

License Plate Recognition via Deep Convolutional Neural Network

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Abstract. With the development of society, road vehicles have increased. Manual identification of license plates is tricky and the real-time efficiency is far less rapid than computer processing. The traditional license plate recognition technology mainly relies on the morphological processing of images. In the harsh environment, e.g. the license plate is blurred, etc.; the recognition rate is significantly reduced. In order to solve this problem of license plate recognition, we propose a new license plate recognition method. In the license plate location, we use the traditional positioning method and support vector machine (SVM) algorithm to locate the license plate. Compared with the traditional identification method—cutting and matching, we use the capability of feature extraction of convolution neural network (CNN) to identify the whole license plate directly, which could avoid the subsequent recognition error caused by the segmentation in the license plate recognition. The experimental results show that the proposed method achieves an accuracy of more than 99% in the license plate location. In the character recognition, it achieved 97.8% accuracy. The overall recognition rate is above 97%. Compared with the traditional method, our proposed method has a superior performance.

1. Introduction

License plate recognition is one of the important components of modern intelligent transportation systems, and it is widely used. Based on digital image processing[1], pattern recognition, computer vision and other technologies, the vehicle image or video sequence will be analyzed to obtain the unique license plate number of each car. Through some subsequent processing methods, it can handle parking lot charge management, traffic flow control index measurement, vehicle positioning, automobile anti-theft measures, highway speeding supervision, red light enforcement, highway tolling and so on. It is of practical significance to maintain traffic safety and urban security, prevent traffic jams, and realize automatic traffic management.

In this paper, we propose a new license plate recognition method, and the flowchart of the whole system is shown in Fig.1. It is mainly divided into two parts, one is the license plate positioning, and the other is the character recognition. The license plate positioning is combined with the traditional technology and the SVM [2]. In the character recognition, the CNN[3] is used to extract the license plate information, and a recognition model is trained for each license plate character. The accuracy of the experimental results is significantly improved compared with the traditional recognition algorithm. We will start from the following aspects. First, the traditional method will be recommended in Section3.1 (see Fig.2) and we will introduce our improvements to the traditional method. Then, how does this



network work will be explained in Section 3.2, the training network will automatically adjust according to the training results. Finally, the trained model is used for prediction. Through experiments, the proposed method has better robustness and higher accuracy on the same data set.

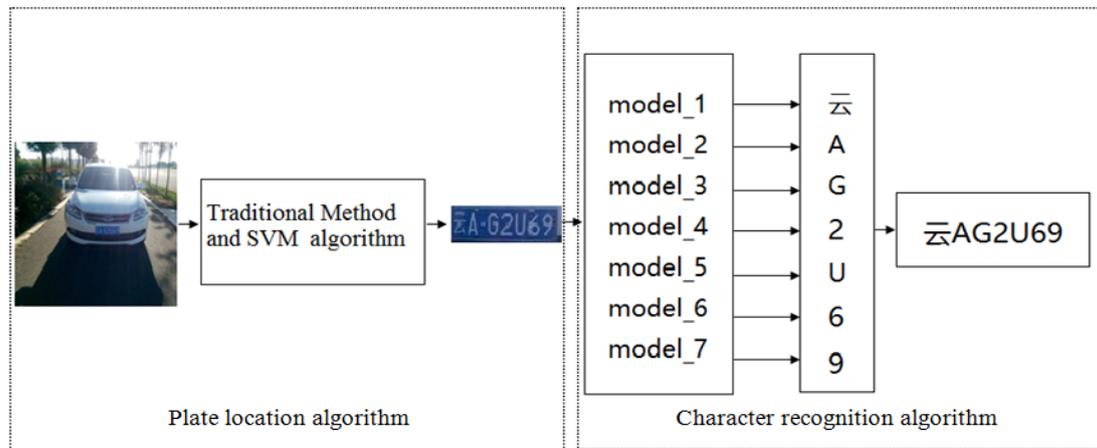


Fig.1 System architecture

2. Related work

With the rise of deep learning, the SVM algorithm and convolution neural networks have been greatly developed. The SVM algorithm is a supervised algorithm and a binary classification algorithm (which can also be used for multi-classification after transformation). It has obvious advantages in nonlinear classification; its principle is to draw data in n -dimensional space (n represents the number of features of the data), and then to find the hyperplane that can divide the data into two categories. There are only two types of license plates and non-license plates in the positioning license plate, it is possible to use the SVM algorithm to achieve the classification effect.

In recent years, CNN continues to influence multiple directions, and has made breakthroughs in speech recognition, facial recognition, general object recognition, motion analysis, natural language processing, and even brain wave analysis. The difference between CNN and ordinary neural networks is that the CNN contains a feature extractor composed of a convolution layer and a sub-sampling layer. In the convolution layer of a CNN, one neuron is only connected to a portion of the adjacent layer neurons. In a convolution layer of a CNN, there are usually several feature planes [4] (Feature Map). Each feature plane consists of a number of rectangularly arranged neurons. The neurons of the same feature plane share weights, and the weights shared here. The value is the convolution kernel. Convolution kernels are generally initialized in the form of a random fractional matrix. During the training of the network, the convolution kernel will learn to obtain reasonable weights. The direct benefit of shared weights (convolution cores) is the reduction of connections between layers of the network while reducing the risk of overfitting. Sub-sampling is also called pooling [5] (pooling), which usually has two forms of mean sub-sampling (mean pooling) and maximum sub-sampling (max pooling). In this paper, the maximum sub-sampling is used as the pooling layer. Sub-sampling can be seen as a special convolution process. Convolution and sub-sampling greatly simplify the model complexity and reduce the parameters of the model. Wen-Min L[6] introduced the image acquisition and license plate location in vehicle license plate recognition system, the positioning accuracy is achieved 96.4%. Wang L et al[7] used the set of step-change pixels in the grayscale of the surrounding pixels in the image to detect the license plate, in the plate recognition, the author divides the extracted license plates and they use the SVM to classify the segmented characters. Its overall recognition rate is around 95%. In this paper, we develop the method of combining traditional positioning and SVM in the positioning stage, the positioning accuracy rate achieved 99%. At the character recognition, the character recognition rate achieved 97.1%, and the overall recognition rate was 95%. The results showed that the new scheme of license plate detection proposed in this paper is effective.

3. License plate recognition algorithm

The traditional license plate recognition process is to first obtain the candidate license plate by image processing, and then traverses each candidate area again, this method can easily cause the wrong positioning of the license plate, and the SVM classification training can be better to filter out the real license plate. In the character recognition, the CNN is used to directly output a plurality of tags by using a multi-tag classification method to identify the license plate.

3.1 License plate location algorithm

The traditional positioning algorithm is shown in Fig.2.

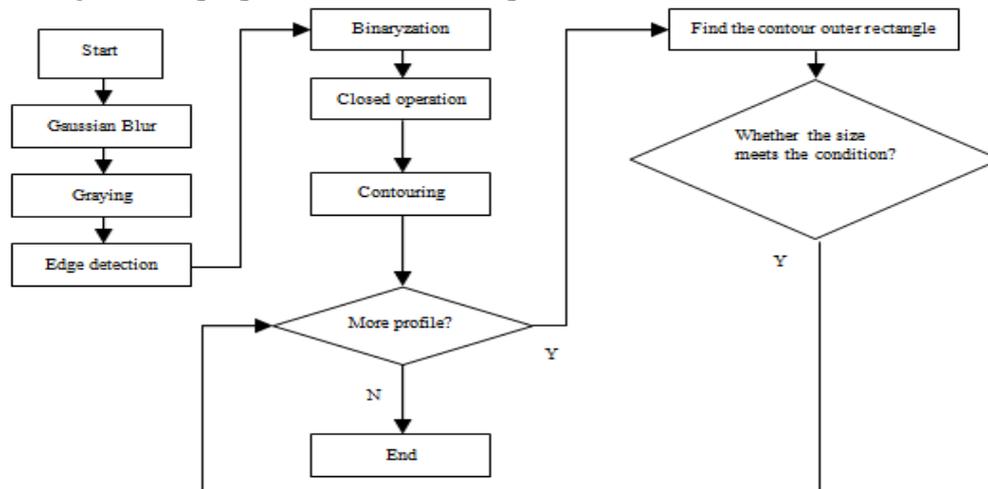


Fig.2 License plate location process

Fig.2 show that the flow of the traditional positioning algorithm. First, the original image is processed by gaussian blur. The function of this step is to remove the noise of the interference for the next sober operator [8]. Next, the image is greyed out and the sober operation is performed on the image to obtain the first-order horizontal direction of the image. Convert greyscale images (256 pixels per pixel possible) into binary images (only 1 and 0 are possible for each pixel); finally, all the graphs outline will be found by using closed operation. This algorithm will calculate the outline of the whole graph; the purpose is to find the minimum bounding rectangle for the contour and verify that the condition is not met. The license plate location effect diagram is shown in Fig.3.



Fig.3 The candidate license plate

As shown in Figure 3, the traditional positioning method will select many non-license plate areas. So in this paper, the SVM module is added to select the license plate from the candidate locations, as shown in Fig.4.

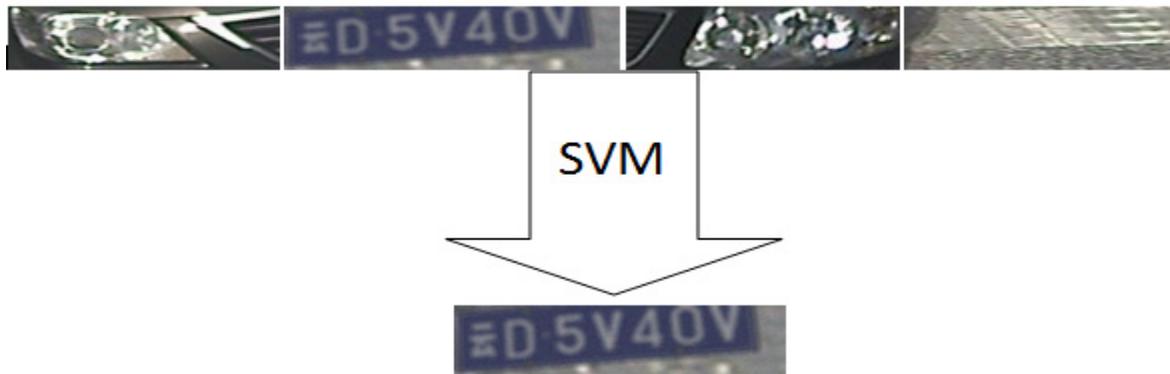


Fig.4 Candidate license plates classify by SVM

The original information input at the beginning of the SVM model is also all the pixels of the image. Then the SVM model analyzes these pixels to output whether the image is a license plate. Next, we will introduce how to obtain the candidate license plate through SVM training.

3.1.1 SVM training

The goal of the SVM training section is to pass a batch of data and then generate a model which contains license plate feature weight. The training process is shown in Fig.5.

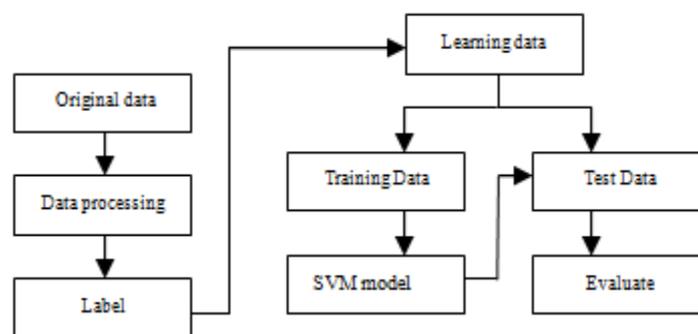


Fig.5 SVM training process

This paper randomly generates 1000 pictures containing various license plates and 1000 pieces of information without license plate information and we will select 100 samples from the dataset of the license plate and non-license plate above as the testing set, all that remains as a training set, the experiment was completed in an environment with Inter(R) Core(TM) i5-3337U CPU@1.80GHz processor, 8GB RAM, 64-bit operating system, python3 environment. The positioning accuracy comparison table is shown in **Table 1** below.

Table 1. Positioning accuracy comparison.

Method	Positioning accuracy (100%)
Traditional method	94.6%
Double-edge detection	95.7%
Our work	99%

3.2 Character recognition algorithm

The CNN model, as one of the most successful deep learning models applied in the field of image recognition, it can automatically learn discriminative pattern features from a large amount of data. When the amount of data used is relatively large, the recognition accuracy of this scheme is close to human

eyes. Therefore, we apply it to the license plate character recognition and adapt to the network structure, and the method achieved a good recognition rate.

3.2.1 Network structure

The CNN structure of the text at the character recognition part is shown in Fig.6.

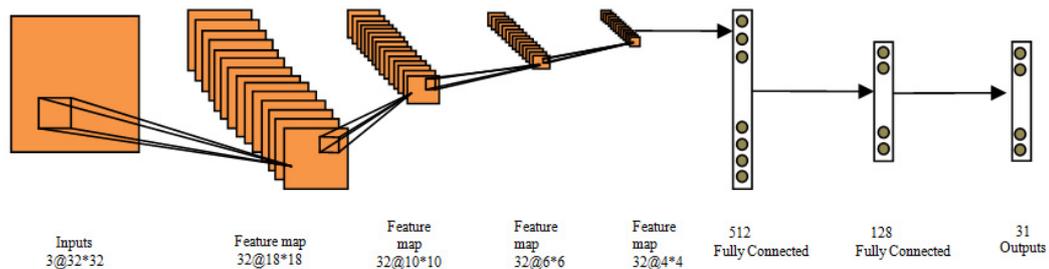


Fig.6 The structure of CNN

As shown in Fig.6, the network consists of four convolution layers, four pooling layers, two fully connected layers, and one output layer. The input is an image that size of $32 \times 32 \times 3$. After a convolution layer with a convolution kernel size of 5×5 and a Max-pooling layer, a set of feature map is obtained. Each of the two feature map passes through a convolution layer and a Max-pooling layer. Using LeakyReLU [9] as the activation function, the loss function is “categorical_crossentropy [10]”, there is a Dropout (rate=0.5) [11] layer in the network before the output layer. Using Adam (lr=0.0001) [12] as the optimizer, and softmax [13] as an output function.

3.2.2 Data preparation and training

The experimental data uses 1000 image data with license plates generated in 3.1.1, as shown in Fig.7 below. Since China's license plate is composed of seven characters, the first one is Chinese characters, and there are 31 categories in total. Then each Chinese character is sequentially numbered from 0 to make the data label of the first character. The other six digits are composed of numbers and letters, with 24 uppercase letters (with O and I removed) and 10 numbers. Then a label has 34 classes. In this way, the data label of each license plate is made separately. The ratio of the training set and the test set is 9:1, and a total of 40 epochs are trained. This training takes a total of 33 hours. The data is imported into the network of the above design in turn, and a prediction model for predicting each bit of the license plate will be generated. The experiment is performed on a processor with Inter(R) Core(TM) i5-3337U CPU@1.80GHz, 8GB memory, 64-bit operating system, python3 environment.



Fig.7 Character recognition training data

3.2.3 Analysis of results

The training results are shown in Fig.8. The abscissa indicates the number of training process and the ordinate indicates the training accuracy. Since China's license plate is composed of seven characters, as shown in the following figure, "Training frist_acc" indicates the accuracy of the first digit of the license plate character; "Training second_acc" indicates the training accuracy of the second license plate, and so on. The seven curves represent the training precision of each bit character. Finally, we obtain the trained model for each character. It can be seen that the prediction accuracy of the first five characters is over 95%, and the accuracy of the last two digits is also above 90%. Compared with the method of license plate recognition of literature [6] and [7], the proposed scheme has a good effect, and the accuracy is obviously improved.

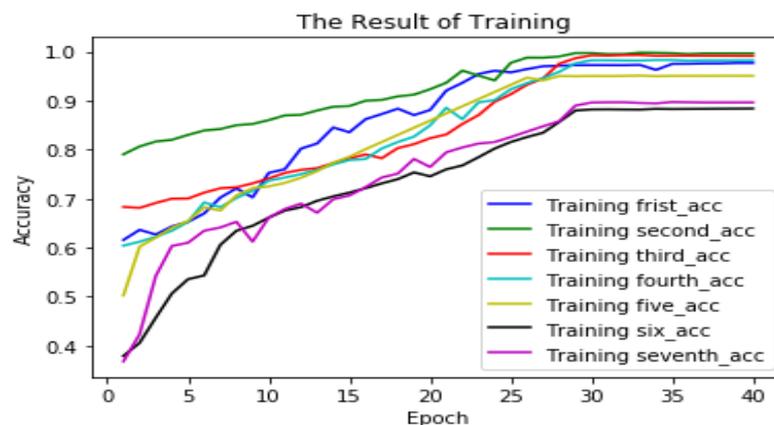


Fig.8 The results of training

4. Conclusion

In this paper, we propose two main improvements of the traditional license plate recognition network. At the license plate location, we use the method that combination of SVM algorithm and traditional positioning algorithm to screen out the tiles most likely to contain license plates, which greatly reduces the probability of positioning of the license plate error. At the same time, in the character recognition, we

propose to use the CNN model to directly identify the whole license plate, and avoid the recognition error caused by the segmentation. Experiments show the method of this paper that effect is obvious.

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References

- [1] Gonzalez R C, Wintz P. Digital image processing[J]. Prentice Hall International, 2008, 28(4):484 - 486.
- [2] Khan M A, Sharif M, Javed M Y, et al. License number plate recognition system using entropy-based features selection approach with SVM[J]. Iet Image Processing, 2018, 12(2):200-209.
- [3] Yang Y, Li D, Duan Z. Chinese vehicle license plate recognition using kernel-based extreme learning machine with deep convolutional features[J]. Iet Intelligent Transport Systems, 2018, 12(3):213-219.
- [4] Zou J, Rui T, Zhou Y, et al. Convolutional neural network simplification via feature map pruning ☆ [J]. Computers & Electrical Engineering, 2018.
- [5] Toliás G, Sicre R, Jégou H. Particular object retrieval with integral max-pooling of CNN activations[J]. Computer Science, 2015.
- [6] Wen-Min L. Research on Image Acquisition and License Plate Location in Vehicle License Plate Recognition System[J]. Computer & Modernization, 2009.
- [7] Wang L, Wang H, Lianghua H E. License plate recognition based on double-edge detection[J]. Computer Engineering & Applications, 2013.
- [8] Yuan C L, Xiong Z L, Zhou X H, et al. Study of Infrared Image Edge Detection Based on Sobel Operator[J]. Laser & Infrared, 2009.
- [9] Xu B, Wang N, Chen T, et al. Empirical Evaluation of Rectified Activations in Convolutional Network[J]. Computer Science, 2015.
- [10] Peng H, Long F, Ding C. Feature Selection Based on Mutual Information: Criteria of Max-Dependency, Max-Relevance, and Min-Redundancy[M]. IEEE Computer Society, 2005.
- [11] Srivastava N, Hinton G, Krizhevsky A, et al. Dropout: a simple way to prevent neural networks from overfitting[J]. Journal of Machine Learning Research, 2014, 15(1):1929-1958.
- [12] Kingma D, Ba J. Adam: A Method for Stochastic Optimization[J]. Computer Science, 2014.
- [13] Elfwing S, Uchibe E, Doya K. Sigmoid-weighted linear units for neural network function approximation in reinforcement learning[J]. Neural Netw, 2018.