubic interpolation[] method to adjust each vehicle data sample size to 70\*827, **where 70 is the median of all sample widths.**

2 Feature extract

Our vehicle classification algorithm is running in the MCU, which is integrated with the PCR sensor. **To save the computing and storage resources of MCU, we need to extract features of vehicle data sample.**

The height of vehicle chassis is an effective feature to distinguish different types of cars. However our data is collected during the fast moving of vehicle and the chassis of vehicle is uneven. Therefore the Envelope data generated from one measurement generally has multiple crests and it’s difficult to accurately compute the height of chassis.

Fig.7 shows the Envelope data when radar is under SUV. According to the principle of Envelope mode, there is a reflector at the position of the wave crest. Because the chassis of vehicles is uneven. The data has multiple different crests. In other word, the wave crest location of Envelope data is related to the height and profile characteristics of the vehicle chassis.



We extract the maximum points of each Envelope data ENV(t) generated from the t-th measurement as the feature for vehicle classification. In particular, the algorithm of feature extract is divided into 2 steps.

In the first step, we select some candidate points meeting the following loose rule

Envit>Env(i+1)t or Envit>Env(i+2)t

These candidate points should include all maximum points. And the goal of the first step is to avoid missing some maximum points of data ENV(t) by using a loose rule. Fig.8(a) shows the result of first step.

In the second step, we select the maximum points from these candidate points which are distributed over multiple regions shown in Fig.8(a). In particular we select the midpoints of the each region formed by candidate points as the maximum points. Fig.8(b) shows the result of second step. Our algorithm to extract the maximum points can effectively avoid the case of missed selection and multiple selection.



We keep the first three sets of maximum points, and fill them with 0 if there are less than three points. Therefore, each piece of Envelope data is converted into a 6-dimensional vector and the feature size of each vehicle data sample is 70\*6.

1. Random forest model for vehicle classification

In the first step of vehicle classification, we convert vehicle data sample into a feature matrix of size 70\*6. The feature matrix reduces the size of vehicle data sample and can effectively preserves the information of vehicle data sample. Then we categorize the feature matrix into vehicle types based on the machine learning algorithm Random forest.

We evaluated three machine learning algorithms SVM[], Random forest[] and CNN[] and concluded that Random forest was the best fit for our problem. CNN can solve the quite multi-class classification problem to the data of high dimensions and each dimension of data doesn’t need to have specific meaning. The cost of these advantages is that CNN need quite a lot of training data and expensive computing costs. In our problem, we just plan to categorize the feature matrix into 5 types and the feature matrix has relatively small dimensions, which have relatively fixed meaning. Therefore CNN is redundant for our problem. Random forest is a combination of Decision trees and Ensemble learning. The outstanding advantages are simple and fast contributed by the Decision trees, and good generalization performance contributed by Ensemble learning. The performance of SVM and Random forest in our problem is close. But Random forest has a bit higher accuracy and shorter training time than SVM.

In particular, our Random forest model contain 100 decision trees. Each decision tree is fitted in turn by randomly selected **10** dimensions data of feature matrix. The feature matrix are sampled from the whole data set based on the Ensemble learning algorithm Bagging[]. As a result, each decision tree contains 10 decision. With these specific settings and the feature matrix set calculated from the collected vehicle data set, we obtain the Random forest model categorizing the road vehicle into 4 types：car, SUV, bus and truck.

**3 EXPERIMENTS**

Some parameters of PCR are important to the vehicle classification task and the configurations of these parameters are shown in Tab.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 a exponential smoothing filter, which reduce the response of Envelope data when vehicle passed over the radar. Therefore we set the weight of the filter which is the parameter average fact 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 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.

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| --- | --- | --- |
| 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.

1. EXPERIMENTAL SETTING
2. EXPERIMENTAL SCENARIO

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 detection node samples at a frequency of 25HZ. The gateway node receives the data of the detection node, and the host computer saves it locally. Finally, 3,000 vehicle data are obtained, including 1,220 cars, 1,035 SUVs, 800 buses, and 330 trucks.

在东莞的多条道路上采集数据。如图6所示，检测节点部署在车道中央，网关节点和上位机放置在检测节点附近并通过串口相连，使用手机记录车型。检测节点以25HZ的频率采样；网关节点接收检测节点的数据，上位机将其保存在本地。最后得到3000条车辆数据，包括1220辆小汽车，1035辆SUV，800辆公交车，330辆货车。



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1. COMPARISON ALGORITHM

The algorithm proposed in this article is called VC\_PCR\_RF. In order to evaluate Random forest was the better fit for our problem than other machine learning algorithms, two other methods are implemented for comparison experiments:

VC\_PCR\_SVM algorithm: the vehicle classification algorithm of PCR based on SVM. What the difference between VC\_PCR\_SVM and VC\_PCR\_RF is that VC\_PCR\_SVM use the feature matrix set to fit a SVM model rather than a Random forest model in VC\_PCR\_RF.

VC\_PCR\_CNN algorithm: the vehicle classification algorithm of PCR based on CNN. We convert each feature matrix into a square with the size 24\*24. then the square feature matrix set are used to fit a CNN model. The configuration of the model is shown in Tab.x.

|  |  |
| --- | --- |
| CNN\_LATER | parameter |
| Running ave.fact | 0 |
|  | 0.1 |
|  | 0.4 |
|  | 25 |

The 5-fold cross-validation method [20] is used to evaluate the three algorithms. The method is to randomly divide the feature matrix 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 matrix set.

1. PERFORMANCE INDICATORS

The precision and recall are used as the performance indicators to evaluate the proposed vehicle classification algorithm. 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 precision and sensitivity can be calculated by

Accuracy=(TP+TN)/(TP+TN+FP+FN)

precision =TP/(TP+FP)

recall=TP/(TP+FN)

1. EXPERIMENTAL RESULTS

The detail experimental results with the three algorithms are summarized in Tab.7, 8 and 9. It can be seen from the table that the performance of VC\_PCR\_RF

is better than other two algorithms and the algorithm VC\_PCR\_CNN perform worst, which is because we didn’t have quite lager vehicle data to fit the CNN model ,causing the model over fitting.

It can be seen from the table that the algorithm VC\_PCR\_CNN perform worst, which is because we didn’t have quite lager vehicle data to fit the CNN model ,causing the model over fitting. In fact CNN is redundant for our problem.CNN can solve the quite multi-class classification problem to the data of high dimensions and each dimension of data doesn’t need to have specific meaning. The cost of these advantages is that CNN need quite a lot of training data and expensive computing costs. In our problem, we just plan to categorize the feature matrix into 5 types and the feature matrix has relatively small dimensions, which have relatively fixed meaning. Therefore CNN is redundant for our problem.

VC\_PCR\_CNN

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | CAR | SUV | BUS | TRUCK |
| Accuracy | 70% | 71% | 76% | 75% |
| precision | 90% |  |  |  |
| recall |  |  |  |  |

VC\_PCR\_SVM

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | CAR | SUV | BUS | TRUCK |
| Accuracy | 90% | 88% | 94% | 92% |
| precision |  |  |  |  |
| recall |  |  |  |  |

VC\_PCR\_RF

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | CAR | SUV | BUS | TRUCK |
| Accuracy | 91% | 92% | 96% | 94% |
| precision |  |  |  |  |
| recall |  |  |  |  |

In the experiment, the performance of SVM and Random forest in our problem is close. But Random forest has a bit higher accuracy than SVM.

The accuracy of car and SUV is relatively low and there are more incorrectly judgments between car and SUV. That’s because the chassis of car and SUV is similar. The bus has the highest accuracy 96%, maybe because the chassis feature of bus is much different from other type vehicles, and the chassis feature of different buses is more similar because the bus model of one city is relatively fixed.

The training time required for three algorithm is shown in Fig.x. we can see CNN need the longest time and the time of RF and SVM is close but RF has the shortest time.

The time required for the algorithm VC\_PCR\_RF to detect and classify different numbers of vehicle samples on MATLAB is shown in Figure 11,and Table 6 lists the detection and classification speeds. The VC\_PCR\_RF

**3.3方法运行效率分析**

三种算法检测不同数量的样本所需的时间如图11所示。MTV用时虽然明显大于ER和MTV-0，但三者的速度都已满足实时性的要求。MTV与MTV-0的主要区别是MTV需要计算扩展特征，而MTV用时明显大于MTV-0，这说明MTV的时间开销主要花在扩展特征的计算上。表6列出了三种算法的检测速度。

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图11算法检测效率对比图

Fig. 11 Detection efficiency comparison

表6 检测速度

Table6 Detection speed

|  |  |
| --- | --- |
| 检测算法 | 检测单个样本所需的时间 |
| ER | 0.002ms |
| MTV-0 | 0.005ms |
| MTV | 0.040ms |

图12是MTV训练不同数量样本所需的时间，其中各类别的样本比例相同，粒子个数设为100，迭代次数设为50。在上述参数设定下，训练时间与样本数成线性增长，这与本文复杂度分析相符。虽然相比ER算法，MTV需要较耗时的训练过程，但在训练完毕后，MTV的检测速度可以满足实时性要求。



图12 MTV训练不同数量样本的时间

Fig. 12 MTV training time for different numbers of samples

**4 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 design a robust method (the main principle is to choose twice) to extract the maximum points from the intercepted vehicle data, which is used as input of a Random Forest model. The model which has been trained by the features generated by all the vehicle data collected in the actual road environment, categorizes the vehicle into 4 types. The experimental result has shown the averaging accuracy of our approach is 94%.

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 [20].

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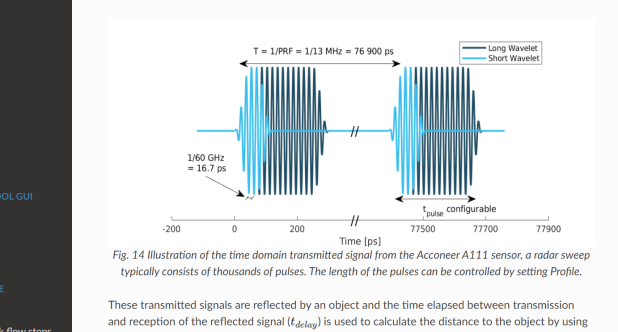
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PCR

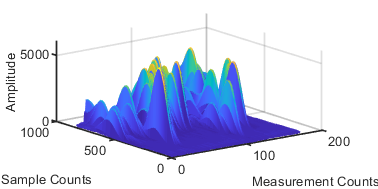
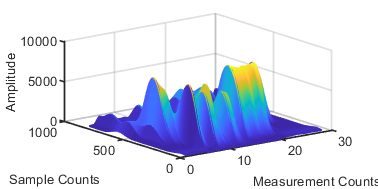


Sensor

30cm

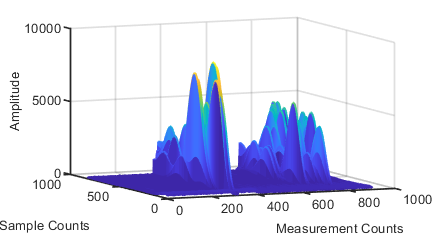
20cm





**SUV**

**bus**



**SUV**

**bus**



Sample counts

measurement counts

because VCRF uses 100 decision tree models for classification, which requires more time than VCSVM using a single SVM model.





Radar2



Radar1