Research on Chinese License Plate Recognition Algorithm Based on Convolution Neural Network

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Abstract. As an important part of intelligent traffic management, license plate recognition has very important research value. In order to solve the problem that the location of traditional license plate detection methods is not accurate and the detection results are easily affected by the environment, this paper proposes a license plate detection algorithm based on Faster R-CNN and Inception ResNet_v2, which realizes accurate license plate detection on VOC license plate data set by means of transfer learning. The effective extraction of a single character is realized by using the pixel statistics method in the detection results, and then the mLeNet5 convolution neural network model is designed to recognize the single character. The experimental results show that the algorithm can achieve efficient and accurate recognition of license plate characters with occlusion and angle tilt.

Keywords: Convolution neural network, license plate detection, character recognition.

1. Introduction
As the only "identity" mark of a vehicle, the license plate number can obtain the type, source, driving record and driver information of the vehicle through the license plate. High-quality license plate recognition system can provide fast, efficient, scientific, safe and high-quality management services for various occasions. In terms of technology, license plate location mainly includes license plate location algorithm based on texture feature [1], color location method based on HSV model [2], location technology based on morphology [3-4], license plate location algorithm based on wavelet transform [5] [6], location method based on machine learning algorithm [7], location algorithm based on neural network and so on. Among them, the color location method is not conducive to deal with the images with similar color of car body and license plate and color distortion of license plate, while the location algorithm based on texture feature analysis and morphology is easily affected by illumination, viewing angle, background environment and distance. although dyadic wavelet transform improves the accuracy, the algorithm is too complex.

The license plate character segmentation part mainly includes the character segmentation algorithm based on vertical projection, the character segmentation algorithm based on template matching and the character segmentation algorithm based on clustering. The character recognition part is mainly based on optics and vision, including the recognition algorithms based on template matching, such as Euler number template matching, BP neural network joint template matching, etc.; the recognition algorithm based on feature statistical matching has double edge features and SIFT features for contour features,
but this kind of algorithm is not conducive to distinguish characters with high similarity. Although the character recognition algorithm optimized by machine learning algorithm, Bayesian classifier or support vector machine SVM algorithm has good performance under specific conditions, it needs a lot of training data to extract features, and the performance is unstable. In recent years, the character recognition method based on convolution neural network has good performance in recognition rate and recognition performance, and derives many deformations and improved algorithms.

In order to improve the license plate recognition rate in all kinds of samples, this paper proposes a license plate detection algorithm based on Faster R-CNN+Inception ResNet_v2 model and a character recognition algorithm based on mLeNet5 network, which can realize accurate character recognition while effectively monitoring license plate.

2. License Plate Detection based on Faster R-CNN+Inception ResNet_v2

In the process of license plate recognition, the vehicle photo contains various image blocks with different features, and the license plate is one of them. It is necessary to separate the target of the license plate from the background for subsequent processing.

In this paper, the Faster R-CNN+Inception ResNet_v2 model is used for transfer learning. The data sets used in the training model are photos collected in various complex environments, marked by hand, and made into VOC data sets.

Faster R-CNN+Inception ResNet_v2 model, using the overall architecture of Faster R-CNN, integrates Inception ResNet_v2 network for feature extraction and final classification and regression.

The network structure of the Faster R-CNN model is shown in figure 1. The original image is first inputted into CNN for feature extraction, and the output feature map is divided into two parts shared by the RPN layer and the RoI Pooling layer. One part of the feature map gets multiple candidate boxes through the RPN layer, and then the candidate frame is projected onto the other part of the feature map to input the RoI Pooling layer for MaxPooling operation. The output fixed-size RoI feature map is used as the input of the subsequent full connection layer for classification and regression. Finally, according to the NMS algorithm, the Bounding-box, is screened to find the best location and the corresponding classification probability.

![Figure 1 Faster R-CNN model structure diagram](image)

ResNet (Residual Neural Network) introduces residual learning unit (Residual Unit) to further improve the level of image classification, which is a relatively complex CNN. After introducing the residual learning unit, the initial input information can be transmitted to the following layer. Assuming that the input $x$ passes through the network, the output without residual calculation should be $F(x)$, and the output is $H(x) = F(x) - x$, which is the residual. Figure 2 shows this process. In the original paper, it is rewritten as $H(x) = F(x) + x$, which is equivalent to changing the output of the network and avoiding the decrease of the accuracy of non-over-fitting factors caused by the deepening of network layers. It is important to note that the difference between output and input needs to be calculated, so the dimensions of input and output should be the same. In ResNet V 2, the residual learning units in each layer of the network use normalization processing.
The structure of the Inception ResNet V2 modular network is shown in figure 3. The network combines the connection of the residual connection (Residual Connections) alternative filter introduced by the slightly soft ResNet2, on the basis of Inception V3, which accelerates the convergence of the network and significantly improves the initial training speed.

3. License Plate character Segmentation based on Pixel Statistics
First unify the size of the license plate picture, and then preprocess the image to distinguish the character from the background as clearly as possible. Graying improves the contrast of the image, selectively suppresses the unwanted features in the image or highlights the needed features. The binarization of Otsu threshold makes the image obviously black and white, which is helpful for the target outline to be more obvious in the background image. At the same time, the amount of data of the image becomes smaller, which makes the subsequent processing simpler.
Secondly, the binary image is optimized. In order to prevent the last character of the license plate from being cut, the left frame is added, and then a certain range of noise points are selected and removed according to the number of black and white pixels. The effect is shown in figure 4.

Finally, the license plate characters are cut through the black-and-white pixel distribution of the image series, and the structure of the algorithm is shown in figure 5.

**Figure 5** Result diagram of license plate segmentation algorithm

### 4. License Plate character recognition based on mLeNet5

Through the improved LeNet5 network to recognize license plate characters, as shown in figure 6, the mLeNet5 network designed in this paper uses all-zero filling, and the number of convolution cores in C1 layer is increased to 32, and the number of convolution cores in C3 layer is increased to 64, so that more license plate character features can be extracted. At the same time, the number of C5 convolution cores is reduced to 64, and the input vector data of full connection layer is reduced. All the lower sampling layers use maximum pooling, adding S6 pooling layer, reducing the amount of data and parameters, and further extracting high-dimensional statistical features. Using ReLU activation function instead of tanh activation function in LeNet5 model is more beneficial to license plate character recognition. The license plate character data is a single-channel image with a width of 32 and a height of 40, so the number of neurons in the input layer is modified to 1280. And the license plate characters involved in this paper contain 10 numbers, 24 letters (excluding I and O in 26 letters) and 7 Chinese characters (due to the limitations in the process of data acquisition, 7 representative Chinese characters are selected here), a total of 41 categories. Therefore, the number of neurons in the output layer is changed to . At the same time, the number of neurons in full connection layer 1 is increased from 120 to 512 in order to obtain more features and improve the performance of the network in multi-class character classification.

**Figure 6** MLeNet5 network structure diagram

The training data is a character picture enhanced by angle offset, left and right offset and upper and lower offset. In order to approach the original ratio, the size is $32 \times 40$, exponential attenuation learning rate is used in training, and L2 regularization and DropOut are added to prevent over-fitting. The network is optimized by back propagation and gradient descent, and with the help of the moving average model, abnormal data and data noise are reduced, making the network model more robust in the test data.
5. Experimental results and analysis

5.1. License plate detection and location
The hardware and software platform of the experiment is as follows: the system is Window10 x86, the deep learning framework is TensorFlow-GPU1.13.1,32G memory, 16g video memory, GeForce GTX 1080 graphics card. The experimental data were taken by mobile phone and downloaded from the Internet, a total of 1200 pictures, including pictures of vehicles in various complex environments (for example, night, strong light, uneven lighting, rainy days, multi-car environment). Pictures of vehicles with different combinations of different colors and license plates, as well as photos of vehicles with varying degrees of tilt, are compared as shown in Table 1.

| Model                              | Training data quantity | Number of training steps | Average accuracy |
|------------------------------------|------------------------|--------------------------|-----------------|
| faster_rcnn_inception_v2(1)        | 400                    | 200000                   | 0.973           |
| faster_rcnn_inception_v2(2)        | 1000                   | 200000                   | 0.993           |
| Faster R-CNN+Inception ResNet_v2   | 1000                   | 70000                    | 0.996           |

It can be seen from Table 1 that the algorithm used in this paper can reduce the time consumption of training and achieve higher accuracy through fewer training steps in the case of the same training set.

5.2. License plate character recognition
The test data cover characters under normal, tilt and occlusion conditions, including 10 numbers (including the numbers of new energy license plates), 24 letters (excluding I and O in 26 letters) and 7 Chinese characters (due to limitations in the process of data collection, seven representative Chinese characters are selected here), the size is 32 × 40, and some samples are shown in figure 7.

![Test picture sample](image)

Figure 7 Test picture sample
Using the above data, LeNet5 and network mLeNet5 networks are tested respectively. The average accuracy of LeNet5 network is 0.94, while that of mLeNet5 network is 0.97. The performance is significantly improved. The comparison between networks is shown in figure 13.

![Comparison of Networks](image)

**Figure 8** The accuracy of license plate characters
6. Conclusions
In this paper, the model obtained by migrating and learning on the VOC license plate data set can detect and locate the license plate efficiently and accurately in a complex environment. For all kinds of color license plate, as well as a small amount of delay and frame noise, the character segmentation method in this paper has achieved good results. And the designed character recognition network model can recognize noisy, occluded, slightly inclined license plate character pictures and new energy license plate character pictures.

However, the license plate character segmentation algorithm requires high image quality, and the segmentation result is not ideal in the case of uneven illumination, and there is no tilt correction for the license plate image with large tilt. At present, the data set of character recognition training in the experiment is relatively small, and the subsequent expansion of the coverage and number of data sets will achieve better results. At the same time, the training speed of the network needs to be improved.

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