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Proposal of On-road Vehicle Detection Method Using WiFi Signal

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Abstract: The vehicle detection method on the road plays a vital role in the urban traffic route planning and the development of the city's transportation network. Nowadays, the main methods of vehicle detection on the road have excellent detection accuracy under certain conditions, each method has certain limitations.In recent years, WiFi signals have been found to be used not only for the transmission of data, but also for the detection of moving targets, and because of the convenience of WiFi signals, the advantages of general use and low consumption, they are often applied to various Indoor moving target detection and positioning system. In this paper, a method of using CSI phase information to classify the initial detection of vehicles on the road is proposed.

Keywords: Channel State Information, Vehicle Detection, Machine learning, Principal Components Analysis Noise Processing

1. Introduction

The Intelligent Transportation System (ITS) is the development direction of the future transportation system. Establish a real-time, accurate and efficient integrated transportation management system that works in a wide range and in all directions. ITS can effectively utilize existing transportation facilities, ensure traffic safety, and improve transportation efficiency. In ITS system, the vehicle is free to drive on the road by its own intelligence, and the road adjusts the traffic flow to the best state by its own intelligence. With this system, the management personnel will have a clear understanding of the road and the vehicle's whereabouts.

The aim of our research is to develop an WiFI vehicle detection system which has features as follows:

(1) Using WiFi signals to detect changes in surrounding moving targets in a complex outdoor environment
(2) Use machine learning to distinguish vehicles and other moving targets (such as pedestrians and bicycles) on the road based on the signals of the detected activity targets.
(3) Further analysis of the type of vehicle acquired for the detected vehicle on the road

2. Realted Works

Recent advances in wireless technology and the widespread deployment of wireless infrastructure has garnered increasing research interest in the use of ubiquitous wireless signals to detect moving targets for an unequipped manner [1]. In principle, human-detection based on wi-fi devices works by extracting and analyzing radio shadows and reflections caused by human motion of pre-deployed wireless monitors, while target users do not carry wireless devices [2]. This device-free human detection mode is particularly advantageous in terms of asset security, emergency response, and privacy protection.

Wireless passive human detection identifies people by analyzing the effects of human motion on received signals, while intruders do not carry any wireless devices [3]. The effects of such motion typically result in dramatic changes in certain received signal characteristics, with the Received Signal Strength Indicator (RSSI) being the most common signal feature due to its ease of access [4]. Recent advances in wireless technology have also generated interest in using PHY layer channel state information (CSI) on commercial WiFi to obtain finer-grained human motion detection [5].

So far, the human detection methods of using WiFi signals are mainly classified into the presence or absence of humans, the detection of human movement types, and the indoor positioning and tracking. In the literature [6] Chang et al. proposed a combination of computer vision. The method of subtracting the background noise during the detection. The WiFi method has a high detection accuracy when performing macroscopic human detection, but in the literature [7] Zhang et al. focused on the subtle activities of human beings, and realized the detection of small changes in the chest during human breathing. The human centimeter level of motion is detected. When using WiFi signals for indoor human detection, the target is often a person. In [8], Domenico et

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al. foucused on the basis of realizing indoor human detection, counted a number of indoor human targets and made the target random. It still maintains a high count accuracy when moving.

In the literature [9], Kotaru et al. realized the high-precision identification of the arrival angle of the signal through the CSI data collected by the multiple sub-channels, and then the indoor target is located through the RSSI signal collected by the AP. In the literature [10], Escudero et al. proposed a CSI-based ranging method to achieve indoor positioning. In the literature [11], Kotaru et al. improved the tracking accuracy when using VR equipment by tracking the signals of VR equipment. In the literature [12], Wu et al. used the native bayes classifier to improve the accuracy of the CSI-based indoor positioning method by the confidence level method. In the literature [13], Wang et al. realized the construction of an indoor finger print eager for CSI signals through deep learning. And by comparing with other indoor positioning methods, it shows higher positioning accuracy.

In the vehicle detection method on the road proposed in this experiment, we mainly face the following three problems.

(1) In the selection of data, the CSI phase information is not as stable as the CSI phase. When facing the outdoor environment, the accuracy and stability are not as good as the CSI phase information. However, the phase information has an unavoidable offset due to the design of the hardware itself, and the useful data of the CSI phase information cannot be extracted without removing the offset.
(2) In the past, most of the previous experiments using WiFi signals were performed indoors. When the experimental scene became outdoor, wide scenes and intense environmental changes would be inevitable. Environmental noise.
(3) The previous research goals are mostly one or plural humans, but the CSI data we collected in this method contains a variety of information such as pedestrians, vehicles and motorcycles.

In the face of the above three main problems, we have proposed the following solutions.

(1) We selected the phase information of CSI to perform detection. For the offset of CSI phase information, we have reduced the influence of offset by increasing the number of antennas. In this paper, we use mathematical methods to reduce the influence of offset on CSI phase information.
(2) In the face of fiercely changing ambient noise, we found that CSI phase and noise are not related to each other, so I propose to use Principal Component Analysis to cut off environmental noise.
(3) Since the main purpose of this article is to detect the vehicle, we use machine learning to distinguish between humans and vehicles.

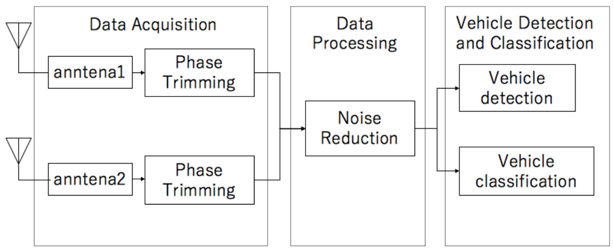

Figure 1 Overview of on-road vehicle detection method

3. Approch

3.1 Overview

Fig. 1 shows the flow of the WiFi based on-road vehicle detection method in this paper. The steps of using WiFi to detect on-road vehicle tactics are roughly divided into the following steps.

Data Acquisition

In this paper, when using the CSI method to detect the vehicle, the phase information of CSI is mainly used as the main data for detection. Compared with the amplitude information of CSI, the phase of CSI is more stable, but the phase of the CSI obtained by the usual means often has an offset. As a result, the measurement cannot be performed normally. The commonly used offset removal method is to reduce the influence of the offset by increasing or decreasing the number of antennas. In this paper, we refer to the offset clipping method in literature [14], and reduce the influence of offset by mathematical methods.

Data Processing

When the vehicle is detected outdoors, the environmental noise has a great influence on the detection result because the outdoor environment changes drastically. In this paper, the principal component analysis (PCA) method is adopted. Because the environmental noise is not related to the main part of the data, only the most relevant part of the data is selected as the main data to be extracted for detection.

Vehicle Detection

Because the data processing CSI phase information will record all the object movement information between RX-TX, in order to distinguish the moving objects such as vehicles and pedestrians on the road, we use SVM's two-class mechanical learning method to make the road. The vehicles and pedestrians are separated. Because the classification accuracy of SVM's mechanical learning methods is only affected by the key vectors, the high-test results can be maintained in the data of a few vehicles in the experiments in this paper.

Vehicle classification

Finally, in order to distinguish different vehicle types, the vehicle information distinguished from the previous step is further subjected to mechanical learning, and the type of the vehicle is identified using the tree multi-classification method.

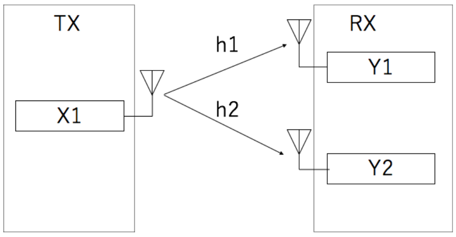

Figure 2 RX2-TX1 system

3.2 Introduction of CSI

In a WiFi standard such as IEEE 802.11a/g/n, the transmitter transmits a complex (cycle number) of different and mutually orthogonal sine waves, each of which is referred to as a subcarrier. CSI (Channel State Information) records information on the amplitude and phase of each subcarrier. At the same time, CSI can not only represent the phy information of each subcarrier, but also describe the weakening factor of the signal on each transmission path, that is, the value of each element in the channel gain matrix H (sometimes called channel matrix, channel fading matrix). Such as signal scattering (Scattering), fading (multipath fading or shadowing fading), distance decay (power decay of distance) and other information [14]. CSI can adapt the communication system to current channel conditions and provide high reliability and high rate communication in multi-antenna systems.

The change in the transmission path of the radio wave recorded by CSI. That is, before the signal reaches the receiving end, the signal is reflected on the surface of various objects in the radio wave propagation environment, and the physical phenomenon such as absorption causes the CSI amplitude and phase to change. The recognition of moving targets in the radio wave transmission environment can be realized by interpreting these changes.

Consider a RX2-TX1 system as shown in Fig. 1. The CSI of this system, the channel gain matrix H can be expressed as

$$\begin{bmatrix} Y1 \\ Y2 \end{bmatrix} = \begin{bmatrix} h1 \\ h2 \end{bmatrix} \mathrm{X} + \mathrm{Noise} \tag{1}$$

$$\mathrm{H} = \begin{bmatrix} h1 \\ h2 \end{bmatrix} \tag{2}$$

$$\mathrm{hi} = \{\mathrm{csi_1}, \mathrm{csi_2}, \mathrm{csi_3} ... \mathrm{csi_{30}}\} \tag{3}$$

where X is the signal transmitted by the transmitter, Y1 and Y2 are the signals obtained by the two antennas of the receiver, h1 and h2 represents the transmission path of the four radio waves. Debilitating factor. It contains 2 radio wave transmission paths, and we can get 2*30 groups of CSI data. The CSI of one of the subcarriers i can be expressed as

$$\mathrm{csi_i} = \mid \mathrm{csi_i} \mid \exp\{\mathrm{j}\angle \mathrm{csi_i}\} \tag{4}$$

Where $\mid csi_i \mid$ is the amplitude of CSI, $j\angle csi_i$ represents the phase of CSI. By obtaining the variation of the weakening factor and time of each subcarrier of each radio wave transmission path, the variation on each radio wave transmission path can be analyzed, thereby detecting the environmental change in the TX-RX.

3.3 Phase Triming

In theory, the phase of the path can be accurately measured in a system where the transmitter and receiver are perfectly synchronized, for example in an RFID system [15]. However, the CSI phase measurement error caused by imperfect equipment and environmental changes has not been widely used in mobile target detection based on WiFi signals. The main causes of the error are the following two.

The first one is carrier frequency offset (CFO) generated by the down-converter for receiver signal, because the central frequencies between the receiver and the transmitter cannot be perfectly synchronized [14]. The other one is the sampling frequency offset (SFO) generated by the ADC, because of nonsynchronized clocks [14]. Moreover, for SFO, the measured phase errors are different for different subcarriers [14].

Reference [16] provides a mathematical technique to eliminate the offset of CSI. The phase of CSI can be expressed as

$$\angle \mathrm{C\hat{S}I_i} = \angle \mathrm{CSI_i} + 2\pi \frac{\mathrm{mi}}{\mathrm{N}} \triangle \mathrm{t} + \beta + \mathrm{Z} \tag{5}$$

Where $\angle \hat{C}SI_i$ is the true phase, t is the time lag caused by SFO, m_i is the subcarrier index of the ith subcarrier, N is the fast Fourier transform (FFT) size, and β is the unknown phase offset caused by the CFO. Z is the measurement noise. We can obtain subcarrier index mi and FFT size N of i 1 to 30 from the IEEE 802.11n specification [17]. In fact, it is impossible to obtain true phase information due to the unknown t and β. However, considering the phase of the entire frequency band, we can perform a linear transformation on the original phase to remove the t and β terms [16].

$$\mathrm{k} = \frac{\angle \mathrm{C\hat{S}I_{30}} - \angle \mathrm{C\hat{S}I_1}}{\mathrm{m_{30}} - \mathrm{m1}} \tag{6}$$

$$\mathrm{b} = \frac{1}{30} \sum_{\mathrm{i}}^{30} \angle \mathrm{C\hat{S}I_i} \tag{7}$$

$$\angle \widetilde{\mathrm{CSI_i}} = \angle \mathrm{C\hat{S}I_i} - \mathrm{km_i} - \mathrm{b} \tag{8}$$

Although the above formula can represent the calibrated CSI phase information, we first need to convert the measured phase to the true value. The algorithm is shown in the Figure. By judging whether the measured phase change between adjacent subcarriers is greater than a given threshold, the measured phase is compensated for multiple 2π.

3.4 PCA Noise Reduction

Because of CSI streams of different subcarriers are linear combinations of the same set of time-varying signals and thus they are highly correlated [18]. Our denoising process takes advantage of this fact. Since the correlation between the noise and the change caused by the change of the main target is not high, the noise reduction of the CSI phase data is completed by finding the most relevant component on the 30 subcarriers and removing the remaining low correlation with the principal component.

In selecting the denoising method, in order to select the most relevant part of the data and remove the uncorrelated noise components, we have chosen principal component analysis (PCA). PCA has been called one of the most valuable results from applied linear algebra, it is used abundantly in all forms of analysis from neuroscience to computer graphics, because it is a simple, nonparametric method of extracting relevant information from confusing data sets, With minimal additional effort PCA provides a roadmap for how to reduce a complex data set to a lower dimension to reveal the sometimes hidden, simplified dynamics that often underlie it.

3.5 Vehicle Detection by Using SVM

The SVM (support vector machine) approach is a widely used method of learning in the classification of statistical classification and regression analysis. The SVM method is different from the existing statistical methods, basically avoiding the problem of probability theory and does not include the law of large numbers. In essence, the SVM approach avoids the process of deductive regression of traditional algorithms, and directly establishes efficient inferences from training data sets to prediction result sets, which greatly reduces the general classification problems and regression problems. And the SVM classification results are only affected by the Support vector, so SVM can not only help us to grasp the key data well, but also avoid the length of the training data set. With a small amount of data, it still maintains high detection results. And the robustness of the SVM is very high, and it will not have an excessive impact on the learning result when increasing or decreasing non-critical data.

After obtaining the denoised csi phase data, we apply the SVM classification method to classify the vehicle's CSI phase data with other data. The SVM classification method goes through the following steps:

(1) the presentation of the feature vector.
(2) the training classifier.
(3) the application classifier to classify the vehicle and the environment.

When selecting the feature vectors, we find that the CSI phase we collected during the passage of the vehicle experienced a very large peak like in **Fig. 3**. Therefore, when selecting the feature vector, we calculate the variance of the CSI phase every 1 second as the feature vector.

3.6 Vehicle Classification by Using Decision Tree

Since the SVM classification method is a two-category approach, we often have to classify vehicles when classifying vehicles, so we have to use another classification method to further classify vehicles. Although the algorithmic improvement of the SVM classification method can achieve the purpose of multi-classification, the accuracy of the classification can not achieve the expected goal, so we chose the decision tree method to classify the vehicle.

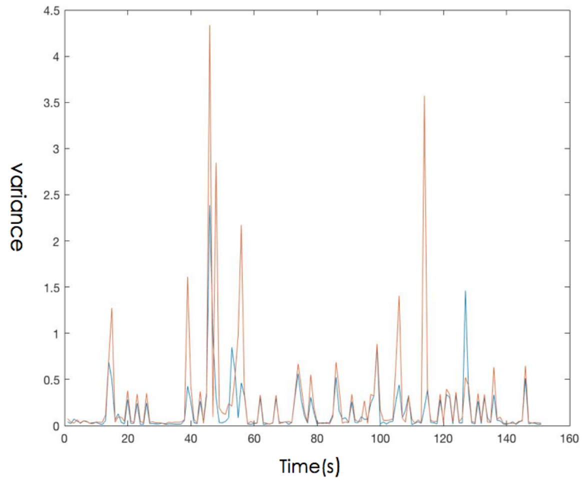

Figure 3 Variance of CSI phase

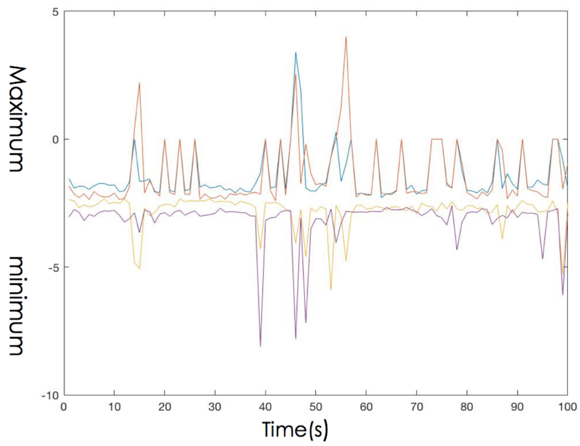

Figure 4 Maximun and minimum of CSI phase

The decision tree is a tree structure (which can be a binary tree or a non-binary tree). Each of its non-leaf nodes represents a test on a feature attribute, each branch representing the output of the feature attribute over a range of values, and each leaf node storing a category. The decision process using the decision tree is to start from the root node, test the corresponding feature attributes in the item to be classified, and select the output branch according to its value until the leaf node is reached, and the category stored by the leaf node is used as the decision result.

When selecting the feature vector, we first use the unsupervised learning method of kmeans to analyze the vehicle data. As shown in **Fig. 4** when selecting the maximum and minimum values of the CSI phase between each second, we find that it is further classified according to the size of the vehicle. Therefore, when selecting the feature vector, we calculate the maximum and minimum values of the csi phase every 1 second as the feature vector.

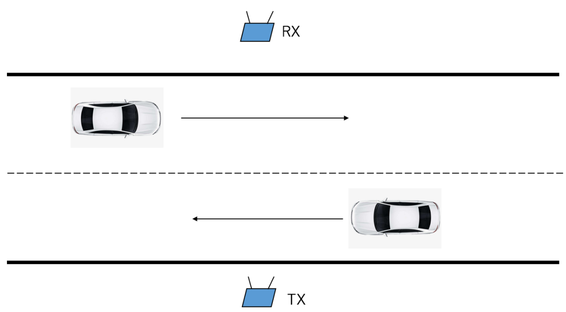

Figure 5 Top view of test scenarios of outdoor vehicle detection

4. Evaluation

4.1 Test Scenarios and Infrastructure

In the outdoor vehicle detection test, we chose a typical urban lane environment. The environment consists of two rows of opposite lanes in the middle and two rows of pavements on the outside. Motor vehicles and motorcycles travel on the driveway, and pedestrians and bicycles travel on the sidewalk. Common facilities such as street trees and signal lights are on both sides of the road. We place the equipment as the transmitter and the receiver on the sidewalks on both sides close to the motorway, and the connection between the transmitter and the receiver is perpendicular to the motorway. The specific scene diagram is shown in **Fig. 5**. We use two dynabook UX/28LWHEM laptops equipped with IEEE802.11a/b/g/n standard wireless network cards as transmitters and receivers for experiments. The transmitter has one antenna and the receiver has two antennas.

4.2 Collecting Data

We placed the two laptops, as the transmitter and the receiver, at the ends of the automatic car. We set the signal to send the pin with a transmission interval of 0.05 seconds. Each time 12000 packets are transmitted, two sets of two TX-RX chains are collected and contain 12000 CSI data. A total of 10 minutes between the vehicles in the natural situation when the information passed on the road as a set of experiments. While recording the CSI data, we placed a camera next to the receiver to record the vehicle's operation on the road so that we can compare it in the next steps. We repeat the above steps to obtain multiple sets of experimental data.

In the data processing, we apply the CSI phase correction described in the previous section and the CSI phase data after the PCA's ambient noise detection method, and the CSI amplitude data directly after the PCA's environmental noise reduction. When observing the phase data comparison and CSI amplitude data of CSI, the CSI phase has better stability and detection accuracy. We apply the cross-validation evaluation method to the data, divide the same set of data to train multiple sorters and classify the data multiple times, and finally statistically classify the results.

4.3 Evaluation Method

We all know that when the amount of data used for model training is larger, the trained model usually works better. So the division of the training set and the test set means that we can't make full use of the data we have at hand, so the resulting model effect will also be affected. Therefore, in the evaluation of outdoor vehicle detection experiments, the Cross Validation method was proposed to evaluate this group of experiments.

More specifically, we used the LOOCV method (Leave one out cross validation) in the Cross Validation method to evaluate this experiment. Like the Test set approach, the LOOCV method also includes the step of dividing the data set into a training set and a test set. But the difference is that we only use one data as the test set, the other data is used as the training set, and this step is repeated N times (N is the number of data in the data set).

Assuming that we now have a data set consisting of n data, the LOOCV method is to take one data each time as the only element of the test set, while the other n-1 data are used as training sets for training the model and Tuning. The result is that we finally train n models and get an detection result each time. The final test result is calculated by averaging the n detection results.

LOOCV has many advantages over the test set approach. First of all, it is not affected by the test set training set partitioning method, because each data has been tested separately. At the same time, it uses n-1 data training models, and almost all the data is used to ensure that the model's bias is smaller.

Then we calculate the final TN, TP, FN, FP, accuracy, recall, precision and F of the data to quantitatively analyze the experimental results. The specific formula is as follows.

$$\mathrm{Accuracy} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}+\mathrm{TN}} \tag{9}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}} \tag{10}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \tag{11}$$

$$\mathrm{F_{measure}} = \frac{2 \cdot \mathrm{Precision} \cdot \mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{12}$$

When classifying the type of vehicle, we first roughly classify the types of vehicles and divide the vehicle into two parts, large and small. Among them, large vehicles include trucks and buses. Small vehicles include relatively small vehicles such as light cars and ordinary cars. On the data, we also select 20 data in one second as a data set, and select the maximum and minimum values of the data set collected by the two antennas as the feature vector of machine learning. In the evaluation method, since the amount of data used in the analysis of the type of the experimental vehicle in the previous step is not very large, we still use the LOOCV method to analyze the experimental results. In this step, we calculate the TN, TP, FN, and FP as a negative solution for a large vehicle, and then calculate accuracy and precision to quantitatively analyze the experimental results.

Table 1 Number of true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN)

	TP	FN	FP	TN
method-1	41	5	29	426
method-2	46	0	3	452

method-1 : detection result by using CSI amplitude
method-2 : detection result by using CSI phase

Table 2 Confusion matrix of two classification

Actual \ Predicted	type-1	type-2
type-1	17	1
type-2	0	41

type-1 : trucks and buses
type-2 : other vehicles

Table 3 Confusion matrix of four classification

Actual \ Predicted	type-1	type-2	type-3	type-4
type-1	9	0	2	0
type-2	2	3	5	0
type-3	1	0	14	2
type-4	1	0	8	0

type-1 : trucks and buses
type-2 : large vehicles
type-3 : ordinary vehicles
type-4 : light vehicles

Table 4 Detection result of on-road vehicle

	accuracy	recall	precision	F
method-1	0.934	0.891	0.586	0.707
method-2	0.996	1.0	0.939	0.969

method-1 : detection result by using CSI amplitude
method-2 : detection result by using CSI phase

Table 5 Two classification result of on-road vehicle

	accuracy	recall	precision	F
type-1	0.983	0.944	1.0	0.971
type-2	0.983	1.0	0.977	0.988
total	0.983	0.972	0.989	0.980

type-1 : trucks and buses
type-2 : other vehicles

We then further categorized the types of vehicles in more detail. We classify vehicles as four types: trucks and buses, larger vehicles, ordinary vehcles, and light vehicles. On the data, we also select 20 data in one second as a data set, and select the maximum and minimum values of the data set collected by the two antennas as the feature vector of machine learning. In the evaluation method, we still use the LOOCV method to analyze the experimental results. In this step, we set each vehicle as a positive solution, set other vehicles as negative solutions, and calculate TN, TP, FN, FP, accuracy, recall, precision and F, finally obtain four sets of quantitative results for this experiment to analysis.

4.4 Experimental Results and Evaluation

The outdoor vehicle detection results are shown in the **Table 1** and **Table 4**. Our main purpose in this set of experiments is to compare the phase information of the CSI with the results of the amplitude information detection. Obviously, the CSI phase information comparison has a higher detection accuracy after the CSI amplitude information. Analysis of precision We know that when the amplitude information of CSI is used, the erroneous detection

Table 6 Four classification result of on-road vehicle

	accuracy	recall	precision	F
type-1	0.553	0.818	0.692	0.755
type-2	0.553	0.3	1.0	0.462
type-3	0.553	0.824	0.483	0.609
type-4	0.553	0	0	0.
total	0.553	0.483	0.692	0.569

type-1 : trucks and buses
type-2 : large vehicles
type-3 : ordinary vehicles
type-4 : light vehicles

occurs more frequently. When the CSI amplitude is used, the classifier mistakes the movement of a moving object such as a human or a bicycle as the movement of the vehicle.

According to the confusion matrix **Table 2** and **Table 5**, when the vehicle is classified to two types, we can get good classification results.But when we categorized the vehicle sa showen in **Table 3** and **Table 6**, the accuracy of the classification dropped significantly.

In the experiments that divided the vehicles into two categories, we obtained higher classification results. However, when we conducted a more detailed classification, the results of the classification have dropped significantly.

The reason for the sharp drop in accuracy during the four classifications is that the WiFi signal distinguishes the vehicle mainly by the cross-sectional area of the vehicle (the size of the area where the signal is blocked). However, many vehicles are difficult to be perfectly classified into a certain type when artificially setting the type of vehicle. And some light vehicles have a cross-sectional area that exceeds some common vehicles. So we can't get a good classifier in the stage of classifier training.

5. Conclusion

In this paper, we propose a method of using WiFi signals to detect vehicles traveling on the road. We have selected the CSI that is currently used in the research of WiFi signals to conduct research. In order to maintain high precision in outdoor scenes, we chose the phase of the CSI instead of the frequently used CSI phase for detection. Because the offset in the CSI phase makes the detection not work properly, we used a mathematical method to cut off the offset of the CSI phase information. Then we used the PCA method to cut off the environmental noise. Since CSI will take information on all the surrounding activity targets, we use the SVM classification method to distinguish vehicle information from information such as pedestrians. In the last step, we use the decision tree to further classify the last extracted vehicle information and further classify it according to the size of the vehicle. At the end of the paper we describe our experimental techniques and analyze the results of the experiments.

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