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Vehicle Feature Extraction and Application Based on Deep Convolution Neural Network

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Abstract: In view of the existing vehicle image features extraction of large amount of calculation, slow speed, extract the characteristics of the uniqueness is not strong, the complex extraction process and so on, is put forward based on the depth of the convolution of the neural network vehicle feature extraction method, and is applied to extract the depth of the characteristics of vehicle brand recognition and deck vehicle identification. The experiment shows that the proposed method can extract the depth characteristics of the vehicle effectively, and obtain good vehicle identification and identification accuracy.

Keywords: Feature extraction; Deep learning; Fake plate vehicles; Vehicle recognition

1 INTRODUCTION

The rapid development of social economy to improve people's living standards, people have chosen in order to facilitate the travel car as a means of transport, the number of motor vehicles increased sharply in the past 10 years, China's motor vehicle ownership has reached 1 billion, has brought tremendous pressure to the traffic security management. Relying on traditional manual way of monitoring video interpretation has been unable to meet the demand, intelligent transportation system arises at this historic moment. Vehicle recognition system as an important part has always been the focus of research.

The existing methods of vehicle model identification are mainly:

(1)Vehicle recognition method based on license plate recognition. In this method, the number of the license plate is first identified, and the vehicle model information is obtained from the identified license plate characters to the intersection data database. This method is simple, but cannot deal with the problem of cloned car.

(2)Model recognition method based on template matching. By building the standard template of the model, the vehicle that needs to be identified is matched with the standard template that is built, and then the specific model is judged. The template is suitable to achieve good results, but the method usually has the problem of complex formwork and poor real-time performance.

(3)Model recognition method based on artificial features. By extracting the feature information of vehicle, such as: SIFT feature, Garbo feature, Hog feature and so on, we can describe the vehicle, identify the vehicle type through feature comparison or feature classification, but the artificial characteristics are often designed for a specific scenario, and the universality is worse than.

Convolution neural network (convolution neural network) is an efficient recognition method which has been developed in recent years and has attracted much attention. The network can directly input the original image, avoid the complex preprocessing of the image, and thus get a more extensive application. In the aspect of the extraction of image features, convolutional neural network (Deep Convolutional Neural Network, DCNN) has the characteristics of strong extraction ability of, through the depth of network training can extract the unique image features highly distinct. Aiming at the existing shortcomings of invariant feature based vehicle recognition, a method is proposed using DCNN extraction method and the characteristics of the vehicle depth, by comparison and the establishment of thelibrary of license plate, vehicle identification, identification and can identify whether the deck.

Vehicle image feature extraction and application system block diagram, as shown in Figure 1 (car head is car face).

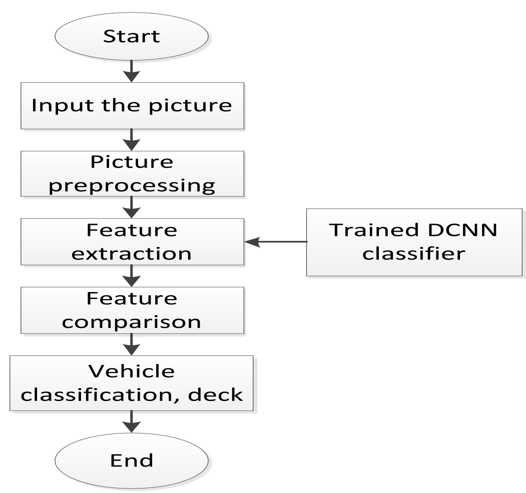

Fig 1: Block diagram of vehicle image comparison

First of all, to the plate as a unit, generating the same car sample set, the sample set to manual review, to ensure the same under license is corresponding to the same car, and set a license plate information stored in the library, the computation and the corresponding complete information and vehicle license plate on

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the base plate. Then we use the trained DCNN model to extract the depth features of the vehicle image, and then compare the

depth features of the head and the corresponding information in the license plate library. The experiment shows that the vehicle feature extraction method proposed in this paper has obtained a good accuracy rate of vehicle recognition.

2 MATERIAL AND METHODOLOGY

2.1 Establish a vehicle alignment database

First, we collect multiple head images (5 or more) of the license plate and the corresponding vehicle of the same car, calculate the Euclidean distance of the characteristic mean of these pictures, Expression is shown in Formula 1.

$$X_m = [x_{m1}, x_{m2,\cdots,}x_{mn}] \quad (1)$$

M is the same as the number of head pictures in the license plate folder; n indicates the dimension of the depth feature of the head image.

(1) Normalization of eigenvalues.
(2) Characteristic mean.
(3) The Euclidean distance of the mean value.
(4) Euclidean distance mean.
(5) Euclidean distance variance.

The license plate is empty when the library is initialized. The current vehicle license plate capture, according to the test results (license plate high degree of confidence in the bottom) query library, if not belonging to the vehicle, directly update the storage; if belongs to an existing vehicle, according to the results of vehicle depth characteristics to determine whether belongs to the deck, if not, then update the storage.

The updating and entering strategy: the sample size in the library is less than 5 copies, and is updated directly into the warehouse. If the sample size in the library is larger than 6 copies, then the minimum distance between the new sample and the library's feature mean is observed. If it is, it is not updated, if it is not updated, it will not eliminate the minimum and update the license plate library parameters.

2.2Vehicle depth feature extraction

Multi-layer neural networks often contain huge training parameters, which cause slow training and take up huge computational memory, even if it is basically impossible to train. The Convolutional Neural Network (CNN) effectively reduces the parameter of the network through the strategy of sharing the [8] with the local perception field and the weight value. By designing different network structures, CNN can learn the representation of all kinds of content from the original image.

The DCNN structure designed in this article is shown in Figure 2. The size of the input image is 224*224. After 1 convolution kernel sizes 3*3 convolution operation, we get 64 feature maps through a maximal pooling operation [9], repeat this operation once. After that, 256 feature graphs are obtained after 3 3*3 convolution operations and a maximum pool operation. Finally, connecting the 2 connection layer, depth characteristics of the last node sequential 4096 dimensional vector output layer is used for vehicle, comparison. The activation function of the network is selected as the (Rectified Linear Units) function. The layer of the network structure is explained as follows:

1) Convolution layer

The convolution layer is the main layer of the network, filtering the input data by defining a filter (convolution kernel). The input data is filtered by different filters to produce different features and map to the next layer. Its calculation is shown in formula 2, which $h$is a core that requires convolution of the input data. Convolution operation embodies the idea of local connection and weight sharing of DCNN.

$$g(i,j) = \sum_{k,l} f(i+k, j+l)h(k,l) \quad (2)$$

2) Maximum pool layer

The maximum pool after convolution of two main functions, one is to extract the invariant features of input feature map, the specific location of ignoring the characteristics, characteristics of the network learned to bear a certain change; another is to reduce the dimensionality of the feature map of the input, reduce network parameter, reduce network the argument will prevent over fitting the training model, improve the generalization ability of the model.

3) Activationlayer

In this paper, we use the linear correction function$Relu$ as the activation function of the network to extract the nonlinear characteristics of the network. Function definition: $f(x) = max(0,1)$, its function is to make it equal to 0 if the calculated value is less than 0, otherwise, it will keep the original value unchanged.

4) SoftmaxLosslayer

The SoftmaxLoss layer is designed to predict the probability of the network output category, which is usually placed on the last layer of the network. The calculation process is shown in the formula 3.

$$\xi(y,z) = -log\left(\frac{e^{z_y}}{\sum_{j=1}^{m} e^{z_j}}\right) \quad (3)$$

It is the category of sample data input, which is the category for the network to predict the sample data. It is the probability value of the network forecast as the correct category.

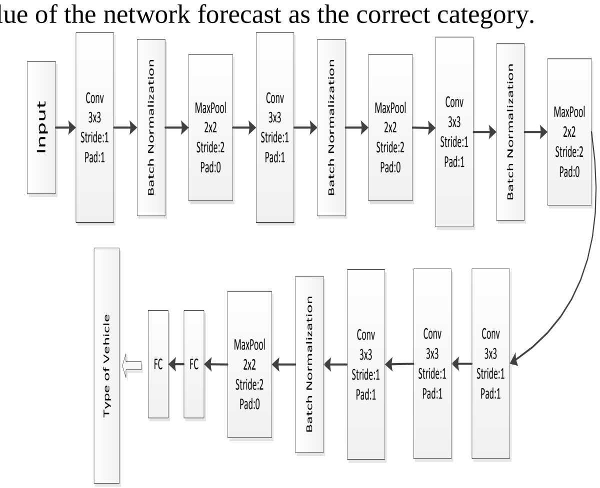

Fig 2:The CNN network structure

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3 RESULTS AND TABLES

Holography invented in twentieth Century is a three-dimensional display technique based on the principle of physical optics, based on the complete recording and reconstruction of light waves of 3D objects. Because of the holographic reconstruction light retains all the information of the original object wave (amplitude and phase information), so the reconstructed image and the original object has a 3D characteristics of exactly the same, capable of providing full depth perception information required for human visual system. When people look at holographic images, they will have exactly the same visual effects as they do when they look at the original. Therefore, holography has been widely recognized as the most promising 3D display technology.

3.1Data set

In this paper, we use about 30 thousand vehicle images captured by the traffic jam monitoring system as training samples, which contain 108 kinds of vehicle sub brands. The vehicle type identified in this paper is vehicle sub brand. According to a certain proportion of the data set is divided into training set and test set, validation set can contain all the best samples, this method is based on the ratio of 9:1 samples will be divided into training set and validation set, and randomly divided into 10 parts, each of a set of verification is not repeated, 10 copies of validation set contains all the basic sample. The experiment has been trained for 10 times. During training, according to the accuracy of the test set, we adjusted the network parameters pertinent to train the best model. The parameter model with the highest accuracy in the 10 training is calculated to be the final test model. In this paper, a simple replication strategy is used to solve the problem of sample imbalance. Small cars account for about 30%, medium-sized cars (minibus, small trucks, etc.) account for about 23%, large buses account for 23%, and large trucks account for 23%. The sample is shown in Figure 3.

Fig 3:The vehicle samples

3.2 Vehicle depth feature comparison results

When the vehicle passes through the traffic card, the car's head image is captured. First, the license plate recognition technology is used to identify the car's license plate number. The license plate database is retrieved using the recognized vehicle license plate, and the corresponding information is found out. The Euclidean distance and the Euclidean distance variance of the license plate are used to test the formula.

The eigenvalues extracted from the image and the value of the Euclidean distance calculated from the corresponding information in the license plate library are calculated.

For statistical threshold, because most of the noise in nature obeys Gauss distribution. Here we think that the feature matching error obeys the standard Gauss distribution, as shown in Figure 4 below. The threshold range between 2.5 and 3.5 is statistically reduced from 0.025 to 0, and the error is largely unchanged when it is greater than 3.5.

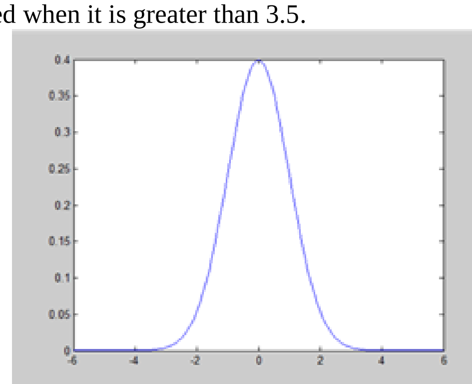

Fig 4:Gauss distribution

The license plate image captured in vehicle license plate is seldom found in the license plate database. If it occurs, the convolution neural network is directly used to identify the vehicle and update the license plate library.

The type was calculated as 0, it is judged as the vehicle deck; the calculation results is 1, the normal vehicle, and the corresponding models of information output base plate.

3.3 Vehicle type judgment and clone car false positive results

The convolution neural network designed in this paper is built under the Caffe framework and trained with the GTX 1060 6G graphics card for about 1 hours. Before using the network to extract features, all the images in the data set are grayscale and shrink to the 300*300 size. (Stochastic gradient descent, SGD) is adopted in the training process of the network.

Table 1 shows that the threshold is relatively low, although the rate of vehicle recognition is very high, but the clone car false alarm rate is also very high, with the increase of the threshold ratio of clone car false alarm rate down very quickly, at the same time, vehicle recognition accuracy is also reduced. Through the analysis: when the threshold is set to 2.75, the lowest rate of false positive clone car identification, vehicle recognition accuracy is the highest.

Table 1: Relationship between threshold and accuracy

Comparison Threshold	**False alarm rate**	**Accuracy rate**

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0	0.04	92.0%
1	0.025	91.6%
2	0.008	89.2%
2.5	0.005	87.1%
2.75	0.0015	86.6%
3	0.001	78.5%

Vehicle recognition features of deep convolutional neural network table 2 compares the characteristics of the use of artificial design and use the extraction accuracy and false alarm rate of the clone car. Can be seen from the table, vehicle recognition using feature extraction depth convolutional neural network accuracy is the highest, while the lowest rate of false positive clone car.

Table 2:Model recognition rate using different feature extraction methods

Method	**Accuracy rate**	**False alarm rate**
Our	89.6%	0.008
Sift	38.2%	0.0620
Hog	15.6%	0.0860
Gabor	14.3%	0.0873

4 CONCLUSION

This paper proposes a method based on deep learning vehicle feature extraction and threshold comparison method, compared with the characteristics of the traditional artificial design models to identify and clone car identification accuracy. Experimental results show that the proposed identification method in the above clone car only about 0.008 of the rate of false positives in the pseudo clone car design data. Due to the high similarity between some vehicle brands, and the influence of illumination, weather and shelter, it is extremely difficult to identify. The author will do more in-depth research on this problem.

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