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A New Method to Detect the License Plate in Dynamic Scene

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Abstract: License plate detection includes license plate positioning, segmentation characters, character recognition. The recognition rate of license plates under dynamic scenes is affected by many factors. Each process deviation may affect the overall system recognition rate, and the accuracy of each part is affected by many factors, in order to reduce this error, we combine the advantages of a variety of algorithms to propose a comprehensive detection model. In the license plate positioning phase, we propose HSV space and morphological methods; in the segmentation character phase, we propose the maximum adjacent character horizontal center distance segmentation method; in the character recognition stage, we choose to use the CNN algorithm. In the final simulation test, there are a set of 1 errors in the 30 groups of license plate recognition, the accuracy is higher.

Key Words: License plate detection, positioning, character segmentation, identify the character

1 Introduction

The application of license plate recognition technology can greatly change the phenomenon of traffic violation and traffic accident, which also can provide evidence for later processing and improve traffic safety [1]. Meanwhile, ITS can reduce amount of vehicles are theft, fake licensing and trafficking in criminal activities. It can provide detailed data about the classification of traffic in order to achieve the optimal road planning and management, providing the basis for smart traffic.

In the era of big data, the license plate recognition system is applied to the parking lots, garages, traffic junctions, mobile patrols, weighbridge systems, terminal management, automatic driving, gas stations and other occasions, constantly moving in the direction of intelligence and unmanned [2]-[3].

For special scenes, such as low light, perspective transformation, low quality blur, license plate recognition rate still needs to be improved. However, no matter the traditional method or deep learning method, some common module technologies still have room for improvement and research value, such as motion area detection, license plate location, perspective transformation correction, and multi-frame fusion output and so on. For the traditional method, character segmentation and character recognition still can improve the space.

1.1 Identification System Research Status

A complete license plate collection system consists of a number of technologies such as image acquisition, image preprocessing, license plate location, character cutting, and character recognition [4]. No matter what kind of programs need to solve two major problems: First, no matter what the scene under the vehicle took photos, try to get a clear and easy to distinguish license plate taking pictures. Second, how to ensure the final recognition rate of license plates under various weather conditions, that is, the generalization ability of the system is strong.

Currently, the commercial license plate recognition system can identify the vehicle information in the video and the still picture, including the license plate number, the license plate color and the license plate shape. The system consists of hardware system and software system. The hardware includes camera module, dimming module, image acquisition module and image processing module. The software system includes image preprocessing, license plate location, license plate correction, license plate cutting module and license plate character recognition module [5]. The working principle diagram is as follows:

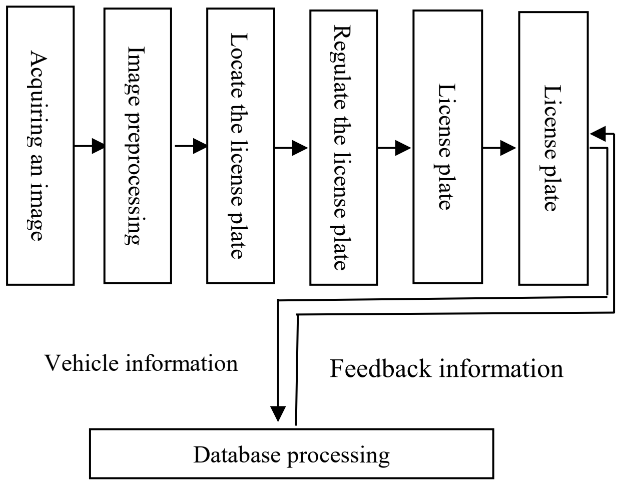

Figure.1 The working principle diagram

A variety of license plate recognition of foreign countries started earlier, well-known systems are: Israel Hi-Tech's See / Car System, ARGUS United Kingdom Alphatech developed in the 80s License Plate Recognition System (RGUS), Singapore's Optasia company developed VLPRS system, suitable for license plates in Singapore, Germany ARTEM7S company SIEMENS system. Although the accuracy of each system is acceptable, but only for the use of the region, from the recognition principle template matching, support vector machine classifier, feature-based classifier,

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artificial neural network classifier, rough set classifier, poly Class analysis and other methods.

In China, the more mature products include Sichuan ChuanDa Intelligent Company's LPR products, ShenZhen ZhenZhi technology company's fire eyes ZhenZhu identification system, the Chinese Academy of Sciences Hanwang series, Hong Kong's Asia Vision's license plate recognition products VECON [6]. Although the recognition rate is above 90, the experimental data are not obtained from the actual working environment. Due to the complexity of the environment, there is no set of identification systems for all environmental and scene changes. In theoretical research, Liu Zhiyong in a 3180 sample set, license plate positioning accuracy of 99.4%, segmentation accuracy of 94.5%. Hu Aiming developed a license plate recognition system used in toll booths with template matching technology, whose recognition accuracy can reach more than 97%. Luo Xuechao and Liu Guixiong proposed a banalization method based on license plate feature information, which can achieve a recognition rate of 96% for the better-performing license plate. FENG Wen-yi and other use of a photoelectric hybrid system for license plate recognition, the system can be completed by the hardware license plate recognition process. Huang Zhibin will be based on the serial classifier character recognition applied to the license plate recognition system, the license plate recognition system classifier carried out a detailed study. Different countries have different recognition systems, especially China's license plate complexity, license plate characters, license plate color, hanging position, character arrangement is not uniform, making identification more difficult

1.2 Research Status of Character Recognition

(1) Characteristic Analysis Method

In order to improve the recognition speed, character structure analysis generally do not do the normalization. The main principle is to analyze the structural features of Chinese characters, numbers, numbers and strokes to achieve character recognition.

(2) Template matching method

The core of this method is to use the entire character as a template or to extract the characteristics of a single character as a template matching the standard dictionary of characters to calculate the maximum match between the two characters to confirm the character.

(3) Artificial Neural Network Algorithm

The character recognition mainly has two directions. One is to extract the feature from the character to be recognized, and then the neural network classifier is trained by the acquired feature. The result of this method is highly correlated with the feature of the special area and takes a long time. The other is to directly enter a single character picture into the neural network, to play the characteristics of network autonomous learning characteristics, training out a specific identification of the structure, and ultimately the output of the characters.

2 Model Preparation

In this paper, for the license plate in complex environment, we use the combination of HSV space and morphological processing to locate the license plate, character segmentation for images using license plate character segmentation based on the maximum character spacing of adjacent characters, based on the end of segmentation on the use of improved CNN algorithm identification.

2.1 HSV space and morphological methods

RGB and HSV models are commonly used color models in image processing. As the three primary colors of RGB are greatly affected by the illumination, when the illumination conditions of the license plate image change, it is difficult to use the color information of the license plate to accurately locate the license plate in the RGB space. The HSV model is represented by H, S, V, where H is the hue, S is the saturation and V is the brightness [7].

H and S contain the color information of the image, V represents the brightness information, and the model is more in line with the human eye feel the color of the way. Depending on the color characteristics of the license plate image, using 3 components in the HSV color space helps to pinpoint the license plate area. The conversion between the two is as follows:

Assuming all color components have been normalized, the range is [0, 1]. Setting the maximum value (max) and the minimum value (min) in the RGB components, the hue component H is:

$$H=\begin{cases}\dfrac{G-B}{V-\min(R,G,B)}\cdot 60^{\circ},\ \ if\ \ V=R\\ (2+\dfrac{B-R}{\max\text{-}\min})\cdot 60^{\circ}, if\ \ V=G\\ (4+\dfrac{R-G}{\max-\min})\cdot 60^{\circ}, if\ \ V=B\\ (6+\dfrac{R-G}{\max-\min})\cdot 60^{\circ}, if\ \ V=B \text{ and } G<B\end{cases} \quad (1)$$

The saturation component S is

$$S=\begin{cases}\dfrac{V-\min(R,G,B)}{\max}, & \text{if } V\neq 0\\ 0 & \text{otherwise}\end{cases}.$$

Brightness component V is $V=\max(R,G,B)$.

Wherein, the range of H is $[0,360^{\circ}]$, the range of S and V values is [0, 1], R is red, G is green, B is blue.

License plate image color space conversion effect shown in Figure 2.

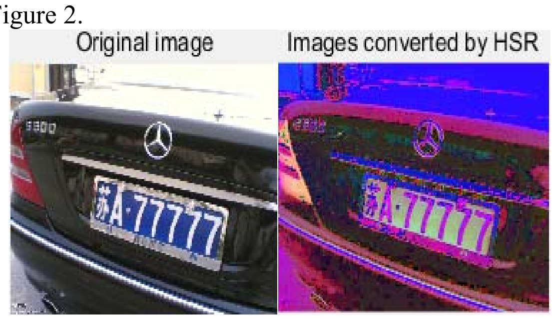

Figure. 2: Conversion effect chart

2.2 Banalization

In order to effectively detect the license plate candidate area by the image morphological processing method, the license plate image needs to be binary processed. The method adopted in this paper is to separately perform the binary operation on the grayscale images of each channel (H, S, V) of the converted HSV color image and then perform an AND operation, so as to obtain an image with most of the background interference removed Binary image. The contrast effect of the banalization results in two color spaces is shown in Fig. 3. Take the blue white license plate as an example:

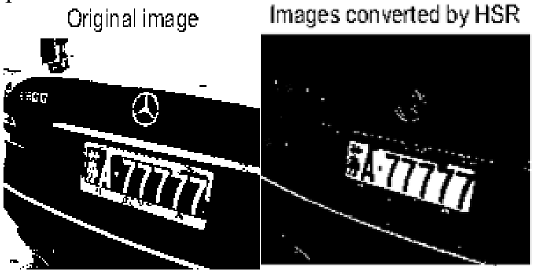

Fig.3: Results comparison chart

Therefore, the banalization in RGB space, its interference is large, especially the headlights and car logo maximum interference, and in the HSV space banalization can be good to exclude these interferences.

2.3 Morphological treatment

For the license is binary processed plate image, the morphological processing method can quickly and effectively detect the connected area, that is, the candidate area of the license plate. Morphological basic operations include corrosion, expansion, open operations and closed operations. Both open and closed operations are made of corrosion and expansion composite, open operation is the first expansion after corrosion, and closed operation is the first expansion after corrosion.

Corrosion (erosion) operation can be defined as:

$$\mathrm{A} \ominus B = \{x, B + x \subset A\} \tag{2}$$

Where, A is the input image; B is the template. A⊖B represent that B in the translation process, all of which may fill the interior of A B's origin.

The expansion (expansion) operation is the dual operation of the erosion operation (inverse operation), which can be defined by the corrosion of the complement.

$$A \oplus B = [A^c \ominus (-(-B))^c \tag{3}$$

Where, A^c denotes the complement of A, and -B denotes rotating B 180 °. The use of -B on the corrosion of A^c, the complement of corrosion results is the use of B to A corrosion results.

Open operation is defined as:

$$A \cdot B = (A \ominus B) \oplus B \tag{4}$$

Closed operation is defined as:

$$A \cdot B = (A \oplus (-B)) \ominus (-B) \tag{5}$$

Closed operation can make the outline smooth, it can usually close a narrow gap, filling small holes. Open operation can make the outline of the image smooth, but also make the narrow connections disconnect and eliminate burr In order to detect the license plate candidate region, morphological approach used in this article are: first by closing the operation to connect to the adjacent target, Then use the open operation to eliminate small objects.

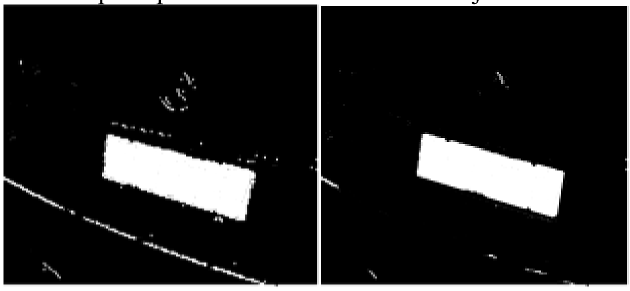

Fig.4: Morphological results

When the candidate plate of the license plate detected by the morphological processing is displayed on the original picture, because the limitation of possible identification of multiple objects, the proportion of the size of the license plate in Chinese car needs to be calculated according to the proportional relationship (the aspect ratio of the blue-white plate is 3.14), So as to eliminate part of the fake license plate, and finally get the real area of the license plate, as shown in the figure 5, which is marked by the red area.

Fig.5: Positioning license plate

2.4 Maximum Adjacent Characters Horizontal Center Distance Segmentation Method

1) Characters are not stuck

Using the method of location interval to obtain the projection value of the binaries image, calculating the horizontal center coordinates d_1 and d_2 of two adjacent characters, if the value of $d_2 - d_1$ is greater than height / 6, the distance is the center distance between the second character and the third character [8].

2) Character sticking

If there is a special case of character adhesion, as shown in fig. 6, in this case, the processing method is no longer using the center horizontal distance of adjacent characters as a criterion, but directly find the maximum gap according to the characteristics of the vertical projection, as shown in fig. 7 as shown.

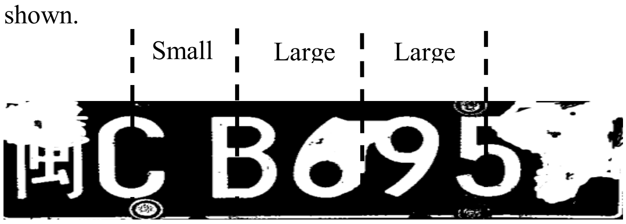

Fig.6: Character horizontal center distance diagram

Fig.7: Adjacent character gap size diagram

The basic idea of the method is: using the positioning interval method to get the projection value of each character $VerProj[i](i=0,1\cdots w)$, w is the license plate image width), according to the value of the array $VerProj[i]$ to get the width of the gap between two adjacent characters [9], then according to the second character and The third character has the largest gap characteristic to get the second character and the third character's horizontal position. Chinese single license plate is characterized by containing seven characters, then you can determine the maximum gap of 5 characters, the maximum gap of 2 characters [10].

The basic idea of getting the seven characters in a specific position is to draw the width of the characters from the maximum gap to the left and to the right, respectively. If the width of the character obtained is greater than height, then there is a character sticking. According to the width of each standard license plate character Height / 2 on the adhesion area reasonable split.

2.5 Character Recognition Based on CNN

The convolutional neural network consists of one or more convolutional layers and a top fully connected layer, as well as associated weights and a pooling layer [11]-[12].

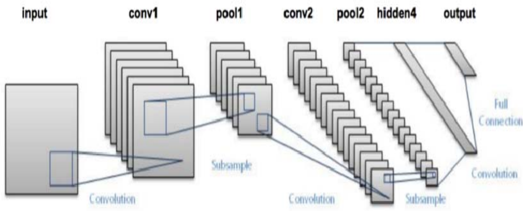

Fig.8: Schematic of the CNN

Local experience wild

In order to reduce the number of parameters, each neuron does not actually need to perceive the global image, only need to perceive the local, and then get the global information by integrating the local information at a higher level. The idea of network connectivity is also inspired by the visual system structure in biology.

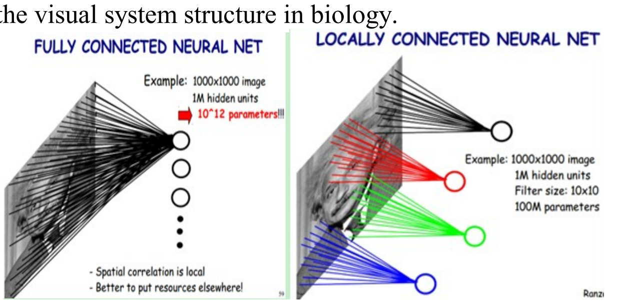

Fig.9: The way of connection

In the upper right picture, if each neuron is connected to only 10 × 10 pixels, then the weight data is 1000000 × 100 parameters, reducing to 0.01%. And 10 × 10 pixel value corresponding to 10 × 10 parameters, in fact, it is equivalent to the convolution operation.

The sharing of weights

In the above partial connection, each neuron corresponds to 100 parameters, a total of 1,000,000 neurons. If 100 of the 1,000,000 neurons are equal, the number of parameters becomes 100.

100 parameters can be seen as a way to extract features. The implicit principle is that part of the image has the same statistical characteristics as the other parts. It also means that the features we learn in this part can also be used in another part, so we can use the same learning features for all the places in the image.

More intuitively, when randomly picking a small piece of image from a large image, say 8x8, as a sample and learning some features from this small sample, we can use the features learned from this 8x8 sample as the detector, applied to any place in the image.

As shown in the following figure, a convolution kernel of 3 × 3 is convoluted on a 5 × 5 image. Each convolution is a feature extraction method, like a sieve, the image of the selected part of the filter out.

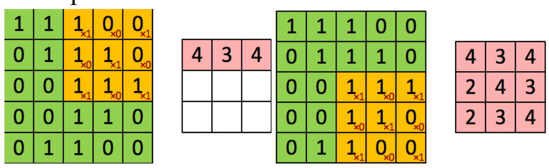
Fig. 10: Volume machine process

When there are only 100 parameters mentioned above, it shows that there is only one 10 * 10 convolution kernel. Obviously, feature extraction is not sufficient [13]. We can add multiple convolution kernels, such as 32 convolution kernels, which can learn 32 kinds of convolution kernels feature. When there are multiple convolution kernels, as shown below:

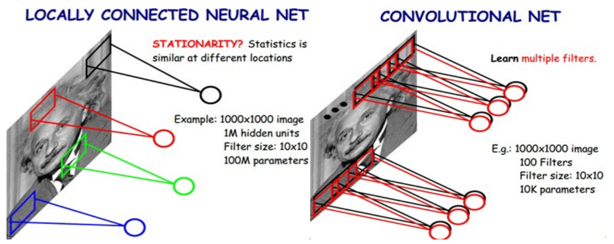

Fig.11: Multi-convolution kernel working principle

The following figure shows the convolution operation on four channels. When there are two convolution kernels, two channels are generated, and activation function is:

$$h_{i,j}^{k}=\tanh((W^{k}*x)_{i,j}+b_{k}) \qquad (6)$$

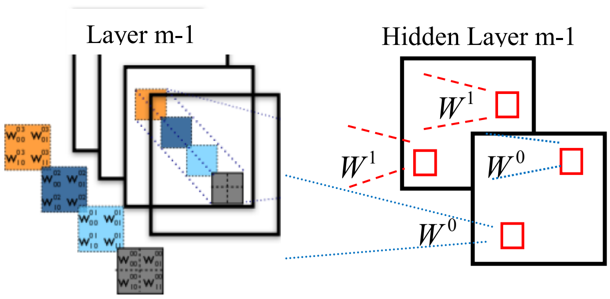

Fig.12: Activation function of the working principle

In the above figure, 4 channels are convoluted to obtain 2 channels. The number of parameters is 4 × 2 × 2 × 2, where 4 means 4 channels, the first 2 means 2 channels and the last 2 × 2 indicates the size of the convolution kernel [14].

Pooling

A very natural idea for describing large images is to aggregate the features of different locations. These summary statistics not only have much lower dimensions but also improve the results (not easily over-fitted). This type of aggregation is called pooling.

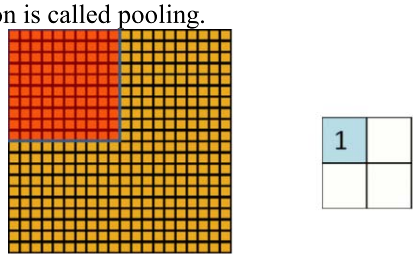

Fig.13: Pooling of the principle

3 Identification System Simulation

3.1 Establishment of recognition model

License plate recognition system involves a number of technologies, and now we create a comprehensive system [15].

(1) Firstly collecting the vehicle's information, and preliminary screening.

(2) RGB color image into HSV style, reduce noise pollution.

(3) The image is divided into H, S, V single-channel grayscale image, remove the noise of each channel, binary and "AND" operation.

(4) Locate the rectangular area by morphology.

(5) According to the location found by the coarse positioning, using the maximum adjacent character horizontal center distance method to achieve license plate segmentation.

(6) For different characters, sticky characters and non-stick characters use different ways to find.

(7) Segmentation of each character in the license plate, interception of each character outline.

(8) Intercept the block. Cutting out the rectangular block in the figure to prepare for the next steps. The interception of the character image is normalized to 20 × 32 rectangular tiles. For example, fig.14.

Fig.14: Interception of the character picture

(10) The image is normalized to a 227 × 227 × 3 in RGB.

(11) Conv1 layer, using 96 convolution kernels of size 11 × 11, using the excitation function (Rell) to ensure that the value of the feature map is within a reasonable range. And 4 pixels move to the right as a unit step, resulting in a (557) × 55 × 96 feature map ((227-11) / 4 + 1 = 55). Further pooling (pool1)and normalizing(norm1), the maximum pooling algorithm ((55-3) / 2 + 1 = 27) was used for the window pooling process of 3 × 3 and the step size of 2 to obtain 96 figure features of 27 × 27, and then these characteristics as input data, the first convolution is completed.

(12) Conv2 layer, 256 convolution kernels of 5 × 5 are used. In order to ensure that the size of the feature map after the convolution operation is constant, the expansion edge is 2 pixels, and a new 256 features ((27-5 + 2 × 2) / 1 + 1 = 27), that is, there will be 256 features of 27 × 27 size. The same ReLU and pool2 and norm2 operations as in (11) are then performed. The characteristic map changes to 256 × 13 × 13, ((27-3) / 2 + 1 = 13).

(13) 384 3 × 3 convolution kernels are used for both the Conv3 and Conv4 layers, resulting in 384 new features of 13 × 13 ((13-2 + 1 × 2) / 1 + 1 = 13) There is no pooling layer on both levels.

(14) The Conv5 uses 256 convolution kernels, each of the expansion edges is 1 pixel, and the pooling layer is used to prevent overfitting, resulting in 256 13x13 (13-3 + 2 * 1) / 1 + 1 = 13), And a characteristic map of a pool 5 size of 6 × 6 × 256 ((13-3) / 2 + 1 = 6) is further performed using a window of 3 × 3 steps of 2.

(15) The DFD phase of fc6 and fc7 is a fully connected layer. Using 4096 neurons, a total of 256 6x6 features are fully connected, a 6x6 size feature map is convoluted into one characteristic point. Then dropout randomly lost some node information from 4096 nodes, and then got a new 4096 neurons.

(16) The fc8 linker, using 65 neurons, fully connected 4096 neurons in fc7 and then passed through a Gaussian filter to get 65 float values, which is the probability of prediction

3.2 Simulation of the model

There are 6,280 license plate numbers, pretreatment to establish a reasonable input layer data set. Select 75% of the picture 4710 license plate as a training set. There are 65 groups of characters in the training set (31 groups of Chinese characters, 24 groups of English letters and 10 groups of digital characters). There are 4,710 Chinese characters, 10,759 English characters and 17501 numeric characters. In the test set, there are 1570 Chinese characters, 3402 English characters and 6018 numeric characters. Iterative training results.

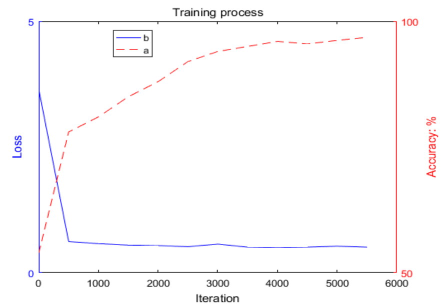

Fig.15: character recognition loss and accuracy curves

This article is intended to develop a highly applicable algorithm that takes full account of time and accuracy. Comparison of various algorithms.

Table1: Comparison of the results

Model	Accuracy	Time (t)
BP-neutral network	92.3%	0.953
Pattern matching method	80.4%	0.192
CNN	98.8%	1.16
The comprehensive model of this paper	96.9%	0.517

4 System Testing

Randomly selected from a collection of 1388 car license plate data from 30 plates to determine the test results are shown in the table 2.

Table 2 License plate recognition results

License plate	Identify the result	License plate	Identify the result
贵AL037K	贵AL037K	苏EG08P9	苏EG08P9
闽CB6957	闽CB6957	苏AFF870	苏APF870
贵AL037K	贵AL037K	云BTL116	云BTL116
京PH3X00	京PH3X00	苏E703Y5	苏E703Y5
粤N02181	粤N02181	鲁L176LL	鲁L176LL
津H821CH	津H821CH	川AT0H69	川AT0H69
苏A2396V	苏A2396V	苏AE22C7	苏AE22C7
鲁Y9D380	鲁Y9D380	赣F16712	赣F16712
苏B755QT	苏B755QT	苏EG26J6	苏EG26J6
鄂AQY228	鄂AQY228	豫A6V979	豫A6V979
津LW0668	津LW0668	鲁D539XF	鲁D539XF
冀A594LG	冀A594LG	京F51Y85	京F51Y85
川A568NB	川A568NB	沪C0TH96	沪C0TH96
鲁BE99A5	鲁BE99A5	粤B8DY18	粤B8DY18
桂A18H6L	桂A18H6L	鲁U38ES3	鲁U38ES3

Obtained through the analysis, there has been a group of recognition errors, F has been identified as P, and the wrong results in following figure. In the positioning stage based on morphological positioning results.

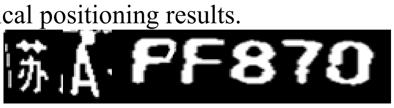

Figure 16 character extraction stage

In accordance with the above identification process, the final result is as shown below.

Figure 17 Final recognition result

Error Analysis: In a dark environment, positioning the license plate, after segmentation characters, resulting in the first F fuzzy, resulting in the recognition as P, while the second P recognition is correct.

5 Conclusions

In this paper, a combination of traditional methods and deep learning is proposed, and a series of optimization of license plate location, license plate region extraction, character segmentation and character recognition are made. A complete recognition system is proposed. In the positioning phase, we use morphological positioning, character segmentation using the maximum adjacent character horizontal center distance segmentation method, and CNN character recognition method to optimize the various processes. Try to overcome the noise in the complex movement of the scene and coordinate the relationship between accuracy and time to form the final model.

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