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Article *in* Proceedings of the Institution of Mechanical Engineers Part D Journal of Automobile Engineering · August 2019

DOI: 10.1177/0954407019851339

Liu Ze
Jiangsu University

Hai Wang
Jiangsu University

Special issue article

Institution of MECHANICAL ENGINEERS

Journal of AUTOMOBILE ENGINEERING

Proc IMechE Part D:
J Automobile Engineering
2019, Vol. 233(9) 2284–2292

DOI: 10.1177/0954407019851339
journals.sagepub.com/home/pid
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Vehicle license plate recognition method based on deep convolution network in complex road scene

Ze Liu, Yingfeng Cai, Long Chen, Hai Wang and Youguo He

Abstract

The license plate robust recognition algorithm in complex road scene has both theoretical and practical values. The existing license plate recognition algorithm can achieve better recognition results under ideal road scenes such as moderate light intensity, good shooting angle, and clear license plate target, but in complex road scenes such as fast speed, blurred aging of license plates, and low illumination such as rainy days, the effectiveness of the license plate recognition algorithm still needs to be improved. Based on the realistic requirements of license plate recognition algorithm and in-depth analysis of the principle of deep convolution network, we designed a deep convolution network for Chinese characters, letters, and numbers in the license plate to automatically learn the essential features of the image to make up for the limitation of the artificial feature recognition of the traditional license plate recognition algorithm. At the same time, according to the convolution kernel, downsampling, and nonlinear operation of the deep convolution network, the nonlinear abstraction ability of the license plate character feature is improved. The experimental results show that the proposed method can quickly and accurately identify the license plate character in complex road scenes. The recognition accuracy is better than the existing license plate recognition algorithm, which improves the accuracy of license plate recognition and achieves an ideal license plate recognition effect.

Keywords

Digital image processing, deep convolutional network, license plate recognition algorithm, character recognition

Date received: 31 January 2019; accepted: 25 April 2019

Introduction

The intelligent transportation system integrates cutting-edge technologies such as image processing, information communication, artificial intelligence, and pattern recognition, and can effectively implement the system science of intelligent management of vehicles, drivers, and roads. License plate recognition technology is an important part of intelligent transportation system.[1–3] The study of computer technology applied to license plate recognition systems by foreign scholars began in the 1980s. At that time, the computer hardware conditions were very backward. The research on the license plate recognition algorithm can only stay on a certain function module of the identification system or an algorithm in the improved function module. After the 1990s, with the continuous improvement of camera technology and the rapid development of computer hardware, computer vision and artificial intelligence technology also received more attention. More and more researchers have begun research on license plate recognition–related topics and have achieved remarkable research results.[4,5] At the same time, the domestic research on the license plate recognition system has also begun, and related supporting products have been developed. In recent years, license plate recognition technology has been widely used to collect illegal information, manage parking spaces, and collect toll parking charges. In addition, as one of the legal identification of vehicles, the license plate is combined with Internet communication technology. In the future, in the application of vehicle networking, the license plate recognition technology can realize the interconnection of

Institute of Automotive Engineering, School of Automotive and Traffic Engineering, Jiangsu University, Zhenjiang, China

Corresponding author:
Yingfeng Cai, Institute of Automotive Engineering, School of Automotive and Traffic Engineering, Jiangsu University, 301 Xuefu Road, Zhenjiang 212013, China.
Email: caicaixiao0304@126.com

vehicles, increase the communication between owners, and increase the driving pleasure.

The license plate recognition technology has penetrated into many fields, and its broad development prospects have long been favored by many researchers. The license plate recognition technology can detect the vehicles on the road under the premise of saving manpower and material resources. In the past, license plate registrations for road vehicle management and parking lot management were done by hand. Although this has a very high accuracy rate, the work efficiency is very low. When it is difficult to get the job done when the traffic volume is large, it is not enough to rely on manpower to handle the traffic control. Computer vision and artificial intelligence technology have also got widespread attention. It has become possible to apply these cutting-edge technologies to the field of traffic management. License plate character recognition is to compare the characters in the image with the known character categories and identify what characters each character is. This is the most important step of the entire license plate recognition algorithm. Different from general character recognition, since the fonts recognized by the license plate characters are all uniform prints, the number of character recognitions is constant. But the identification of similar characters, such as the Arabic number "6" and the capital letter "G," will give us an algorithmic challenge. In addition, factors such as the license plate being too small in the whole picture will increase the missed detection rate and false detection rate of the license plate recognition. The complex road scene in license plate recognition refers to the large traffic volume leading to license plate occlusion, the light intensity of the license plate image caused by factors such as rainy days or strong direct light is too large or too small, and the license plate character recognition caused by license plate posture, body color, and so on. Ideally, if the light intensity is moderate and the license plate position is ideal, the license plate recognition is called a simple road scene.

The rest of the work is arranged as follows. In the "Related work" section, we provide an overview of related work. In the "Methodology" section, we derive our algorithms. First, we discuss convolution layer learning, downsampling layer learning, and fully connected layer learning. Subsequently, we present our robust license plate recognition method based on deep convolution network. In the "Results" section, we discuss our results and finally give a summary.

Related work

At present, common license plate character recognition algorithms are generally divided into feature statistics–based recognition algorithms, template matching–based recognition algorithms, and machine learning–based recognition algorithms. The character recognition algorithm based on template matching is a classic character recognition algorithm in the field of license plate character recognition.[6,7] This method first builds a standard template library of license plate characters. For license plate recognition, its template library contains 32 Chinese characters, 10 Arabic numerals, and 24 uppercase English letters. Matching the normalized character image to be recognized with each character template is based on the logical operation of the corresponding pixel. By calculating the similarity between the two, the template with the largest similarity is the output. The license plate character recognition algorithm for template matching has the advantages of convenient operation, simple implementation, and small calculation amount. However, since the template matching method attempts to express by the template and structure of the character, the recognition accuracy depends on the accuracy of the license plate location. In the actual experiment, it is verified that the anti-interference of the algorithm is poor, and the recognition effect of character deformation, unclear characters, and noise interference is not ideal. The license plate character recognition algorithm based on feature statistics is also widely used.[8–10] It is a statistically based classification method that does not require precise positioning of the license plate and allows for a wider range of recognition than a template-based matching method. For the segmented characters, the characteristics of the characters, such as network features, texture features, histogram features, and so on, are judged, and then some of the extracted features are trained, thereby classifying the characters. The weakness of this approach is that it relies on the expression of character features and the "learning-training" approach. The recognition algorithm based on machine learning has the advantages of fast recognition speed, accurate classification, and strong anti-interference.[5,11,12] Among them, the support vector machine and Adaboost method are the two most classic classification methods. By training a large number of samples of Chinese characters, English letters, and numbers, the classifier learns the mapping relationship between input and output to perform character recognition. A good license plate recognition algorithm should have a high image essential feature expression, and is robust to shape, size, occlusion, noise, illumination, and the like. However, the traditional manual selection of machine learning can only take into account a specific feature such as illumination and the feature expression ability is not perfect.

Deep learning is an important branch of machine learning. It is a data-driven algorithm that combines feature extraction and classification.[13,14] Deep convolutional networks have the advantages of parallel data processing, self-learning, and fault tolerance, and have been widely concerned by researchers in recent years.[15] The rapid development of deep learning, designing, and improving the deep convolutional network structure and applying appropriate training algorithms make it suitable for China's license plate character recognition to have important research value. Improving the accuracy of the license plate recognition algorithm and speeding up the operation are of great significance for the research of license plate recognition.

Methodology

In 1989, the famous American scholar LeCun proposed a convolutional neural network learning structure model by simulating the human brain hierarchical structure.[16,17] Subsequently, the convolutional neural network was applied to handwriting recognition and achieved remarkable results, which set off a research boom of neural networks. The classifiers based on convolutional neural networks belong to the shallow learning category, and the convolutional neural networks use single-scale neural networks or improved multi-scale convolutional neural networks. The improved method is based on the single-scale convolutional neural network. The multi-scale convolutional neural network adds a downsampling layer, so that the input has more features and more scales. Convolutional neural networks combine local connections, weight sharing, and spatial downsampling. This not only greatly reduces the training parameters of the network but also makes the learned features remain invariant to the translation, scaling, and distortion of the input samples, thereby improving the robustness of the classification. In 2012, image processing expert Alex Krizhevsky et al.[18] proposed a deep convolutional network structure. The deep convolutional network is an extension of the convolutional neural network.[19–20] It directly takes the image pixels as input, compared to a convolutional neural network with only multi-layer neural networks. It has several hidden layers, feature results, and a convolutional neural network with training methods, which improves the classification accuracy and the generalization ability of the model. In the latest deep convolutional network applications, Hongbo Gao et al. used convolutional neural network–based fusion of vision and lidar to achieve target classification in autonomous vehicle environment perception. By creating a point cloud of LIDAR data upsampling and converting into pixel-level depth information, depth information is connected with Red Green Blue (RGB) data and fed into a deep convolutional neural network. Experimental results are presented and show the effectiveness and efficiency of object classification strategies.[21] Simulating the principle of brain cognitive things, the deep convolutional network learns semantic features step by step from the low-level information level. The deep convolutional network structure is shown in Figure 1. We use Cx to represent the convolutional layer network, Sx to represent the downsampling layer network, and Fx to represent the fully connected layer network.

As can be seen in Figure 1, the first layer of the deep convolutional network is the input layer, typically taking the pixels of the picture as input. Next layers are the convolutional layer and the downsampling layer. The role of the convolutional layer is to reduce training parameters and reduce training complexity based on local connections and weight sharing. The output of the convolution operation is a feature map, and the convolution layer can output a plurality of feature maps by convolution operations. Generally, the downsampling layer is followed by the convolutional layer. The downsampling layer takes the feature map of the convolution layer as an input and fuses the feature map of the convolution layer into a feature through a pooling operation, further reducing the feature dimension and improving the generalization ability of the model. There are several "convolution-downsampling" processes in a deep convolutional network, which reduces the resolution of features and achieves translation, distortion, and scaling invariance. After the convolution and downsampling operations, the next network layer is the fully connected layer and the classifier layer. The fully connected layer is a splicing of two-dimensional features into one-dimensional image features, and the classifier outputs classification results according to the feature learning results of the previous network layer.

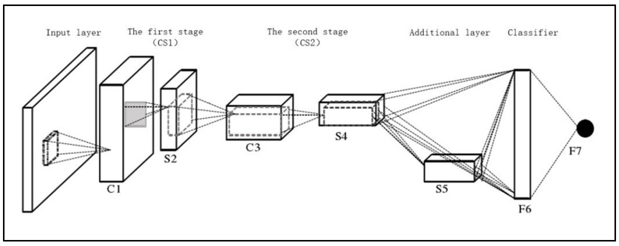

Figure 1. Deep convolution network structure.

Deep convolutional network

The convolutional layer of the deep convolutional network, convolution with the convolution kernel with learning ability, and the feature graph, and using the activation function f, we obtain the learned features by formula (1)

$$h_j^k = f\left(\sum_{i \in M_j} h_i^{k-1} * W_{ij}^k + b_j^k\right) \tag{1}$$

where k represents the number of layers of the neural network, W represents the convolution kernel, b represents the correction function, M_j represents the feature map, and * is the convolution operator symbol. In order to prevent over-fitting of learning features, we need to perform nonlinear operations on the features learned by convolution.[5,22,23] The nonlinear activation function used in this paper is the ReLu (Rectified Linear) function.

After the image is input to the deep convolution network, the convolution kernel is scanned from left to right and from top to bottom for pooling

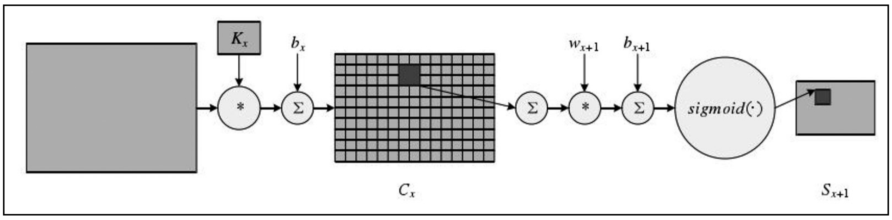

Figure 2. Convolution downsampling flow chart.

operation.[5,18,24,25] The C1 layer is generated, and the N convolution kernels generate an N-dimensional C1 layer, but the size of the feature map becomes smaller, and C1 is downsampled to generate an N-dimensional S2 layer. Among them, the purpose of downsampling is to fuse and enhance the local features. After downsampling, the size of the S2 layer is significantly reduced compared with the C1 layer. The process of convolution downsampling is shown in Figure 2:

The features output from the downsampling layer can be obtained by equation (2)

$$h_j^k = f\left(down\left(h_i^{k-1}\right) \cdot \omega_j^k + b_j^k\right) \tag{2}$$

In equation (2) w is the weight coefficient, b represents the correction function, and down() represents the downsampling function.

The above is the first feature extraction from the input to the generation of the C1 layer to the S2 layer. Next, for the second feature extraction, we take S2 as input and generate M-dimensional C3 layer by M convolution kernel convolution, usually $M \geqslant N$. The C3 layer performs a downsampling operation to generate an M-dimensional S4 layer, and the S4 layer is again subjected to downsampling to generate an S5 layer. The S4 layer and the S5 layer are fully connected to form an F6 layer. Thus, the F6 layer has both global and local features. The number of weights in the deep convolution network is significantly higher than that of the single-scale convolutional neural network and the improved multi-scale convolutional neural network. After the learning feature ends in the deep convolutional network, a small number of tagged data input networks are used to fine-tune the parameters, and the network is continuously optimized.[17,21,26,27,28]

The output of the fully connected layer k can be obtained by weighting the inputs and by the effect of the activation function

$$h^k = f\left(\sum_{i \in M_j} h_i^{k-1} * W_i^k + b^k\right) \tag{3}$$

where k represents the number of layers of the neural network, W represents the convolution kernel, b represents the correction function, M_j represents the feature map, and * is the convolution operator symbol.

Robust license plate recognition method based on deep convolution network

This paper attempts to construct a deep convolutional network structure and apply it to license plate recognition, which helps to improve the accuracy and robustness of license plate recognition. On one hand, the license plate image will be affected by the light intensity, wear and aging, object occlusion, and so on, and the artificially designed features cannot obtain the expected learning ability. On the other hand, the traditional neural network generalization ability is poor. Based on the above two reasons, this paper mainly explores the license plate recognition method based on the structure of deep convolution network. Without loss of generality, the feature of the license plate character image is directly extracted based on the deep convolution network license plate recognition method, and the character recognition classifier is trained using the learning algorithm. Considering that the Chinese characters in the license plate are more complicated than the numeric characters and alphabetic characters, in order to improve the detection rate, our approach takes a Chinese character, six numbers, and alphabetic characters on the license plate image as the input, and use stereo convolution kernels, add new downsampling layers, and increase data dimensions, A character recognition network is trained for the number, alphabetic characters, and Chinese characters of the license plate, respectively. In order to allow deep convolutional networks to be fully learned, our approach improves some of the details of the deep convolutional network in the process of license plate feature extraction. The first improvement is the improvement of the activation function. In the past, we used the two functions of equations (4) and (5) as the activation function

$$f(x) = \tan(x) \tag{4}$$

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

When we use the gradient descent method to train deep convolutional network parameters, using the above two nonlinear activation functions will increase the training time consumption. In Wang et al.,[29] we can see that when we use functions, we can think of neurons as ReLu units, so that the time spent training deep convolution networks will be reduced accordingly. The process can be expressed as

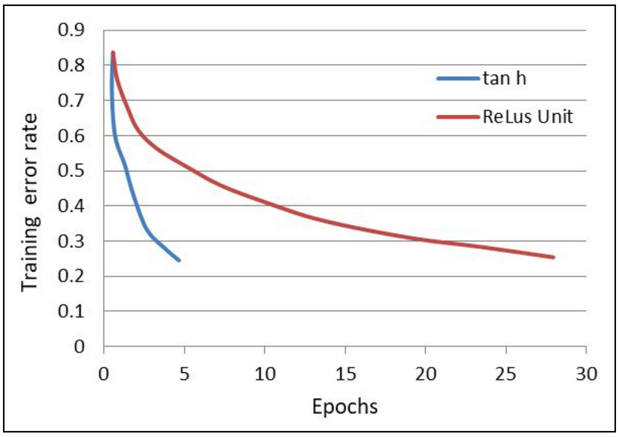

Figure 3. Effect of two activation functions on training time.

$$h_j^k = \max\left(h_j^{k-1}\right) \tag{6}$$

Here, a seven-layer deep convolution network with a relatively simple structure is used to illustrate the effect of different activation functions on training time as shown in Figure 3:

We can intuitively see that using the ReLu unit as the activation function saves about 6 times the activation time compared to using the traditional tanh function.

The second improvement is to add a pre-training process to the deep convolutional network. That is, the next layer of parameters is trained from the input layer, and each time the next layer of parameter training is completed, the next layer of training is automatically performed in combination with the specific input. According to this method, the final trained parameters are used as the initial weights of the model. Fine-tuning the weights is our final model. Compared with random initialization, pre-training is equivalent to adding prior knowledge, which can solve the dilemma that random initialization is easy to fall into local optimal solution. At the same time, it can solve the problem that it is difficult to effectively train deep parameters with the increase of the number of network layers, and obtain better training effects.

Results

The training set used by our approach is divided into the character set obtained by the license plate

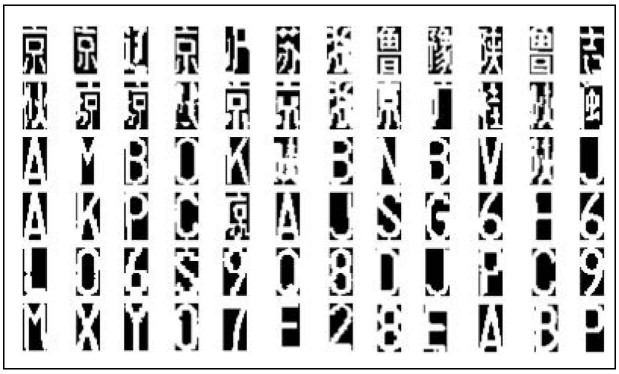

Figure 4. Character training set and test set samples.

characters collected by ourselves and some resources derived from the network. There are 80,634 data samples of 10 digits and 24 uppercase English letters, with an average of 2371 samples per character. There are 69,425 data samples for 31 Chinese characters, with an average of 2239 samples per character. Randomly select 90% of each character's template as our training set, then the remaining 10% of the sample as a test set. The hardware involved in the algorithm experiments mentioned in this paper mainly include Windows 10 64-bit operating system computer, Tianmin SDK3000 image acquisition card, and Sony ATM micro-square camera. The software is mainly Visual Studio 2012. Our approach uses Visual Studio 2012 to configure Open CV2.4.9 computer vision function library for license plate recognition development.

First, the license plate location algorithm is used to detect the license plate character area on the captured image, the license plate characters are cut and all samples are normalized to a 28×64 binarized image, as shown in Figure 4:

Each character image is labeled, the number and letter labels are as shown in Table 1, and the Chinese character labels are as shown in Table 2:

After the label is set, the sample is input into the deep convolution network to start training. The training frequency is set to 10,000 times.

In order to visualize the performance of the classifier, we use the more difficult to distinguish letters B, G, Q as examples to test the sample, as shown in Figure 5:

We use a well-trained deep convolutional network for sample testing and arbitrarily extract some feature maps and confidence maps of the third, fifth,

Table 1. Number, alphabetic character classification label.

Label	0	1	2	3	4	5	6	7	8
Character	0	1	2	3	4	5	6	7	8
Label	9	10	11	12	13	14	15	16	17
Character	9	A	B	C	D	E	F	G	H
Label	18	19	20	21	22	23	24	25	26
Character	J	K	L	M	N	P	Q	R	S
Label	27	28	29	30	31	32	33		
Character	T	U	V	W	X	Y	Z		

Table 2. Chinese character classification label.

Label	0	1	2	3	4	5	6	7	8
Character	京	津	冀	晋	蒙	辽	吉	黑	沪
Label	9	10	11	12	13	14	15	16	17
Character	苏	浙	皖	闽	赣	鲁	豫	鄂	湘
Label	18	19	20	21	22	23	24	25	26
Character	粤	桂	琼	渝	川	贵	云	藏	陕
Label	27	28	29	30					
Character	甘	青	宁	新					

Figure 5. Test hard examples.

and eighth deep convolution networks, as shown in Figure 6:

Take the remaining 10% of the test samples for algorithm testing and performance analysis. We use the traditional representative LeNet-5 model, Faster R-CNN, and AlexNet as a comparison. The test results are shown in Table 3:

It can be seen from the performance comparison test results in Table 3 that the license plate recognition algorithm based on deep convolution network is better than the traditional model–based license plate recognition algorithm. However, the deep convolutional network in recognition time is slightly longer than the traditional model. The average character image is extended by about 1 ms, so the real-time performance of the whole system is not affected enough to meet the practical requirements. Of course, when multiple license plates appear in one image, it can detect all the license plates in the image.

In order to verify the effectiveness of the proposed algorithm, the application examples of the license plate recognition algorithm are verified in several common complex road scenarios as shown in Figures 7–12:

The experimental results in Figures 7–12 show that our approach based on deep convolutional network license plate recognition method can achieve better detection results in most complex road scenarios. The algorithm is robust and can reach the level of practical application.

Conclusion

License plate recognition technology is an important research topic in pattern recognition technology and computer technology in intelligent transportation systems, and is an important part of intelligent transportation systems. It is widely used in various parking lots, community monitoring, toll gates, highway supervision, and so on, which greatly liberated manpower and material resources. Based on the in-depth study of the existing algorithms for license plate recognition, combined with the actual needs of the license plate recognition algorithm, the method constructs a deep convolution network for license plate recognition for the problem of high license plate miss detection rate under complex road conditions. The activation function was improved during the network training process and the pre-training process was added. Compared with the traditional license plate recognition algorithm, this method has stronger feature learning and feature expression ability, and has a more abstract representation of the

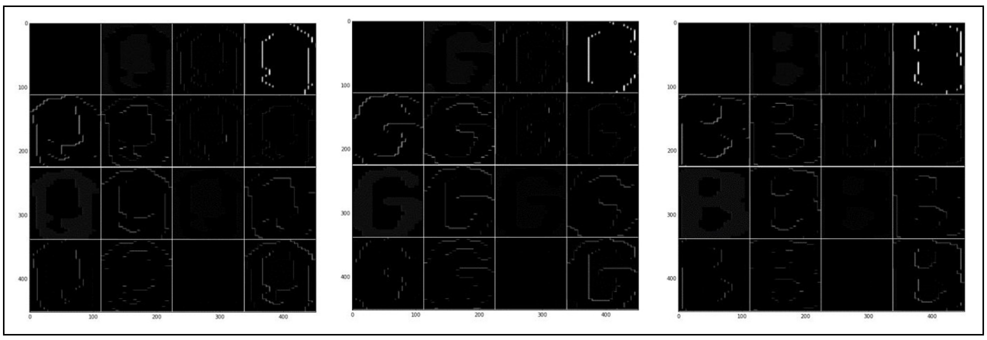

Figure 6. Partial feature map and confidence map of the second, fourth, and fifth layer networks.

Table 3. Performance comparison test.

Algorithm test	Number, alphabet character recognition rate (%)	Chinese character recognition rate (%)	Recognition time (s)
Deep convolutional network model	99.32	99.64	5.35
Faster R-CNN	93.49	91.23	3.46
LeNet-5 model	96.82	97.43	4.12
AlexNet	97.13	96.76	4.79

Figure 7. Car number plate is occluded by stains. In this picture, the license plate characters are covered by snow, but the algorithm still accurately recognizes the license plate characters.

Figure 8. The body and license plate are basically the same color. In this picture, the color of the license plate is roughly the same as the color of the car body. The license plate location is very difficult. According to the algorithm, the license plate characters are accurately identified.

Figure 9. Skew angle recognition. In this picture, the car body is tilted and the license plate outline is skewed. The license plate recognition algorithm in this paper can accurately identify the license plate characters.

Figure 10. Rainy day recognition. In this picture, we can clearly see that the light intensity is greatly reduced in rainy days, and the small water droplets in the air will also increase the noise. The license plate recognition algorithm in this paper can accurately identify the license plate characters.

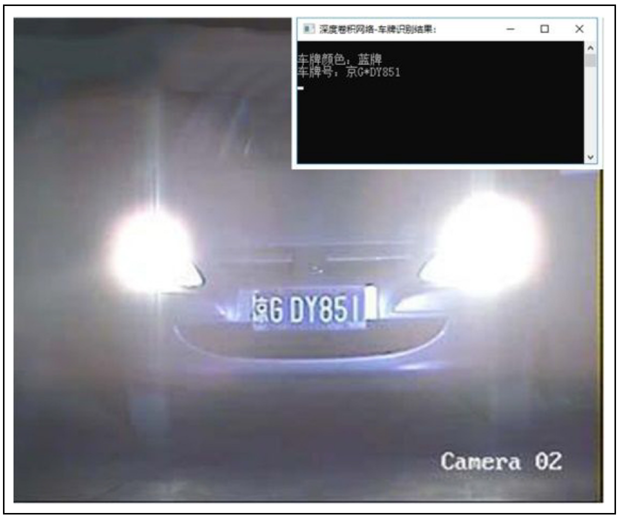

Figure 11. Direct light. In this picture, we can clearly see that the direct light will increase the light intensity locally and make the brightness of the license plate characters uneven, but the license plate recognition algorithm of this paper completes the task of license plate character recognition.

Figure 12. Shadow sunlight recognition. In this picture, the license plate is in the shadow sunlight, that is, the illumination intensity of the license plate is different. The license plate recognition algorithm in this paper can recognize the license plate characters under the shadow sun.

image. Finally, the algorithm proposed in this paper is verified by several algorithms in several typical complex road scenarios. The experimental results show that our approach has high accuracy and robustness and can meet the needs of license plate recognition.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This study was supported by the following: Fund Project: National Key Research and Development Program (2018YFB0105003); National Natural Science Foundation of China (U1564201, U1664258, U1764257, U1764264, 51875255, 61601203, 61773184); Jiangsu Natural Science Foundation (BK20180100); Jiangsu Provincial Key Research and Development Program (BE2016149); Six Talents Summit Project of Jiangsu Province (2018-TD-GDZB-022); and Major Special Project for Strategic Emerging Industry Development in Jiangsu Province (Sufa Reform High Technology Development (2016) No. 1094, (2015) No. 1084).

ORCID iDs

Ze Liu https://orcid.org/0000-0002-0801-236X
Youguo He https://orcid.org/0000-0003-2648-0025

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