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Research on Perception System of Automated Driving Based on the Monocular Vision - Vehicle Detection

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Abstract— *In order to build self-driving sensing system based on monocular vision, this paper studied the detection of vehicles in the driving environment based on HOG (Histogram of Oriented Gradient) features and SVM (Support Vector Machine) classifier. To solve the problem of low detection efficiency which will be caused by the higher dimensions of HoG feature space, a HoG-PCA (principal component analysis) feature based on the dimensionality reduction was proposed. After testing, it was proved that the feature after the PCA dimensionality reduction does not affect the detection accuracy. In the process of classification based on the SVM classifier, the distribution of data was unknown, so the kernel function of SVM was studied. At the same time, Adaboost (Adaptive Boosting) algorithm was used for the classifier comparison. Based on the ensemble learning method, a new classification model based on SVM classifier with different kernel functions and Adaboost algorithm was built. After testing, the new model can achieve a higher accuracy of 98.5%. Finally, the new model was used to detect the vehicles in the video and the deep learning model SSD (single shot multibox detector) was introduced to compare with this new model. The results show that, even compared to the latest object detection method based on the deep learning method, the traditional classification methods based on feature still have some reference value.*

Keywords— *Monocilar vision, HoG-PCA+SVM, Adaboost, Ensemble learning, Vehicle detection, SSD.*

I. INTRODUCTION

To make up for the weakness of traditional vehicle driving methods, improve the driving safety and liberate people from tedious driving work, self-driving technology has been rapidly developed in recent years with the promotion of the traditional car manufacturers and Internet companies [1]. The self-driving system is mainly divided into three layers, perception layer, processing layer and execution layer. In the perception layer, the system senses the current driving environment through the sensors installed in the car; In the processing layer, the system makes the driving decisions based on the environment information sensed by the perception layer and the current driving conditions; In the execution layer, the system issues control commands to the execution components of the car based on the decision from the processing layer [2]. In the self-driving system, the perception layer is the basis of the system. In this paper, the sensing system of the self-driving car was studied.

At present, sensors which are mainly used in the sensing system are LIDAR (Laser Imaging Detection and Ranging), millimeter-wave radar, ultrasonic radar and camera [3]. Ultrasonic radar is mainly used in the vehicle reverse system; millimeter-wave radar and LIDAR are mainly used for long-distance measurement and the surrounding environment perception [4]; camera is mainly used for traffic signal recognition and object detection [5]. But with the development of machine vision and deep learning, the function of the camera has also been greatly expanded [6]. With the monocular vision, system can complete the objects recognition and tracking in the driving environment; with the binocular vision, system can complete the self-location and the distance measurement. In this paper, the vehicle detection in the driving environment based on monocular vision was mainly studied.

At present, the research on vehicle detection based on monocular vision mainly focuses on the image recognition based on machine learning. The researchers started their studies mainly on the feature extraction of vehicle image and the choice of the system classifier. Cao and his team built the recognition system to realize the detection of vehicles in the video based on the HoG features and linear SVM classifier [7]; Atibi Mohamed established a real-time vehicle detection system based on haar-like features and neural networks [8]; Alberto Broggi completed the vehicle detection of the surrounding environment based on the haar-like feature and the Adaboost classifier for car parking [9]. Quanfu Fan [10] built the vehicle detection system based on a deep learning model Faster-RCNN. In this paper the vehicle detection system was built based on the traditional image recognition methods.

To improve the training and learning efficiency and the accuracy of the recognition system, two improvements of the recognition system were proposed in this paper: 1. To solve the problem of low efficiency caused by the high dimensions after traditional feature extraction, the feature reduction method based on PCA(Principal Component Analysis) was adopted, and the feature of HoG-PCA was used as the input of the system classifier; 2. To improve the classification accuracy of the system, a new classification method with the combination of multi-classifiers based on the ensemble learning method was used as the system classifier. At last, the vehicle detection systems based on traditional machine learning method and deep learning method were compared by the detection results of the video based on the new method proposed in this paper and the SSD model.

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II. THE CONSTRUCTION OF THE DETECTION SYSTEM

A. *Vehicle Detection System Based on Machine Learning*

In this paper, an image recognition method based on the machine learning was used to build a vehicle detection system in a driving environment. The composition of the system can be divided into two parts: the stage of supervised learning based on teacher signals and the stage of vehicle detection of the images captured with the perception system. The flow chart of the learning of the detection system is shown in figure 1, which is mainly composed of two steps: feature extraction of the training images and parameter learning of the classifier. During the process of feature extraction, the system reads the image from the training database and normalizes the size of the image, then uses the feature extraction method to process the image after the pre-treatment, and in some studies the feature after being extracted will be processed to improve the performance of the system, at last builds a feature database of the training database with the extracted feature. The system learns the parameters of the initialized classifier by using the processed feature database.

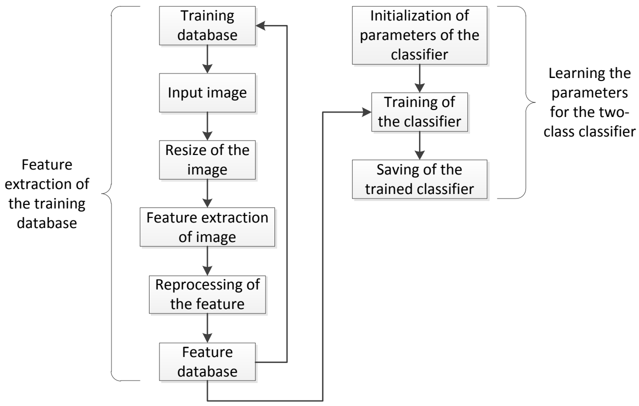

Fig. 1. Flow chart of the learning of the system.

The flow chart of the detection of the system is shown in Figure 2, the detection process can be mainly divided into three parts: the choice of the ROI (region of interest), the vehicle detection in the ROI, and the merger of the region in which the vehicle has been detected. In this paper, the traditional step-by-step method is used to extract the ROI from the input image, and the trained classifier is used to judge the ROI to determine whether the vehicle exists in the region. Finally, the regions where vehicles may exist are merged based on the IoU (intersection over union) method, in order to locate the vehicles existed in the image.

B. *Training database of System*

In our work, the image database GTI collected by the Image Processing Group at the Universidad Politécnica de Madrid(UPM) have been used as the training database for the classifier training [11]. The image database includes 3425 images of the vehicle rears taken from different angles of the view and 3,900 images taken from the driving environment not containing the vehicle. The size of the image in the database is 64*64, some images from the GTI database are shown in Figure 3.

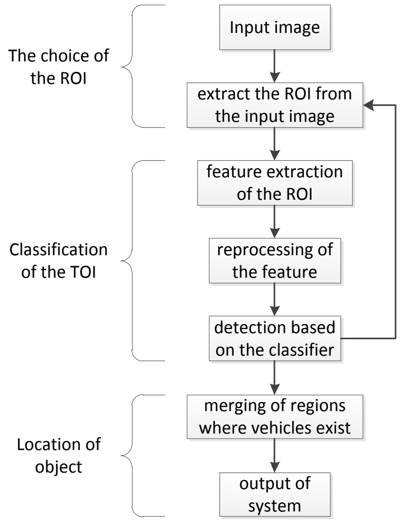

Fig. 2. Flow chart of the detection of the system.

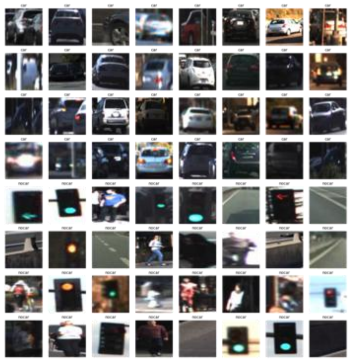

Fig. 3. Images of the training database.

III. THE FEATURE EXTRACTION OF VEHICLES BASED ON THE HOG

A. *The image feature based on HoG - Introduction of HoG*

The feature extraction process based on HoG is shown in Figure 4, at first the pretreatment of the input image is processed which is composed of normalization of the color feature space and the division of cells (for example: 3 * 3 / 1 cell). The gradient of input image after the pretreatment is calculated as eq. (3.1) - (3.3).

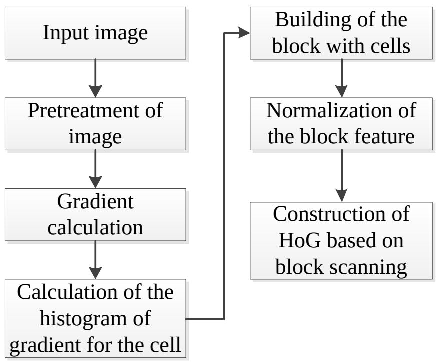

Fig. 4. Flow chart of the feature extraction based on HoG

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$$\begin{cases} G_x(x,y) = H(x+1,y) - H(x-1,y) \\ G_y(x,y) = H(x,y+1) - H(x,y-1) \end{cases} \quad (3.1)$$

$$G(x,y) = \sqrt{G_x(x,y)^2 + G_y(x,y)^2} \quad (3.2)$$

$$\theta(x,y) = \tan^{-1}\frac{G_y(x,y)}{G_x(x,y)} \quad (3.3)$$

$G_x(x, y)$ and $G_y(x, y)$ denote the horizontal and vertical gradients of the point (x, y) of the input image; H(x, y) denotes the pixel value of the point (x, y); G(x, y) and θ(x, y) denote the gradient magnitude and direction of point(x, y).

The histogram of gradient of the cell is constructed based on the gradient calculation, and the direction of the gradient is divided into 9 bins. The direction of gradients of the cell are calculated based on the 9 bins to build the histogram of gradient of the cell. The block is composed of the cells (for example, cells of 2 * 2 will build a block), and the histogram of gradient of the cells are combined into a feature of the block. To improve the robustness of the histogram for external environment, the block's features are normalized after the feature calculation. By the step-by-step scanning of the whole image, the histogram of gradient of the block in the image can be obtained, and finally the Hog feature of the image can be obtained.

The feature of the image from the training database was extracted based on the HoG feature extraction method. The visualized feature is shown in figure 5. With the RGB input image, the figures of three channels of Y (Luma), C_r(difference between red component and Luma) and C_b(difference between blue component and Luma) were extracted based on the HoG feature.

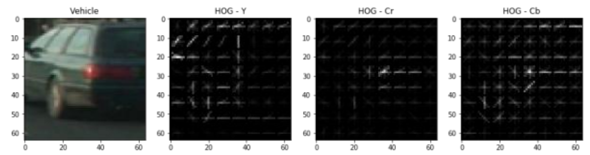

Fig. 5. Figures of the visualized feature.

B. The image feature based on HoG - The choice of the parameters of HoG

In the process of the feature extraction based on HoG, the choice of the step length of block scanning may directly affect the dimensionality of HOG features and the training accuracy of classifiers. To choose the step length which can achieve the highest accuracy, the vehicle detection system was built based on the SVM classifier (which will be described in detail below) and the HOG feature; and was trained based on different step lengths of the block scanning. The system was trained on a host which uses an Intel Core 2 Quad Q9400 processor with a max turbo frequency of 2.66GHz and has a memory of 6G bytes. The program for the system training was built with the Visual Studio2008 and Opencv2.3. The results are shown in the table I.

TABLE I. Training results of the system based on the HoG and SVM(RBF)

Size of image	HogSize	Dimensions of feature	Processing time	Accuracy
64×64	4.4	6084	3.5 hours	95.50%
64×64	8.8	1764	3 minutes	98.00%
64×64	16.16	576	1minute	97.50%

In the table, the hogsize denotes the step length of the block scanning; we can see that, when the hogsize reduced, the dimensionality of the HoG feature will be higher, also the training time will be longer. When we chose the step length of 8 pixels, a relatively higher training accuracy can be got.

C. Dimensionally reduction based on PCA

As studied above, the dimensions of the feature extracted from the image based on the HoG feature descriptor was 1764, which would be a high cost for the vehicle detection system based on the machine learning method. To improve the efficiency of the system, the dimensionally reduction of the extracted features was done in this system. To reduce the loss of information while the process of dimensionality reduction, the PCA method was used for the dimensionality reduction of the HoG features in our research. PCA is able to translate a set of possibly correlated data into a set of linearly uncorrelated data which can extract key features from the high dimensional data. In previous studies, PCA has been widely used for the dimensionality reduction of image features [14].

D. Dimensionally reduction based on PCA - Introduction of PCA

1） A matrix X is built based on the features of the images in the training database, so $X = (x^{(0)}, x^{(1)}, x^{(2)}, \dots, x^{(m-1)})$.

2） The matrix X is processed with each line for a zero mean input, the formulas of the processing are as follows:

$$M = \frac{1}{m}\sum_{t=0}^{m-1} x^{(t)} \quad (3.4)$$

$$X = X\text{-}M \quad (3.5)$$

3） A covariance matrix C is built with X:

$$C = \frac{1}{m} XX^T \quad (3.6)$$

4） The eigenvalue λ_i and the eigenvector μ_i of the covariance matrix C are calculated.

5） According to the magnitude of the eigenvalues, the eigenvectors are arranged from top to bottom to form a new matrix; take the first K rows of the new matrix to constitute a matrix P.

6） The dimensions of the feature is reduced to K with the formula:$y^{(t)} = Px^{(t)}$.

E. Dimensionally reduction based on PCA - Choice of the dimensions for the PCA method

The dimensionality reduction based on the PCA can reduce the dimensions of the image feature data to improve the efficiency of the system, but at the same time the accuracy of the system needs to be ensured with the PCA method. The vehicle detection system was built based on the HoG-PCA image feature and the SVM classifier, and the training accuracy of the system was tested. The results of the training accuracies are shown in the table II:

TABLE II. Training results of the system based on the HoG-PCA and SVM(RBF)

Size of image	HogSize	Dimensions of PCA	Processing time	Accuracy
64×64	8.8	400	10 minute	98.00%
64×64	8.8	500	10 minute	98.25%
64×64	8.8	600	10 minute	98.00%

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From the table we can see that, after the dimensionality reduction based on the PCA the training accuracy of the classifier has not been affected, when the dimensions of feature K was selected as 500, the system accuracy has been improved.

IV. THE CLASSIFIERS FOR VEHICLE DECTION SYETEM

A. Classifier based on the SVM

SVM is a machine learning method with the supervised learning model, always used to solve the problems of statistical classification and regression analysis. Before the deep learning method, SVM are widely used in various fields as a good classifier by researchers. In the field of image recognition, SVM has also been widely used [15].

B. Classifier based on the SVM - Introduction of the SVM

When dealing with the two-class classification problems of the two-dimensional data set, the SVM is a straight line. When the data set is in high-dimensional space, the hyperplane used for the classification of the high-dimensional data set will be built. In the two-class classification problems, the farther the data in the high-dimensional space is from the hyperplane, the higher the reliability of the hyperplane used for the classification of the data set will be. At first, we build the hyperplane f(x) for the classification,

$$f(x) = W^T x + b \qquad (4.1)$$

The W is the characteristic parameter of the hyperplane, the dimensions of W is as same as the dimensions of the data, and b is the bias parameter. The classification based on the hyperplane is shown as eq. (4.2).

$$\begin{cases} y\big(f(x)\big) = 1 & \text{if } f(x) > 0 \\ y\big(f(x)\big) = 0 & \text{otherwise} \end{cases} \qquad (4.2)$$

Based on the geometric knowledge, the distance from the point x to the hyperplane in the high-dimensional space is given by eq. (4.3):

$$\gamma = \frac{W^T x + b}{\|W\|} = \frac{f(x)}{\|W\|} \qquad (4.3)$$

The distance γ needs to be maximized for the optimal classifier, so

$$max\frac{f(x)}{\|W\|} \to max\frac{1}{\|W\|} \to min\frac{1}{2}\|W\|^2$$

W and b of the optimal hyperplane are obtained based on the Lagrange Multiplier.

C. Classifier based on the SVM - The kernel functions of SVM

The data set may be linear inseparable when used for classification based on SVM classifier. To solve the problem, the data set need to be mapped to higher dimensional space, to make the data set linearly separable. The curse of dimensionality may occur when the parameters are optimized in high-dimensional space, so a kernel function will be provided for transforming data set from low to high dimensions. The commonly used kernel functions of OpenCV are as follows:

RBF(radial basis function) Kernel：

$$K(x, x') = \exp\left(-\frac{\|x\text{-}x'\|^2}{2\sigma^2}\right) = \exp\left(-\gamma\|x\text{-}x'\|^2\right) \quad (4.4)$$

LINEAR Kernel：

$$K(x, x') = x \cdot x' \qquad (4.5)$$

POLY(polynomial) Kernel：

$$K(x, x') = (x \cdot x' + 1)^d \qquad (4.6)$$

Sigmoid Kernel：

$$K(x, y) = \tanh(\mu < x, x' > +\delta) \qquad (4.7)$$

When the data are linear separable, the SVM classifier will use the linear kernel function for the classification, with which can achieve faster computer speed of the system; when the data sets are linear inseparable, the RBF kernel function will be used for the SVM classifier to achieve a higher accuracy; when the distribution of the data from data set is complicated, better results can be obtained based on the POLY kernel function; Because of the problem of the parameter setting, the SVM classifier used for the image recognition based on the sigmoid kernel function is not good. The vehicle detection system was built based on the HoG-PCA feature and the SVM classifier. The system was tested with different kernel functions of the SVM classifier. The results are shown in the table III:

TABLE III. Training results of the system based on the HoG-PCA and SVM (Different kernel functions)

	Size of image	HogSize	Dimensions of PCA	Processing time	Accuracy
RBF	64×64	8.8	600	10 minute	98.00%
LINEAR	64×64	8.8	600	15 minute	94.50%
POLY	64×64	8.8	600	15 minute	96.25%
SIGMOID	64×64	8.8	600	10 minute	11.25%

D. The classifier based on Adaboost algorithm

Adaboost is a method which can get a strong classifier with the combining of weak classifiers. The accuracy of the weak classifier is slightly better than the random guess based on the Probably approximately correct (PAC) learning framework. The new learning model built with the combination of weak classifiers based on the ensemble learning method can improve the generalization ability of the whole model. Adaboost algorithm is one of the ensemble learning methods based on the boosting framework [16].

The Adaboost algorithm based on the Boosting framework make the model pay more attentions to the misclassified samples with increasing the weights of misclassified samples and reducing the weights of the correctly classified samples when the model learns the next weak classifier. At the same time, the Adaboost algorithm based on the weighted majority voting method increase the weights of weak classifiers with small classification errors and reduce the weights of weak classifiers with large classification errors to reduce the roles of the classifiers with large classification errors in the voting. Through the above process, the Adaboost algorithm can build a strong classifier with higher accuracy by the learning of the weights of the training samples and the weights of the weak classifiers.

The vehicle detection system built with the HoG-PCA features and the Adaboost algorithm achieved a training accuracy of 96.5% after being tested.

E. The classifier based on the ensemble learning

The generalization ability of classifiers can be improved with the combination of weak classifiers based the ensemble learning method. To fulfill the requirements of vehicle

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detection system, with the problem of the unknown distribution of the image features, a new model for the image classification can be built by the combination of the SVM classifiers with different kernel functions and the Adaboost algorithm to improve the generalization ability and robustness of the system. The framework of the new classifier model based on the ensemble learning method is shown in Fig.6.

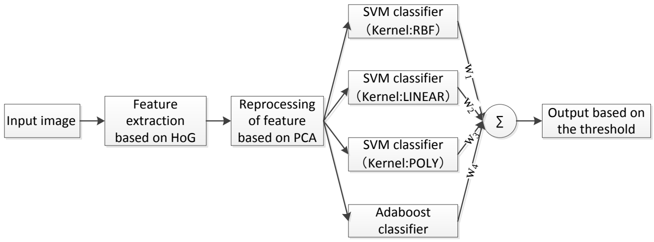

Fig. 6. The framework of the combination of classifiers.

Comparing the weighted summation of the outputs obtained from the classifiers with the defined threshold K, the output of the new model f(x) can be obtained. The formulas used for calculating the output of f(x) are shown as eq. (4.8) - (4.10):

$$\begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix} = \frac{1}{e^{C_{RBF}} + e^{C_{LINEAR}} + e^{C_{POLY}} + e^{C_{Adaboost}}} \begin{bmatrix} e^{C_{RBF}} \\ e^{C_{LINEAR}} \\ e^{C_{POLY}} \\ e^{C_{Adaboost}} \end{bmatrix} \quad (4.8)$$

$$k_{out} = [O_{RBF} \quad O_{LINEAR} \quad O_{POLY} \quad O_{Adaboost}] \begin{bmatrix} w_1 \\ w_2 \\ w_3 \\ w_4 \end{bmatrix} \quad (4.9)$$

$$\begin{cases} f(x) = 1 & k_{out} > K \\ f(x) = 0 & \text{otherwise} \end{cases} \quad (4.10)$$

The eq. (4.8) is used to calculate the weights for the outputs of classifiers, $e^{C_{RBF}}$ is the training error of the vehicle detection system based on the SVM classifier with the RBF kernel function; eq. (4.9) is used to calculate the weighted summation of the outputs based on the weights calculated by eq. (4.8), O_{RBF} is the output of the SVM(RBF) classifier.

When the new model is used for classification, the selection of the threshold will directly affect the final accuracy of the detection system. Testing the system with the change of the threshold, the test results are shown in the table IV:

TABLE IV. Training results of the system based on the new classifier model with changing of the threshold

Threshold	Accuracy(%)
0.50	98.00
0.55	98.25
0.60	98.25
0.65	98.25
0.70	98.25
0.75	98.50
0.80	95.75
0..85	95.75
0.90	95.75

Comparing the accuracy of the new model with the change of threshold with the HoG-PCA + SVM (RBF) model, the result is shown in Fig.7. From the figure, we can see that the optimal accuracy of the current vehicle detection system based on image recognition can be obtained when the threshold is set to 0.75.

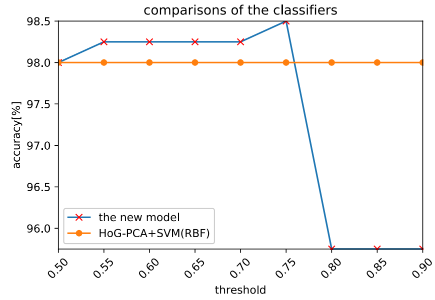

Fig. 7. Comparison of the accuracies of the classifiers.

V. THE EXPERIMENTS OF VEHICLE DETECTION SYSTEM

In recent years, with the development of the deep learning method, it has been widely used in the fields of object detection [17]. The deep learning methods used for the object detection can be divided into two directions. One is to consider object detection as the classification of images with the ROI (region of interest) generation, feature extraction of images and the location of the object. The other one is to use the regression model to predict the target object. The latest deep learning models for object detection based on image classification are the Faster R-CNN (Regions of CNN features), Mask R-CNN, etc.; the models based on the regression are YOLO (You Only Look Once) [18] and SSD [19]. The detection part of the vehicle detection system uses the trained model to determine the regions where the vehicle may exist. In this paper, the parameters of the trained SSD were used to predict the location of the vehicle in the driving environment, and the results based on SSD model were used to compare with the detection results based on the HOG-PCA feature and the proposed new classifier model to verify the vehicle detection system based on the traditional image recognition.

In our work, the experiment of vehicle detection was carried out in the notebook LENEVO Legion Y520, which uses an Intel Core i7-7700HQ processor with a max turbo frequency of 3.8GHz and has a memory of 16G bytes. the detection program was designed based on Ubuntu16.04 and python3.5; based on opencv3.2 the image processing program was completed; based on tensorflow1.0.1 the trained deep learning model was loaded. The video taken by the laboratory was used for the vehicle detection test, the video contained 4077 frames, the size of the image was 1920 * 1080 pixels, the test results are shown in Fig. 8.

The detection results of the 1794,1859 and 2129 frames from video based on the new model

The detection results of the 1794,1859 and 2129 frames from video based on SSD model

Fig. 8. Comparisons of the detection results based on the new model and SSD model.

From the Fig. 8, we can see that the problem of false alarm has occurred in the results of vehicle detection based on the new model, but the regions where the vehicles existed have been detected. Although the SSD model has made some improvements based on the YOLO model, the problems of the missed detection still existed for vehicles in the distance of the detected figures. Comparing with the results of the location of vehicles, the SSD model was more accurate. During the detection of the video, the detection based on the proposed model in this paper needed 2.35 seconds for each frame and the SSD model could detect 1.25 frames per second. The efficiency of the detection system based on SSD model was about three times of the system based on the new classifier model. After comparison, we can see that the detection model based on the image classification has the higher accuracy, but the efficiency of the model is not good.

VI. Conclusion

In this paper, the dimensionality reduction based on the PCA method was used for the HoG feature of the images. At the same time, the results showed that the loss of information caused by the dimensionality reduction did not affect the accuracy of the system. Based on the ensemble learning method, a new classifier model was built to improve the generalization ability of vehicle detection system. The results showed that the training accuracy of the system based on the new classifier model was improved. The vehicle detection results of the video showed that the accuracy of the detection system based on the image classification was higher, but the efficiency of the detection was lower. In the future research, we can build a new object detection model based on the combination of deep learning (Faster-RCNN) and ensemble learning method to improve the generalization ability of the system.

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