

Research on Vehicle Target Detection Method Based On Deep Convolution Neural Network

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Abstract: In order to solve the problem of complex calculation and low recognition rate in vehicle target detection method and improve the accuracy of vehicle target detection, a vehicle target detection method based on Deep Convolution Neural Network (DCNN) is proposed. With the help of deep learning and based on the Inception structure of the main module of GoogleNet, an 11-layer network structure is designed, and an experiment is carried out on about 20,000 images of the rear of the vehicle. The experimental results show that the proposed method can improve the accuracy of vehicle target detection effectively, and the time consuming is short and the robustness is high.

Key Words: deep learning; Deep Convolution Neural Network(DCNN); objection detection

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I INTRODUCTION

Vehicle target detection is a research problem that needs to find out the vehicle to be selected in complex environment. In recent years, Intelligent Traffic System (ITS) has developed rapidly in driving technology. As an important part of ITS, vehicle target detection plays an important role. However, vehicle type features are complex and varied, the scene environment is complex and changeable, vehicle target detection has become one of the technical difficulties in the research of ITS.

With the development of deep learning^[1] technology, the analytical ability of complex data sets have been greatly improved by building a deep neural network similar to the structure of the human brain. The inputted images and other datas are analyzed in depth^[3], and the depth learning method^[2] is applied more and more in the detection problem. The introduction of deep learning into ITS is an innovative change. The goal is to train a large number of data samples by building a multi-level neural network, which can greatly improve the effectiveness of feature extraction and improve the accuracy of target detection.

For this, many scholars at home and abroad put forward relatively effective methods to solve the problem of vehicle target detection. In the traditional algorithm model, the principle of local selection based on sliding window and manual design feature^[4] is usually used to solve the problem of difficult recognition of vehicle target detection. In reference [5] [6] [7], we used Haar, Histogram of Oriented Gradient, etc., to detect vehicles, but it is easy to cause false detection and frame loss. These traditional algorithms are weak in generalization ability and can not deal with a large number of images. The selection of sliding window regions is easily affected by human subjective factors. In addition, the traditional vehicle target detection algorithm has been unable to meet the needs of the complex real traffic scene. With the deepening of the theoretical knowledge of in-depth learning, the continuous improvement of practical operations, there are new solutions to this kind of research problems.

In order to overcome the shortcomings of traditional vehicle target detection methods, in 2014, R-CNN framework was designed in literature [8], and the solution of region proposal (candidate region) was proposed. In reference [9], a vehicle target detection method based on fast region convolution neural network^[16] (Fast R-CNN) is proposed, which can not realize an end-to-end detection process of samples and networks. A Convolutional Neural Network (CNN) classifier and convolution algorithm based on Convolutional Neural Network (CNN) is presented in [10]. The algorithm is robust and can not avoid the problem of missed detection. In order to solve the problem that the vehicle detection effect is not good when the illumination and scene change occur, based on the Faster R-CNN [17] target detection method, the improved LocNet algorithm is proposed in literature [12], which improves the accuracy of vehicle target detection, but can not detect small target. However, aiming at the problem of accurate detection and location of small targets, a method of air-to-ground vehicle detection based on regional convolution neural network (Faster-RCNN) model is proposed in literature [13]. However, the number of samples are not sufficient and are limited to the detection of minibus models.

In view of the shortcomings of the above research methods, this paper, inspired by the architecture of Inception^[14], proposes a vehicle target detection and recognition method based on deep convolution neural network^[15] (DCNN). On the basis of a large number of collected data samples, the network model is trained, and the same data samples are trained by other methods to carry out comparative experimental analysis. The feasibility of DCNN model in vehicle target detection is obtained.

II RESEARCH ON VEHICLE TARGET DETECTION MODEL BASED ON DCNN

1.1 Basic structure of DCNN

Deep convolution neural network can extract complex information from feature maps. According to the results of many experimental methods, the most suitable network structure is designed. The network structure is shown in Figure 1. The network uses 11 layers of network. The first layer is the input layer. In this paper, the original image is used as the input of the network directly. Ci is the convolution layer of the network, which has a good ability to perceive the local features of the image, and can perceive the relationship between pixels and pixels^[18]. When the convolution layer function is convolution on the whole feature graph, the parameters remain unchanged, the number of parameters is greatly reduced, and the training difficulty is reduced. The output of the convolution layer is compressed by the pool layer, which makes the local characteristics converge, thus finding a higher level rule in further convolution^[19].

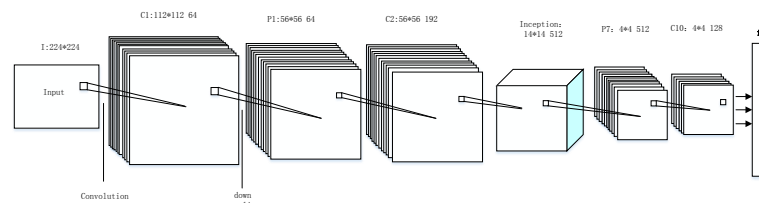


Fig. 1 DCNN structure diagram

Specifically, using 64 filters of 7*7 to convolve the input image, 64 characteristic maps of 112*112 are obtained, and the feature maps are reduced to 56 * 56 by downsampling, and the feature maps are normalized by channel - to - channel summation of 5. And then deconvolution P1 with 192 filters the size of 3, We get 192 feature maps of 56 *56. The feature graph is normalized between channels with the sum of 5 channels. By downsampling, the feature graph is reduced to 28*28. Inspired by the GoogleNet framework, the following three classes of Inception structure, the input feature map for a deeper map to reduce to 4*4. The final convolution layer uses a filter of 1*1 to process 128 feature graphs of 4*4. The fully connected fc1 layer fuses the front feature map into a 1024 dimensional feature vector fc2 layer outputs the probability of measuring the rear features of the vehicle.

The Inception structure convolution module is shown in Figure 2. By changing the number of 1 * 1 convolution kernels, the effect of reducing the thickness of the feature vector graph is achieved by changing the number of the 1 * 1 convolution kernels, so that the training parameters can be reduced and the training complexity is reduced.

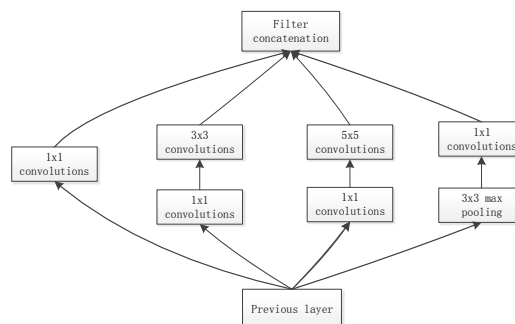


Fig.2 Inception structure convolution module

III DCNN PROCESS OF VEHICLE TARGET DETECTION

The method is divided into training stage and testing stage. In the training stage, the proposed convolution neural network structure is trained with the collected data samples, and the training model is obtained. In the test stage, the test sample datas are put into the trained model and the target detection results are obtained.

As shown in Figure 3, the approach presented in this article consists of the following steps:

- 1) Designing convolution neural network structure.

- 2) Using the training sample data set to pre-train and get the pre-training parameters.
- 3) Repeated training for many times to get a better training model.
- 4) Using the final training model to test the detection data samples and get the vehicle target detection effect.

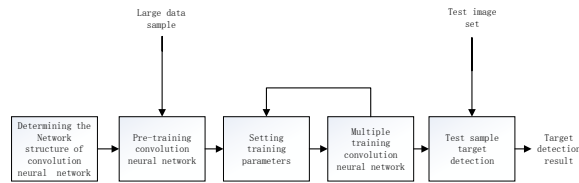


Fig.3 The process of vehicle object detection based on DCNN

IV. TEST RESULTS AND ANALYSIS

4.1. Test data samples

In order to ensure the requirements of the convolutional neural network for the sample size, this paper uses the open Caltech1999 data set and some pictures collected by the vehicle camera as the data samples of the model, and divides them into training samples and test samples according to the 9:1 scale. Before training with DCNN, the color image with the size of 224*224 is normalized and the zero mean value is used to achieve the preprocessing effect. Through multiple training, the network parameters are adjusted, and a better training model is obtained. Some vehicle samples are shown in Figure 4. The partial negative sample of the contrast experiment HOG is shown in Figure 5.

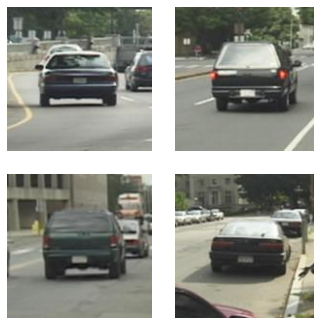


Fig. 4 Sample data set

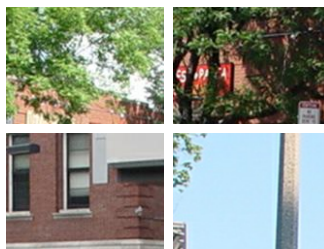


Fig. 5 Negative samples in HOG

1.2 Test environment

In this paper, we use Caffe framework to carry out GPU acceleration calculation under Nvidia K5200. The training time of a model is about 40 minutes. The whole training process adopts batch random gradient descent algorithm to optimize the parameters of each layer.

1.3 Test results and analysis

1.3.1 Contrast experiment of vehicle Target Detection

Under the condition that the sample data set is the same, the experimental data is retrained many times with the HOG of the traditional method, the training time is 50 minutes, and the test sample data set is obtained after a good training model. From the view of Figure 7, the HOG algorithm can only detect the vehicle in front of the vehicle, but can not detect the driving vehicle in the side lane, so it is easy to miss the detection.

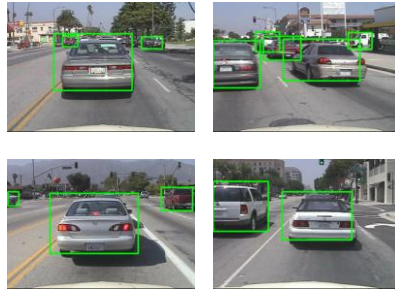


Fig.6 DCNN method for detecting target vehicle effect

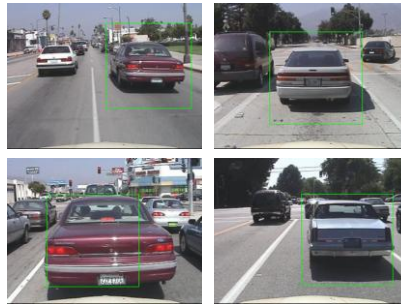


Fig.7 Vehicle detection effect of HOG algorithm

Table 1 compares the time and accuracy of using the HOG algorithm for vehicle detection. By comparing the data in Table 1, it can be seen that the proposed network model is more accurate than the HOG algorithm.

Table 1 Vehicle detection rate using different methods

Methods	Input picture size	Color / Gray	Accuracy	The time taken to process pictures
This paper method	224*224	RGB	94.92%	40min
HOG+SVM	224*224	RGB	90.45%	50min

Figure 8 is a line diagram of other depth learning networks for detecting vehicle targets . The accuracy increases with the increase of epoch times. When epoch reaches 100, the accuracy rate tends to be stable and close to convergent state. The results show that the detection effect of DCNN is better than that of Lenet-5 and Caffe-net. All recent methods of comparing bar charts are shown in Figure 9.

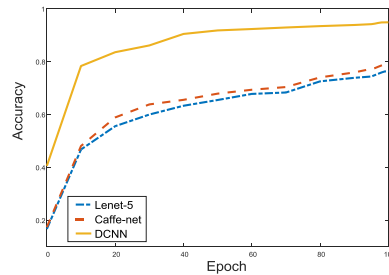


Fig.8 Other network comparison experiment line chart

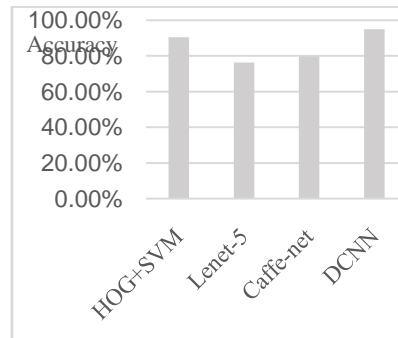


Fig. 9 Vehicle target detection method bar chart

V. CONCLUSION

The research of deep learning is becoming more and more perfect, and the technology of target detection is developing rapidly. In the future, it will manifest its superiority in a wider application field, and will have a great influence on DCNN as a classical convolutional neural network, which is an improved structure network. Its generalization ability is strong, the robustness is high, and it has certain feasibility.

Based on depth learning theory, a vehicle target detection method based on DCNN is proposed in this paper. The network designed 11 layers of convolution neural network, the input image data feature is extracted. Compared with the traditional method HOG, other network Lenet-5 and Caffe-net are tested and compared in the same data set, and the accuracy of each network is obtained. The results show that DCNN is much better than the other three methods in vehicle target detection under the same data set, and the accuracy is higher, the robustness is higher and the speed is faster. It provides a new way of thinking for the future intelligent auxiliary driving system.

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