License Plate Recognition Based on Rough Set

Xin-Yan Cao and Chen-Ming Zhang

Abstract License plate recognition belongs to the field of computer vision and pattern recognition, and plays an important role in the field of intelligent transportation. The license plate location is a key technology in license plate recognition; the accuracy in the positioning of a license directly affects the accuracy of character segmentation and character recognition, and has a direct impact on the efficiency of the license plate recognition system. In this chapter, a plate positioning system is constructed based on the knowledge acquisition and knowledge reduction ability of a rough set, as well as the learning ability and generalization ability of a neural network,. By combining the rough set with neural networks and fuzzy logic, a rough fuzzy neural network recognition is proposed. The experimental results show that this system not only simplifies the structure of the system but also improves the generalization capability of knowledge, and improves the accuracy of character positioning.

Keywords Rough sets • License character recognition • Genetic methods • Neural network

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1 Introduction

The vehicle license plate recognition system is an important part of intelligent transportation systems. It is based on a computer vision system on vehicle licenses for a specific target and is one of the important research topics of computer vision and pattern recognition technology in the field of intelligent transportation applications. It can be widely used in automatic toll management systems of highways, bridges, tunnels, urban transport vehicle management, intelligent community, intelligent parking management, license plate validation, detection of stolen vehicle tracking, traffic statistics, and other fields; it has broad application prospects.

License plate location is finding the location of the vehicle license from the intake of car images and accurately segmenting the license plate from the region for use in character segmentation. Therefore, the determination of the license area is one of the important factors that affect system performance. The accuracy of license positioning directly affects the accuracy of character segmentation and character recognition, and has a direct impact on the efficiency of the license plate recognition system.

Vehicle images are collected from the natural environment in which the imaging conditions of the license plate and the background are generally not controlled, especially for lighting conditions and complex background information. This, coupled with the different shooting distances and angles, could result in significant difficulties to the target search. The plate area is very difficult to distinguish from the various interferences, and the special nature of the application requires that license plate location is completed quickly and accurately. So if there is no efficient search method, a lot of computing time and storage space will be consumed. License plate positioning technology has always been a difficult thing and is a key component of license plate recognition technology.

According to the different characteristics of the license plate, different positioning methods can be used. There are many ways of license plate positioning. The main license plate location methods are those based on edge detection and Hough transform [1], morphological processing and window searching [2], neural network [3], license plate of the scan line positioning, as well as the texture-based license plate location method [4]. This chapter combines rough set knowledge acquisition capability with neural network classification, and the study and implementation of an automatic positioning system for license plate images, and has a certain theoretical and practical value.

2 License Plate Image Acquisition

Before the previous license plate location, we must first obtain a license plate image. In the past, vehicle detection was mostly acquired by a pressure-sensitive coil embedded in a fixed location of the road. The disadvantages of this approach are the complexity of the installation process, the device is easy to damage, there could be damage to the road surface, and it involves relatively high maintenance costs. With detection methods based on laser sensor and red sensor, human interference is relatively large. In comparison, the video-based road traffic monitoring system, which has a wide detection range, flexible installation, low maintenance costs, and easy application process, does not destroy the road surface, even though there are some defects, such as vulnerability to the impact of the external environment interference and low detection accuracy. With the continuous development of computer hardware and software technology, however, it has gradually become an emerging technology in detection of traffic parameters [5].

In dynamic vehicle license plate recognition, image acquisition and subsequent identification are closely linked in order to reflect the real time, without a long delay; otherwise, there is not much practical value. The sense coil and capture card, which is the core of the license plate collection system, consists of a lane before coil sensors, a capture controller, a CCD camera, a frame grabber, auxiliary lighting equipment, and industrial computer equipment. The lane before coil sensors uses the coil sensors to send signals to the capture controller, and the capture controller controls the vehicle images received by the image acquisition card and digitizes them into the computer in order to gain information on the license plate image.

3 License Plate Image Preprocessing

For these smudges and uneven illumination license plate images, image enhancement must be done to complete character segmentation. This chapter mainly conducts low-pass filtering and grayscale expansion treatment on these images [6]. We first make the segmented color car brand image gray, and then use Wiener filtering to remove noise from grayscale images, and, finally, we make the license clear through histogram equalization.

3.1 Grayscale Conversion

With the license plate image acquisition technology, the original images obtained are all colored. Colored images contain a large amount of color information, so they require large storage space, and this would mean spending a lot of system resources for processing, thus reducing the speed of system execution. So, we use grayscale images, with a 256 luminance value, to do colored image processing. The vehicle images captured by default are 24-bit true color images. First, the original image is transformed from RGB space to YCbCr space, and then only the Y component is extracted, thus generating grayscale images.

3.2 Wiener Filter

The image quality is reduced due to the interference of the license, so the image filtering denoising is necessary. This chapter adopts two-dimensional adaptive filtering, estimates according to the statistics of the local neighborhood of each image, and conducts pixel-adaptive Wiener filtering. The Wiener filter design steps are as follows:

Step 1: Digitizing samples on input signal $s(t)$
Step 2: Seeking the autocorrelation function of the input sample, thereby obtaining an estimate of $R_x\ (\tau)$
Step 3: Calculating the Fourier transform of $R_x\ (\tau)$ to obtain $P_x\ (s)$
Step 4: Digitizing a sample of the input signal in the case of no noise
Step 5: Obtaining the cross-correlation function of the signal samples and input samples, thereby estimating $R_{xs}(\tau)$
Step 6: Computing the Fourier transform of $R_{xs}(\tau)$ to draw the $P_{xs}\ (s)$
Step 7: Calculating the Wiener filter transfer function $H_0\ (s)$ with the formula

3.3 Grayscale Transformation Enhancement

Due to the limited brightness of the imaging system, there is often insufficient image contrast and the visual effect is poor, which will directly affect the subsequent processing of the image. The contrast can be enhanced by gradation transformation in order to improve the visual effect.

Grayscale Transformation. The gray transform method can enhance the grayscale range and enrich gray levels, so as to achieve the purpose of the enhanced image contrast. Using a linear single-valued function for the linear expansion on each of the pixels within the image will be effective to improve the visual effect of the image [7]. Let us consider the original image $f\ (x, y)$, where most of the pixels are within a relatively small range of gray levels. If we are interested on the gray level only in a certain range of the pixel, we set this grayscale range as $[a, b]$. After linear gradation transformation, the grayscale range $[a, b]$ can be extended to the image g (x, y) in a relatively large gradation range $[c, d]$, where the image after gradation conversion is $g\ (x, y)$, and $\mid d - c \mid > \mid b - a \mid$. The grayscale transformation relationship between $f(x, y)$ and $g(x, y)$ is formula (1):

$$g(x,y) = \begin{cases} c, & f(x,y) < a \\ \dfrac{d-c}{b-d}[f(x,y) - a] + c, & a \le f(x,y) < b \\ d, & f(x,y) \ge b \end{cases} \tag{1}$$

Histogram Equalization. If the grayscale images are concentrated in a narrow range causing the details to be fuzzy, in order to make the image details clear and some of the objectives prominent for enhancing the image, we improve the ratio between the brightness of each part by implementing the histogram adjustment method. Setting the original total number of pixels as N, the histogram equalization calculation steps are as follows:

Step 1: List the original image gradation r_i, $i = 0,1, \ldots, L - 1$, where L is the number of the gray level.
Step 2: Define statistics of the gradation number of pixels $n\,(r_i)$, $i = 0,1, \ldots, L - 1$.
Step 3: Compute the respective gray level frequency of the original image histogram $P(r_i)$:

$$P(r_i) = \frac{n(r_i)}{N}, \quad i = 0, 1, \ldots, L - 1 \tag{2}$$

Step 4: Calculate for grayscale transformation function $T(r_i)$:

$$T(r_i) = \sum_{i=0}^{i} \frac{n(r_i)}{N}, \quad i = 0, 1, \ldots, L - 1 \tag{3}$$

Step 5: Calculate the gradation of the output image after mapping s_j:

$$s_j = \mathrm{INT}[(\mathrm{s_{max}} - \mathrm{s_{min}})\mathrm{T}(\mathrm{r_i}) + \mathrm{s_{min}} + 0.5], \quad \mathrm{i} = 0, 1, \ldots, \mathrm{P} - 1 \tag{4}$$

Step 6: Count each grayscale pixel number after statistical mapping $n\,(s_i)$
Step 7: Calculate the output image histogram $Q(r_i)$:

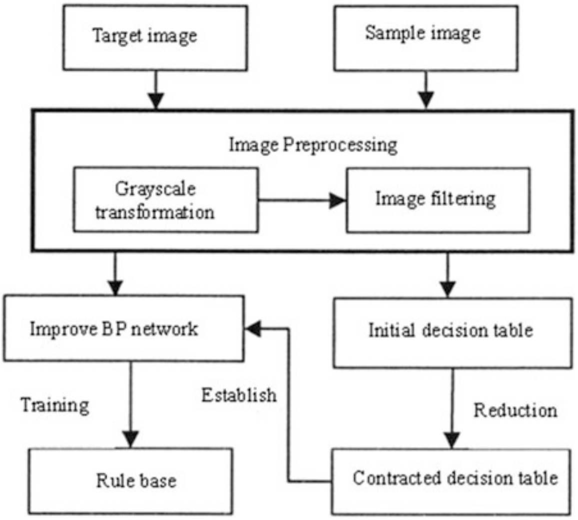
$$Q(r_i) = \frac{n(s_i)}{N}, \quad i = 0, 1, \ldots, P - 1 \tag{5}$$

Step 8: Use the r_i and s_i mapping relationship to adjust the gradation of the original image histogram, thus obtaining an approximately uniform output image distribution.

4 Plate Location Based on Rough Set and Neural Network

Given the computational complexity of the neural network and the long training time required, the learning process can be accelerated by using the rough set method to train data preprocessing, reducing the information table, eliminating redundant data input value, and decreasing input in the number of nodes and the right value, so that the learning time can be shortened. Using the knowledge of the rough set reduction capability for the training of data analysis in order to obtain an outline of the decision rules, and mapping these rules to the corresponding fuzzy

Fig. 1 RS-BP network model



neural network model, or using the self-learning neural network and global approximation ability to optimize the rule parameters, may eventually solve the problem of optimal control rules [8]. The BP model is of great significance in every respect, and its application is very broad, but it also has some disadvantages. Therefore, it needs to be improved in order to locate the license plate more accurately and quickly. The rough set theory is introduced into the BP neural network, which will bring great improvement to the license plate positioning algorithm based on the neural network.

First, to improve the neural network appropriately, the output dynamic range generally needs enhancement, on the S-type compression function (0, 1), which is not necessarily superior. From the weight adjustment formula, we know that the changes in the value of the weights are also proportional to the output of the previous layer, and half of them tend to 0; this will cause a reduction in the amount of weight value adjusting or no adjusting, thereby lengthening the training time. To solve this problem, this chapter makes the output range of the S-type function become ($-1/2$, 1/2). Experiments show that the improved activation function can significantly reduce the convergence time.

Although the rough set theory and BP neural network deal with the problem in two different ways, they have strong complementarity. Therefore, license plate positioning, which combines the two to deal with the technology of intelligent transportation systems in the complex environment, is of positive significance. This chapter presents a license plate positioning system based on rough sets and neural network theory; the model is shown in Fig. 1.

Target data and sample data after data cleaning, data discretization, and data reduction process in Fig. 1, in addition to the inconsistent and redundant data, trains the refined data as the target and sample data of the improved BP neural network and generates a control rule base. The rough set–neural network model of learning and testing processes is shown in Fig. 2.

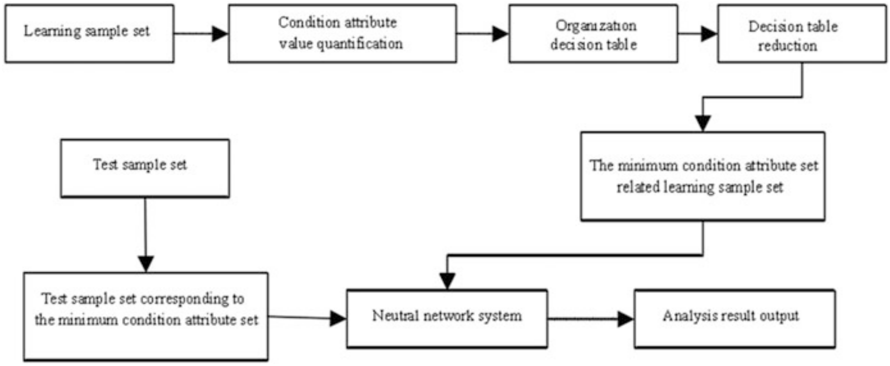


Fig. 2 Learning and testing processes of RS-BP

4.1 Neural Network Learning Algorithm

In this chapter, a dynamic adaptive network model is used, which is based on the nearest neighbor clustering algorithm. The algorithm is an online adaptive clustering linear algorithm and does not require a predetermined number of hidden layer units; the network obtained by clustering is optimal, and this algorithm is available through online learning. The specific process is as follows:

Step 1: Select an appropriate width of the Gaussian function r to define a vector A(l) used to store, which belongs to various types of output vectors, and a counter B (l) to count the number of various samples for statistics.

Step 2: From the start of the first data (x^1, y^1), establish a cluster center so $c_1 = x^1$, A(l) $= y^1$, B(l) $= 1$.

Step 3: Consider the second sample data (x^2, y^2), and make out the distance x^2 to c_1 of this cluster center: $|x^2 - c_1|$.

If $|x^2 - c_1| \leq r$, c_1 is the nearest cluster of x^2, and make A(l) $= y^1 + y^2$, B(l) $= 2$.

If $|x^2 - c_1| > r$, and consider x^2 as a new cluster center, make $c_2 = x^2$, A(2) $= y^2$,B(2) $= 1$.

Step 4: If we consider the sample data k (x^k,y^k), $k = 3,4,\ldots,N$, there are m cluster centers, and its center is $c_1,c_2,\ldots,c_M$. Then make out the distance from x^k to m cluster centers, respectively: $|x^k - c_i|, i = 1,2,\ldots M$.

If $|x^k - c_i| > r$, consider x^k as a new cluster center, make $c_{M+1} = x^k, M = M+1$, A(M) $= y^k$, B(M) $= 1$.

If $|x^k - c_i| \leq r$, calculate as follows: A(j) $=$ A(j) $+ y^k$, B(j) $=$ B(j) $+ 1$. When $i \neq j$, $I = 1,2,\ldots,M$, maintain the value of A(i),B(i) as unchanged.

Step 5: According to the above established BP network, its output is

$$f(xk) = \frac{\sum_{i=1}^{M} w_i \exp\left(-\frac{|x^k - c_i|^2}{r^2}\right)}{\sum_{i=1}^{M} \exp\left(-\frac{|x^k - c_i|^2}{r^2}\right)} \tag{6}$$

4.2 License Plate Location

Based on the RS-BP model car license locator, which uses an M × N sliding window to traverse the preprocessed image pixel by pixel, producing data of the subimage within the window after normalizing the input to the neural network as the input vector, one can determine the location of the sliding windows either with a license plate if the neural network output is high, or otherwise without a license plate.

Sliding Window Selection. Based on the license plate characteristics, the sliding window should be a long strip, but not too large, or the neural network scale will be too large; the positioning accuracy is not high but at the same time it cannot be too small, or it will not be enough to make the network extraction license plate features achieve generalization.

Search Strategy. When using the sliding window traversal image, the search strategy should be paid attention to. No matter what the sliding window, there is a top-down or bottom-up traversal order. For the specific issues of license plate location, it should be said that the bottom-up traversal strategy is superior.

Image Normalization. The neutral network output must be normalized data. Therefore, the pretreated image should be normalized. The specific algorithm is formula (7):

$$\overline{f_d(x,y)} = \frac{f_d(x,y) - \min\limits_{i,j}\{f_d(x,y)\}}{\max\limits_{i,j}\{f_d(x,y)\} - \min\limits_{i,j}\{f_d(x,y)\}} \tag{7}$$

License Plate Coarse Positioning. A normalized subimage is inputted to the neural network; if the output is high, it indicates that this region may have plates, and one must note down the coordinates of the upper left corner of this region as well as the neural network output values of this position. After the sliding window traverses the entire vehicle image, it may get some coordinates of the license plate image area, as well as the neural network output values. Remove the difference between the output value and a desired value in order to sort them. Mark the minimum

Table 1 Experimental results of license plate positioning

Collect environment	Total positioning	Accurate positioning	Positioning accuracy (%)
General situation	148	136	91.9
Rainy day or night	65	55	84.6
Comprehensive	213	191	89.4

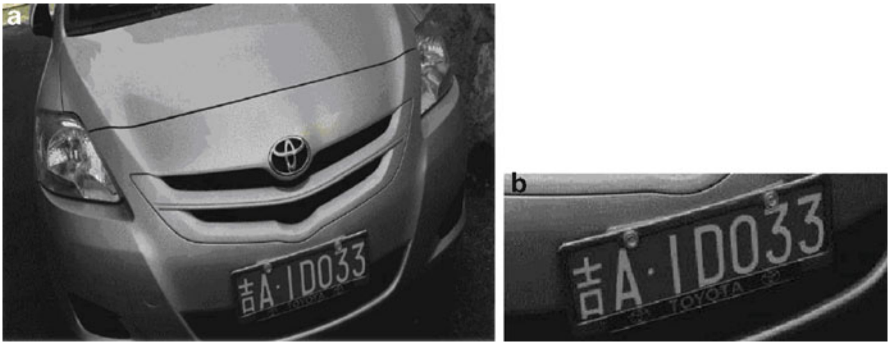


Fig. 3 License plate positioning result: (**a**) original car license image and (**b**) image after the positioning

coordinates of some locations for statistical processing, as this can determine the rough location.

Precise Positioning for License Plate. The exact coordinates of the license area location can be directly extracted from the original image using a threshold value.

4.3 Analysis on License Plate Positioning Results

With the help of the plate positioning system, we collected more than 100 sheets of vehicle images in a parking lot. The experimental test results on 213 vehicles containing license plate images are shown in Table 1.

Colored vehicle positioning input, through algorithm processing, and the final positioning of the license plate are shown in Fig. 3.

5 Conclusion

The automatic identification system of the license plate image is an important application of computer vision and pattern recognition technology in the field of intelligent transportation. The key technologies in the license plate recognition system are vehicle location, character segmentation, and character recognition. License plate positioning is the premise and foundation of the last two steps, and has a direct impact on the processing effect of the last two steps. This chapter discussed the basic principles of a neural network and proposed the license plate positioning algorithm based on the combination of rough sets and neural networks. The experiments show that the license plate positioning achieved using this method is of high accuracy. The shape of the plate region, the proportion of the features, and the gray transition characteristics were used to achieve the precise positioning of the license plate.

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