A Research on Vehicle Identification based on Deep Learning

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Abstract

In order to confirm the domestic license plate damage, fake brand car and clone car, the vehicle specific information mainly rely on artificial experience for recognition, as well as the vehicle manufacturers to produce more models not effectively identify a problem on issues such as the introduction of models, deep learning theory, puts forward a specific vehicle sub deep learning does not depend on the license plate class identification method based on. Compared with the traditional manual method, this method has the characteristics of automatic learning and can be used in the structure of the convolution neural network can be directly input image and so on. Based on Mxnet depth learning architecture, using InecptionAB-Net model for feature extraction, using Softmax classifier for vehicle classification. The results of experiment showed that the InecptionAB-Net model has a high recognition of vehicle sub class accuracy, fast training speed, has good robustness to illumination changes in the larger image, on different occasions, weather conditions of the vehicle image effectively vehicle recognition.

Keywords

information technology;deep learning;vehicle recognition; clone car recognition; convolutional neural network

1. Introduction

In recent years, with the comprehensive national strength of our country has been increasing, the process of urbanization is also accelerating, the number of motor vehicles continues to increase, urban road traffic pressure continues to increase, traffic accidents occur, such as accident escaping, deck vehicles, License plate and so further exacerbated the difficulty of traffic regulation. Video surveillance has become an important means in the field of modern traffic regulation, monitoring the classification of car models in video images, as an important extension and extension of pattern recognition in the field of intelligent transportation system, which has a very significant effect on intelligent transportation development.

Image recognition is a large branch of computer vision. The early feature extraction of image recognition is mainly done by HOG, SIFT, PCA, LBP and other algorithms in an artificial way. This method is inefficient and the effect is not ideal. In 2006, Hinton's greedy layer-by-layer training algorithm solved the difficulty of deep learning and training, which led to the development of deep learning in the field of research and application development . Convolution neural network (CNNs), as a key technology of deep learning, has been successful in the training of deep neural networks and has been successfully applied in the field of image and speech recognition. The convolution neural network reduces the complexity, generalization ability and recognition efficiency of the network model by using the local receptive field and shared weight method.

At home and abroad in the depth of learning based on the identification of models is still in its infancy. In 2016, Zhang Jun proposed a method based on deep convolution neural network for the specific five models to classify vehicle models, and improve the vehicle recognition rate. In order to solve the problem of vehicle identification in expressway environment, the corresponding feature extraction algorithm is introduced by convolution neural network (CNNs) theory, and the identification system is constructed with SVM classifier. The identification of three types of vehicles on the expressway, cargo and small Test to achieve better results. The above-mentioned depth learning model network structure is relatively simple, only to achieve a specific characteristics of the simple classification of simple models, can not meet the needs of many car subclass classification, practicality is poor.

In this paper, based on the characteristics of the existing sub-categories of automobile manufacturers, the convolution neural network is used to construct the depth learning model, and combined with the Softmax classifier, it can automatically learn the characteristics of different models and then classify the models. The experimental results show that the method proposed in this paper achieves high accuracy in vehicle subclass recognition.

2. Vehicle identification method

2.1 Vehicle identification method to achieve

Based on the depth of learning model sub-class recognition method is divided into two types of vehicle training and identification process, the flow chart shown in Fig.1.

The method steps are as follows:

1) Determine the structure of the convolution neural network depth learning model. Including setting the hierarchy and number in the network, the internal structure in each layer, the size of the convolution kernel, the number of filters and the classifier.

2) Using training data to complete the training of convolution neural network depth learning model. The weight matrix and the offset of each layer in the network model are determined, and the network has been able to extract the characteristics of the vehicle and classify the vehicle.

3) Test the convolution neural network depth learning model. Use the test data to test the trained network model and get the test results.

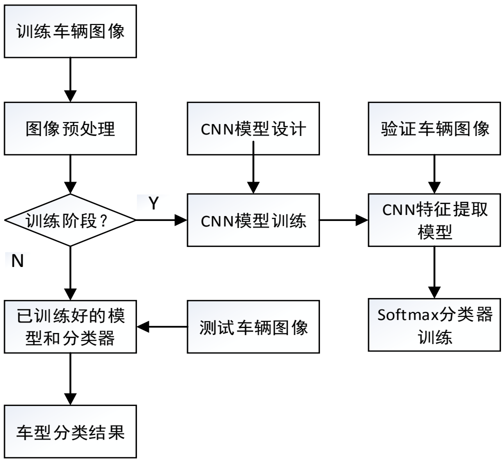

Fig.1 Vehicle identification flow chart

2.2 Convolution neural network depth learning model construction

In this paper, the InecptionB-Net depth learning model adopts a four-stage CNN network for the identification of sub-categories of automobile models. The structure of the network model is shown in Fig.2.

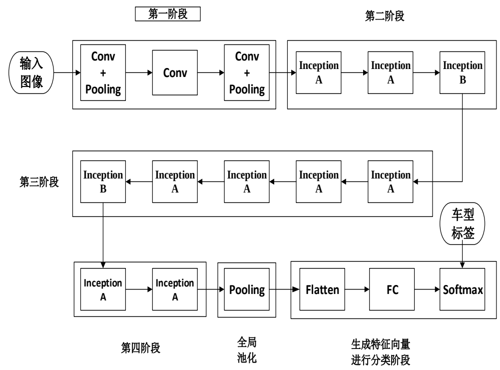

Fig.2 InecptionAB-Net depth learning model

Inception AB-Net is mainly composed of Inception A and Inception B. The convolution layer consists of 13 mixed layers, where the InceptionA structure is shown in Fig. 3, and the steps of all convolution cores in InceptionA are both 1. Inception B structure shown in Figure 4, each of its branch network has a convolution layer of the convolution kernel step length of 2. The convolution kernel of the first convolution layer of the first stage of the InecptionAB-Net model network is 7 ×7, the step size is 2, the effect is to remove the edge of the vehicle image background, the remaining convolution of the mixed layer and pool The convolution nuclei of the layers are 3 ×3 or 1 ×1. The global pooled layer has a convolution kernel size of 7 × 7 and a step size of 1, which is to provide a one-dimensional feature vector for the next stage of the classifier. The feature network structure is the core part of the learning model. The above feature extraction method can realize the full extraction of the characteristics of the car image in order to realize the accurate classification of various subtypes of the vehicle.

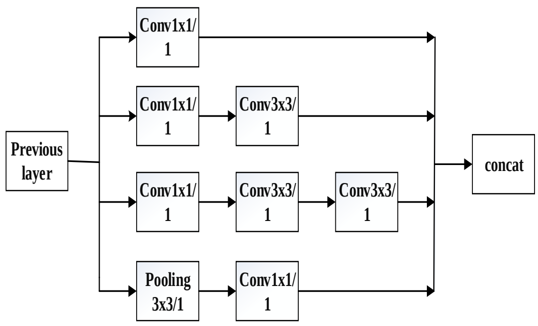

Fig.3 Structure of InceptionA

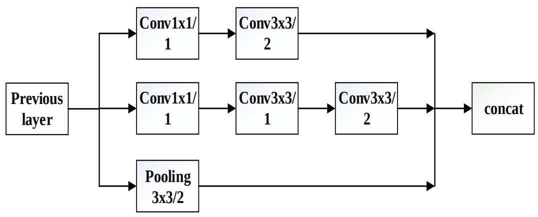

Fig.4 Structure of InceptionB

Table 1. Model network parameters of InceptionAB-Net

Network layer	Convolution core / step size	Number of convolution cores	M1 Convolution number	N1 Convolution number	N2 Convolutional nuclei	P1 Convolution number	P2 Convolution number	P3 Convolution number	Q1 pool type	Q2 Convolution number
convolution	7x7/2	64								
max pool	3x3/2									
convolution	1x1/1	64								
convolution	3x3/1	192								
max pool	3x3/2									
InceptionA			64	64	64	64	96	96	avg	32
InceptionA			64	64	96	64	96	96	avg	64
InceptionB				128	160	64	96	96	max	
InceptionA			224	64	96	96	128	128	avg	128
InceptionA			192	96	128	96	128	128	avg	128
InceptionA			160	128	160	128	160	160	avg	128
InceptionA			96	128	192	160	192	192	avg	128
InceptionB				128	192	192	256	256	max	
InceptionA			352	192	320	160	224	224	avg	128
InceptionA			352	192	320	192	224	224	max	128
avg pool	7x7/1									

Note: InceptionA lines are named M, N, P, Q, each line of the network according to their depth with the number 1, 2, 3 named, then Inception A line specific name: M1, N1, N2, P1, P2 , P3, Q1, Q2, Inception B and Inception A network after the three-line structure is similar, so InceptionB line network specific name: N1, N2, P1, P2, P3, Q1.

The classifier structure shown in Figure 5, the use of Softmax classifier as the method of the classifier, the probability of sub-class to determine the formula for the

$$d_j^{(i)} = \frac{\exp\left(W_j^T x^{(i)} + a_j\right)}{\sum_{j=1}^{223} \exp\left(W_j^T x^{(i)} + a_j\right)} \tag{1}$$

Where W=[W1,W2,…,W222,W223] ∈ Rd × 223, a =[a1, a 2,…, a222, a223] ∈ Rd × 223 is the classifier parameter $d_j^{(i)}$, which is the probability that the classifier corresponds to class j to sample x (i). Get the maximum value of $d_j^{(i)}$, then determine the corresponding vehicle belongs to the j-type sub-category.

Fig.5 Structure of classifier

3. Experiment

3.1 Experimental data set

In order to verify the performance of the convolution neural network depth learning model, the experiment uses the "VehicleID" database as the test object. The database has a total of 38,998 pictures, including 223 different models, each type of vehicle map number distribution shown in Figure 6, part of the model image shown in Figure 7.

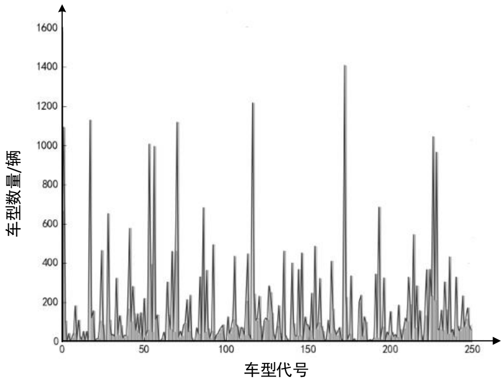

Fig.6 Vehicle data distribution diagram

Fig.7 Part of the vehicle sample

Seventy percent of the images used to train the network, 20 percent as a verification of online training, and the remaining 10 percent for testing.

The image of the vehicle is normalized to 224 * 224, the picture is compressed and entered into the network. Taking into account the reality of the problem of vehicle mirroring, so the network training before the start of data enhancement processing that is left and right mirror, which at the same time make the training data doubled.

3.2 Experimental platform

This experiment in the Intel i3-6100 3.7G + Mxnet + CUDA8.0 + NVIDIA GTX1070 (GPU), 16G memory windows10 platform. Which Mxnet depth learning architecture compared to Caffe has a fast computing speed, support stand-alone multi-GPU, multi-machine distributed, GPU memory consumption and so on.

4. Experimental results and analysis

The experiment contains 38,998 vehicles in the actual intersection of vehicles, there are 223 brands of sub-categories of vehicles, and each picture of the license plate parts all occlusion, only through the vehicle's other attributes for vehicle identification. Before you use InecptionAB-Net to extract image features, convert all the images in the dataset to grayscale images. In order to show the experimental results of this algorithm, we use GoogleNet algorithm and VGG19 algorithm as a contrast. Select one of the models as an example, showing the characteristics of each stage, as shown in Figure 8.This experiment in the Intel i3-6100 3.7G + Mxnet + CUDA8.0 + NVIDIA GTX1070 (GPU), 16G memory windows10 platform. Which Mxnet depth learning architecture compared to Caffe has a fast computing speed, support stand-alone multi-GPU, multi-machine distributed, GPU memory consumption and so on.

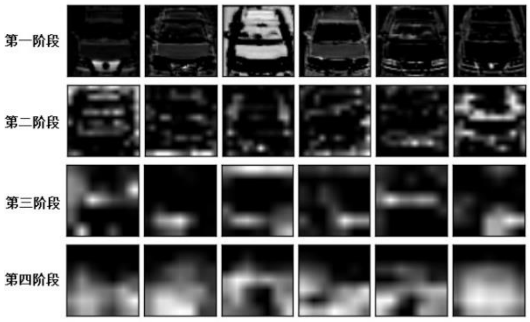

Fig.8 Vehicle feature map

The number of iterations and convergence of the algorithm As shown in Figure 9, the InecptionAB-Net algorithm converges the fastest and the iteration reaches 12 times, and GoogleNet and VGG19 need to iterate at least 40 times to achieve stable Convergence effect, we can see InecptionAB-Net algorithm convergence speed of the best.

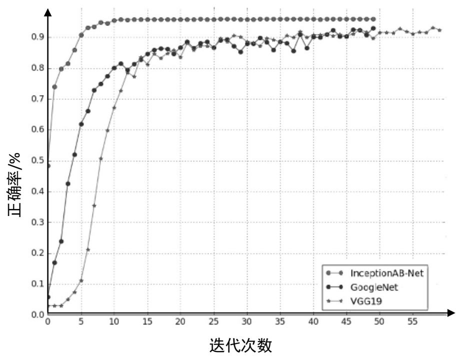

Fig.9 The convergence rate of different algorithms

Use the test set (about 3901 photos) to test the network of the above training, the network model after the test the correct rate shown in Table 2. It can be seen from Table 2 that the InecptionAB-Net algorithm proposed in this paper is higher than the VGG19 and GoogleNet in the correctness of the verification set and the test set, and the accuracy rate is better in the subclass recognition. From the results of the identification of errors found that the main reason leading to the wrong classification is because some manufacturers produce different types of car shape is very similar, coupled with other factors of image shooting interference, bringing a greater difficulty in identification.

Table 2. The accuracy of different algorithms

Network structure	InecptionAB-Net	VGG19	GoogleNet
Verification set correct rate /%	95.97	92.41	92.29
Test set correct rate /%	96.01	92.45	92.31

5. Concluding remark

This paper presents a convolution neural network model for subclass recognition based on depth learning. The convolution neural network is used to construct the model, which makes the model can learn the characteristics of the model independently, which avoids the shortcomings of the traditional image recognition and the extraction of the feature efficiency. In this paper, the structure, network layer and convolution kernel size of InecptionB-Net depth learning model are introduced and explained in detail. And the model parameters training and vehicle identification test were carried out by using the "VehicleID" data set. The experimental images were from reality and the license plate parts of each picture were obscured. The data set contained different weather, environment and light Image. InecptionAB-Net algorithm has the best convergence rate, which can reduce the number of iterations by 75% for GoogleNet and VGG19. InecptionAB-Net algorithm achieves 96.01% accuracy in test set, better than GoogleNet and VGG19. Experiments show that the InecptionAB-Net algorithm proposed in this paper is applied to the classification accuracy of the model subclass, which is very good for the noise such as illumination change, and has certain value and significance.

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