Research on License Plate Recognition Algorithm in Dark-light Environment Based on Deep Learning

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Abstract. The advent of intelligent transportation technology has witnessed substantial advancements in license plate recognition technology, thereby assuming a crucial role in contemporary traffic monitoring. Nevertheless, conventional license plate recognition technology is inherently constrained by lighting conditions, severely impeding its nocturnal application. Given the escalating demand for license plate recognition technology in nighttime traffic surveillance, traffic violation documentation, and parking facilities, there exists a significant scholarly impetus to investigate nighttime license plate recognition technology. This study primarily focuses on nocturnal license plate recognition and employs deep learning techniques to execute comprehensive license plate recognition tasks. By leveraging this approach, the accuracy of license plate recognition in low-light environments can be substantially enhanced, thereby fortifying nocturnal traffic supervision and augmenting vehicular safety levels.

Keywords: monitoring. Nevertheless, recognition technology, substantially enhanced.

1. Introduction

Amidst the wave of digital transformation, automobiles have transcended their traditional industrial role and seamlessly assimilated into the fabric of people's daily activities and livelihoods. As a result, individuals now seek enhanced levels of safety, comfort, and even customizable features in their vehicles.

License plate recognition system (LPRS) [1] plays an important role in the information management of traffic roads in government departments and improving the daily travel efficiency of the public. The widespread use of this system has greatly improved the efficiency of traditional management mode. By combining with the technology of artificial intelligence, we can avoid the traditional related manual scheme, which is slow and has low accuracy, and realize direct end-to-end recognition of license plates, which improves the speed and accuracy of recognition. At the same time, with the promulgation of policies such as "Implementation Plan for Promoting Convenient Transportation in ‘Internet Plus’ and Promoting Intelligent Transportation Development", it can be seen that license plate recognition is of great significance for exploring the future development direction of green travel and serving the country's "double carbon" goal.

Compared with the development of foreign related technologies, the domestic license plate recognition technology started late. Due to the different types and styles of domestic license plates, the ways and positions of hanging license plates such as cars, buses and trucks are not fixed, which increases the difficulty of license plate positioning. Meanwhile, the abbreviation of provincial and prefecture-level cities and the diversity of combinations among characters also increase the complexity of license plate styles, so the foreign license plate recognition system cannot directly meet the requirements of license plate recognition in China. However, in recent years, domestic related technology development companies have continuously overcome difficulties and gradually caught up with the development of foreign related technology, for example, efforts made by Vision Zenith in Chengdu, and Beijing JAYA Technology Co., Ltd., etc. In addition, Liu D Y et al. put forward an identification algorithm based on BP neural network [2]. However, in some special scenes, the training time consumes a lot of time, and the overall model has certain redundancy. As far as practical application is concerned, the timeliness of the algorithm needs to be improved. Ma Shuang et al. put forward a multi-feature license plate recognition scheme [3], which firstly extracts the edge features,

fills the edge regions with relevant templates, thus forming the corresponding connected regions, then corrects the shape of the license plate through Hough transform, and finally inputs the depth and curvature features of the license plate image into the model network for the final stage of character recognition. Du Wei et al. put forward a license plate recognition scheme based on machine learning [4]. This scheme mainly uses the edge features of the image and HSV (Hue, Saturation Value) model, and uses neural network to recognize the character information in the location area of the license plate, and the effect is good. Zherzdev S et al. put forward the concept of LPR-Net [5], which is composed of a lightweight convolutional neural network, which does not need character pre-segmentation and uses end-to-end recognition. The experimental results show that the recognition accuracy of this model can reach 95%.

Foreign academia started early in related fields, SP Peixoto et al. used convolution neural network and other technical schemes to recognize the characters of license plates [6], and Rohith Polishetty et al. put forward a feature-weighting algorithm [7] aiming at the related characteristics of background and characters. This method added the related characteristic information of license plate background into the research, which has good adaptability to complex environment and improved the recognition rate. Abdullah S, proposed an algorithm for identifying the license plate of Marcia, used blob label and clustering strategy to segment the image, and at the same time, according to its edge features, used Kirsch detector to extract features and classified the final results [8]. Yuntao Cui proposed an algorithm [9] that uses Markov field technology to extract features and then binarizes them. This scheme has a good recognition effect on the number of samples. Masood S Z et al. use deep convolution neural network to fuse an efficient and accurate algorithm [10]. During the training process, the relevant parameters are adjusted, and the model has good robustness, and the effect is excellent in scenes with poor meteorological environment. The algorithm proposed by Ha P S et al. firstly uses FMH filter to filter out image noise, adopts Canny edge detection in license plate location, and chooses template matching technology in license plate recognition. Finally, the recognition rate of the system is improved obviously [11], and the anti-noise effect is also excellent. R.Mullot et al. studied a set of compatible recognition algorithm [12], which is mainly characterized by the texture of characters, and can locate and recognize the commonness of container and license plate images. Its applicability is much wider than that of the general single scene recognition algorithm. The recognition algorithm [13] proposed by Bolotava Y A et al. integrates many technologies, such as image filtering, connected component analysis, and memory model recognition. The main process of the algorithm is to collect the target image area with a binarization scheme, and then use the connected component analysis and memory model recognition technology to recognize the collected image at the character level, which has achieved good recognition results. D.F.Llorca et al. used the combination of MSER (region feature extraction) and SWT (stroke width transform) to detect the segmented character region [14], and finally used Hough transform to detect the edge of the license plate, but this method will be affected by other texts in the image background.

2. License Plate Location Detection

2.1 License plate image enhancement and preprocessing

In low-light conditions, license plate images often suffer from issues such as blurriness and decreased contrast ratio, which pose challenges in accurately identifying the license plate number. To address these challenges, the Retinex algorithm is employed to enhance the license plate image, thus highlighting the license plate target within the vehicle color image captured in nighttime environments. By applying the Retinex algorithm, the quality of the license plate image is improved, enabling more precise license plate number identification.

The Retinex image enhancement algorithm operates on the fundamental principle of decomposing the original image into two components: the reflection component and the highlight component. The reflection component represents the color and surface characteristics of the object, while the highlight component conveys information about the intensity and position of the light source. This

decomposition process substantially enhances the image's contrast ratio and clarity while preserving its color information. To elucidate further, an image can be perceived as a composition of an incident image and a reflected image. When incident light illuminates a reflective object, the reflected light reaches the human eye, resulting in the formation of an image perceived by humans (as illustrated in Figure 1). In this study, the Retinex algorithm is employed to enhance the license plate image, thereby improving its contrast ratio and clarity. By applying this algorithm, the license plate number can be more effectively identified.

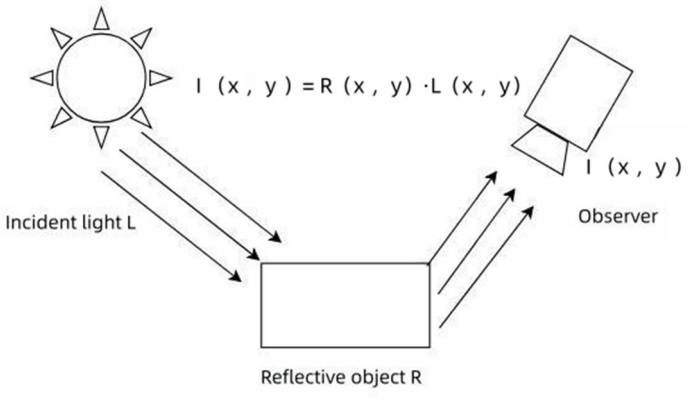


Figure 1. Basic principle of Retinex image enhancement algorithm

The resulting image can be expressed as:

$$I\ (x,y\ ) =\ R(x,y) \cdot L(x,y) \tag{1}$$

Where $R(x,y)$ is a reflection image, which has nothing to do with illumination, and the high-frequency part of the corresponding image determines the true face of the image, while $L(x,y)$ is an illumination image, which has nothing to do with the scene and reflects the dynamic range of the image. Equation (1) can be converted into:

$$\ln(I(x,y)) =\ \ln(R(x,y)) + \ln(L(x,y)) \tag{2}$$

So as to reduce the amount of computation and conform to the nonlinear characteristics of human perception brightness. Let $i\ =\ ln(I(x,y)), l\ =\ ln(L(x,y))$ and $R\ =\ ln\ (r\ (x,y))$ to obtain:

$$i = r + l \tag{3}$$

The core of Retinex is to estimate L, that is, to estimate and remove the L component, and then get the original reflection component R, that is:

$$l = f(i) \tag{4}$$

$$r = i - f(i) \tag{5}$$

Retinex method regards the picture image seen by the observer as an image with multiplicative noise, and the incident light components are relative and multiplicative, so Retinex algorithm is to estimate the noise position reasonably and remove it. In extreme cases, it can be considered that the components in the whole image are uniform, and the simplest way to estimate the illumination L is to average the whole image after transforming the image into logarithmic domain. The logarithmic transformation formula is:

$$Log(R(x,y))\ =\ Log(I(x,y)) - Log(L(x,y)) \tag{6}$$

It is only necessary to get $L(x,y)$ to get $R(x,y)$, but according to the theory of mathematics, $L(x,y)$ cannot be obtained precisely, and can only be obtained approximately. That is, $L(x,y)$ is approximately represented by the convolution of $I(x,y)$ and a Gaussian kernel. So $R(x,y)$ can be expressed by the following formula:

$$Log(R(x,y)) = (Log(I(x,y)) - Log(I(x,y) * G(x,y))) \tag{7}$$

The color image obtained by Retinex image enhancement algorithm contains a lot of color information, which will increase the processing time and occupy a lot of resources. Therefore, the

enhanced license plate image is grayed, binarized and the license plate edge is extracted. We removed useless colors, reduced the amount of calculation and improved the processing efficiency. The obtained gray license plate map is shown in Figure 2:



Figure 2. Graying the license plate image

The grayed image still contains many elements. In order to highlight the character elements more, other unnecessary elements are ignored, and further binarization is carried out to make the RGB threshold of the white character part become (255.255.255), and all pixels outside the white character area are assigned to (0.0.0). The binarized license plate map obtained after completing the binarization mask operation is shown in Figure 3:



Figure 3. Binarizing the grayed license plate

2.2 License plate location and filtering

After enhancing and preprocessing license plate images, several license plate regions, along with their corresponding mask regions, are typically obtained. However, these regions may include irrelevant areas, requiring the filtration of such areas to accurately select the correct license plate regions. This task can be framed as a binary classification problem, distinguishing between correct license plate areas and irrelevant ones. To address this challenge, the study employs a binary classification model trained using support vector machine (SVM) algorithms. SVM is a well-established machine learning technique capable of effectively categorizing data into two distinct classes. In this context, the SVM-based binary classification model is utilized to filter and identify license plate regions accurately. By leveraging SVM training, the study aims to enhance the accuracy and reliability of license plate region recognition.

The objective of dataset classification learning is to identify a partition hyperplane that effectively separates different types of data. The SVM model offers both binary and multiclass classification, with this paper focusing on the simpler binary classification problem. By searching for an optimal linear classification hyperplane, the SVM classifier learns to differentiate between positive and negative classes, in this case, to identify license plate regions. The SVM classifier is trained using relevant theories and algorithms, enabling accurate localization of license plate positions for subsequent tasks. In this study, feature vectors extracted from images are utilized to train a binary classification SVM license plate recognition classifier. The dataset comprises 1916 positive samples and 3978 negative samples. The positive samples consist of license plate contours obtained through previous operations, encompassing various license plate types such as blue cards and yellow cards, as well as license plate area images captured under different lighting conditions and backgrounds. The negative samples consist of images depicting non-license plate areas under diverse background conditions. The positive and negative sample sets are illustrated in Figure 4:



Figure 4. Positive and negative sample sets

After creating labels for license plate areas and non-license plate areas, they are classified and placed in two folders. The license plate training data set is trained by SVM two-classification classifier, and all the positive and negative samples of license plate that need to be trained are loaded into the classifier. SVM initially loads all the pixels of the image, preprocesses and extracts the features of the loaded image, and then starts training. The purpose of SVM training is to get the weight value of license plate region, and judge whether the candidate region is a license plate region by this weight value. The flow chart is shown in Figure 5:

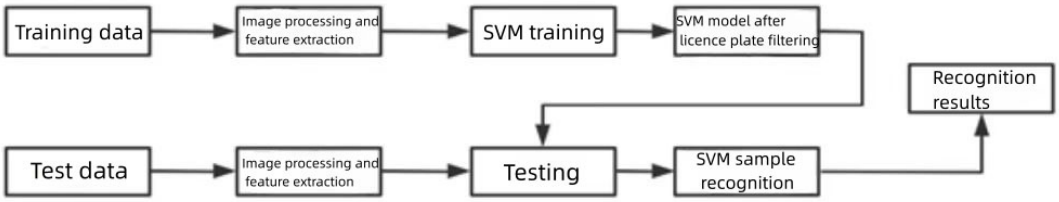


Figure 5. SVM license plate filtering flow chart

The test samples are imported into the model for testing, and the experimental results are as follows:

Table 1. Accuracy of license plate location

	Number of training sets	Number of test sets	Accurate number of positive and negative sample classification	License plate location accuracy
Positive sample	1931	100	98	98%
Negative sample	3968	100	100	100%
Total	5899	200	198	99%

Experimental evaluations were conducted on the test set, and it was observed that the SVM classifier, trained to filter license plate areas, effectively eliminated non-license plate regions, retaining only the desired license plate areas. The results demonstrate that the trained model exhibits a high level of accuracy and reliability, providing a solid foundation for subsequent license plate recognition tasks. Moreover, a series of experiments were performed to compare the performance of different algorithms. The experimental results confirm that the SVM classifier trainer delivers excellent results in license plate recognition, exhibiting both high accuracy and robustness. Based on these findings, we can confidently assert that this method is effective, feasible, and holds significant promise for practical applications in various scenarios..

3. License Plate Character Segmentation

Character segmentation remains a significant challenge in license plate recognition due to the variability in character size, font, and arrangement. However, the proposed method in this paper, which combines horizontal and vertical cutting techniques, offers an effective solution to overcome this difficulty. By applying this method, the license plate image can be accurately divided into distinct character regions, providing precise inputs for subsequent character recognition processes. Moreover, this paper takes into account the potential impact of small dot elements present on license plates during character segmentation. By incorporating a width limitation on the character regions, these interfering dot elements can be effectively filtered out, leading to an improved accuracy in character segmentation. This consideration ensures that the character segmentation process is robust and capable of handling various license plate variations encountered in practical applications.

3.1 Horizontal projection segmentation

The edges around the license plate often contain white edges, which are always the same as the digital color of the license plate, which will cause great interference in license plate segmentation and character extraction by vertical projection. We can filter the continuous white lines by horizontal projection first.

The specific operation steps of horizontal projection are as follows:

(1) Firstly, read the height and width values of a license plate picture, set a horizontal projection index mark, and filter the parts with the contour length of the license plate less than 20% and more than 80% in the horizontal direction,

(2) Project the processed binary license plate horizontally on the Y axis, calculate the continuous length after projection, and manually end the final projection length accumulation work according to the projection index mark to complete the horizontal projection.

(3) Calculate the value of the projection length in the height of the whole intercepted license plate. When the ratio is greater than 0.5, it is regarded as the longest projection.

(4) By calculating the top and bottom values of the longest projection, the range of the license plate area is set to achieve the effect of horizontal projection.

After horizontal projection, the horizontal projection effect of the license plate is shown in Figure 6. As can be seen from the figure, after the horizontal projection operation, part of the border of the license plate is trimmed, the proportion of the character area in the picture is increased, and the horizontal white border is further removed, which provides a favorable environment for the subsequent vertical projection.



Figure 6. Horizontally projected licence plate image

3.2 Vertical projection segmentation

The purpose of vertical projection is to obtain the number of pixels in the vertical direction by scanning the license plate area vertically, and to determine the character area and the non-character area by counting the number of pixels, so as to complete the character cutting work. The specific operation of vertical projection segmentation is as follows:

(1) Based on the horizontally segmented image, scan from left to right, column by column to obtain the number of edge pixels in each column.

(2) Processed the statistical data, and whether the pixel point of each column can exceed 60% of the average value is taken as the basis for judging whether it is a character region.

(3) Set the width limit of the character area, and take the license plate width /12- license plate width /5 as the width limit of the character, otherwise it will not be regarded as the character area.

(4) Based on the above requirements, character segmentation is carried out according to the license plate boundary conditions. The segmentation result is shown in Figure 7.

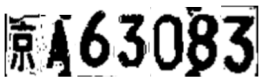


Figure 7. Character segmentation and extraction results

4. License Plate Character Recognition Based on Convolutional Neural Network

For the license plate image that has been segmented, this paper adopts a character recognition method based on Convolutional Neural Network (CNN), which is excellent in adaptability and accuracy, but needs a large number of character sample libraries to train the CNN model. In character

recognition, some preprocessing techniques have been used to improve the recognition accuracy, such as character binarization and character size normalization, which can effectively reduce the influence of image noise and image size change on character recognition.

4.1 Convolutional neural network structure

Convolutional neural network (CNN) is a type of feedforward neural network, and its artificial neurons can respond to the partial coverage of surrounding units. CNN has an excellent performance in dealing with large images. The essence of CNN is a mapping from input to output. It can learn a large number of mapping relationships between input and output without accurate mathematical expressions. By training the known patterns, CNN can have the mapping ability between input and output.

Convolutional neural network is mainly composed of convolution layer, pooling layer and fully connected layer. The convolution layer uses convolution algorithm to extract different features of images from different input images, while preserving their spatial relationship. At this time, the dimension of the feature image obtained by convolution layer is still high, so it is necessary to replace the value of the obtained high-dimensional feature image by pooling layer, and the commonly used replacement values are maximum and average. Through the pooled image, the amount of parameters and calculation are effectively reduced. Then, through the matrix multiplication of the fully connected layer, the useful information is transformed in space and integrated.

The convolutional neural network structure adopted in this paper is the classic LeNet-5 model, which is a relatively simple but classic convolutional neural network model. The model includes three layers of convolution, three layers of pooling and three layers of full connection, as shown in Figure 8.

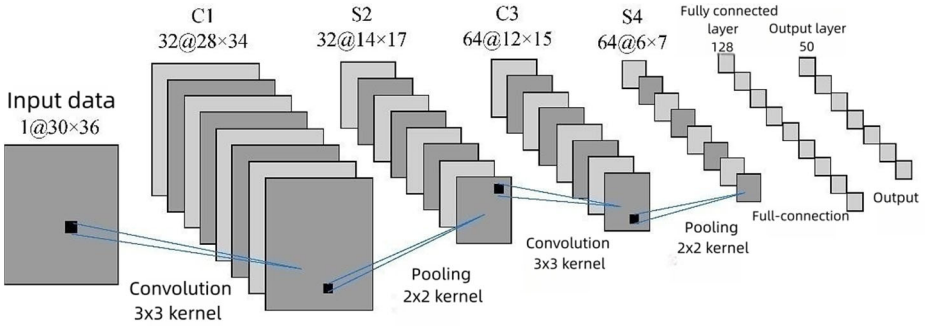


Figure 8. LeNet-5 model

Input layer: input the processed character image into the network, and this is the input layer. The first convolution layer: there are 32 convolution kernels in this layer, which are defined as the training parameter w1. At the same time, the number of offset items b1 is consistent with w1, and Relu function is used for nonlinear conversion, followed by pooling layer and down-sampling layer. The second convolution layer and the third convolution layer have 64 convolution kernels and 128 convolution kernels respectively. Fully connected layer: the results of three convolution calculations are continuously input to three fully connected layers, and the Softmax function is used for nonlinear fitting. After the character features are fused, a total of 65-dimensional results are output, and each value represents the probability value of its corresponding label.

4.2 Model training and testing

Orthographic projection method is used to obtain all standardized single character information of national license plates, including abbreviations of 33 provinces, municipalities and autonomous regions, 24 uppercase English letters (except I and O) and ten Arabic numerals. Considering the characteristics of characters and the size of data set, this paper constructs the character data set based on morphological algorithm. In order to better understand the training situation of characters, this paper cuts each character separately to form a new character data set. The data set contains 11 classes,

and each class contains 7000 character images, all of which are in JPG format of 20px*20px, as shown in Figure 9.



Figure 9. License plate character data set

The constructed recognition data set is mainly divided into three categories: Chinese characters, numbers and letters, with a total of 25,200 different characters. On the basis of each category, 80% of the total is randomly taken as the training set and the remaining 20% as the test set. The training framework of this paper is TensorFlow1.12. Firstly, the training set is transferred to tfrecord type to save memory, unify the format and improve the calculation efficiency. The superparameter settings are shown in Table 2. During network training, 128 batches of iterative training were conducted for 30,000 times, and the initial learning rate was set to 0.001.

Table 2. Accuracy test of character recognition

Type	Quantity/sheet	Correct/sheet	Recognition rate/%
Chinese character	1400	1375	98.2
Number	1400	1397	99.8
Letter	1400	1399	99.9

As shown in Table 2, there are 1400 characters in each category. By comparing the recognition effects of different data types in the network, it can be concluded that CNN has a very significant advantage in character recognition.

5. License Plate Recognition Test in Dark-light Environment

The identification process of the method proposed in this paper is shown in Figure 10:



Figure 10. License plate recognition process in dark-light environment

In this paper, 400 license plates are randomly scrambled from the license plate data set in dark-light for adaptive recognition. The accuracy of the algorithm designed in this paper can reach 97.5%, the number of wrongly recognized license plates is acceptable, and the overall recognition effect is good.

Table 3. License plate recognition results in dark-light environment

Parameter/algorithm	Algorithm in this paper
Random image/sheet	400
Correct number/sheet	390
Number of errors/sheet	10
Recognition rate/%	97.5
Average time /ms	34
Adaptability	Good

6. Conclusion

In light of the rapid advancements in intelligent transportation technology, license plate recognition has emerged as a crucial component of its extensive applications. Nevertheless, license plate recognition in low-light environments presents numerous challenges, including uneven illumination, reflection, and shadows. To overcome these challenges, this paper focuses on studying a deep learning-based license plate recognition algorithm specifically designed for low-light environments. The algorithm primarily addresses the issue of accuracy in license plate recognition under low-light conditions. It achieves this by optimizing the recognition channel to enhance both accuracy and efficiency. Additionally, the character recognition module integrates deep learning methods, further improving the overall recognition accuracy. The proposed deep learning-based license plate recognition algorithm demonstrates promising results for license plate recognition in low-light environments. However, there are still challenges and areas for improvement in practical applications. One such challenge is the requirement for more training data and higher model accuracy to enhance recognition rates and robustness. Moreover, as lighting and environmental conditions change, the introduction of more robust algorithms is necessary to ensure the stability and reliability of license plate recognition systems. Continued research and development are crucial to address these challenges and further enhance the performance of license plate recognition in low-light environments.

References

[1] Coetzee C, Botha C, Weber D. PC based number plate recognition system[C]//IEEE International. Symposium on Industrial Electronics. Proceedings. ISIE'98 (Cat. No. 98TH8357). IEEE, 1998, 2: 605-610.

[2] Liu D Y, Song H, Pan Q. License Plate Recognition Based on Neural Network Algorithm to Improve Research[C]//Advanced Materials Research. Trans Tech Publications, 2014, 860: 2892-2897.

[3] Ma S, Fan Y, Lei T, et al. A practical license plate recognition method based on multi-feature extraction [J]. Computer Application Research, 2013, 30 (11): 3495-3499.

[4] Du W. Research on license plate recognition algorithm based on machine learning [D]. Shenyang Normal University, 2017.

[5] Zherzdev S, Gruzdev A. LPRNet: License Plate Recognition via Deep Neural Networks[J]. ar Xiv preprint ar Xiv:1806.10447, 2018.

[6] Peixoto S P, Cámara-Chávez G, Menotti D, et al. Brazilian license plate character recognition using deep learning[C]//Proc. of XI Workshop de Visão Computacional. 2015.

[7] Polishetty R, Roopaei M, Rad P. A next-generation secure cloud-based deep learning license plate recognition for smart cities[C]// 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA). IEEE, 2016: 286-293.

[8] Abdullah S N H S, Khalid M, Yusof R, et al. Comparison of feature extractors in license plate recognition[C]//First Asia International Conference on Modelling & Simulation (AMS'07). IEEE, 2007: 502-506.

[9] Cui Y, Huang Q. Automatic license extraction from moving vehicles[C]//Proceedings of International Conference on Image Processing. IEEE, 1997, 3: 126-129.

[10] Masood S Z, Shu G, Dehghan A, et al. License plate detection and recognition using deeply learned convolutional neural networks[J]. ar Xiv preprint ar Xiv:1703.07330, 2017.

[11] Ha P S, Shakeri M. License Plate Automatic Recognition based on edge detection[C]//2016 Artificial Intelligence and Robotics (IRANOPEN). IEEE, 2016: 170-174.

[12] Mullot R, Olivier C, Bourdon J L, et al. Automatic extraction methods of container identity number and registration plates of cars[C]// Proceedings IECON'91: 1991 International Conference on Industrial Electronics, Control and Instrumentation. IEEE, 1991: 1739-1744.

[13] Bolotova Y A, Druki A A, Spitsyn V G. License plate recognition with hierarchical temporal memory model[C]//2014 9th International Forum on Strategic Technology (IFOST). IEEE, 2014: 136-139.

[14] D. F. Llorca et al., "Two-camera based accurate vehicle speed measurement using average speed at a fixed point" Proc. 19th Int. Conf. Intell. Transp. Syst., pp. 2533-2538, Nov. 2016.