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Research on Algorithm for Automatic License Plate Recognition System

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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 accurate positioning of a license or not 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 paper, based on knowledge acquisition and knowledge reduction ability of rough set, as well as learning ability and generalization ability of neural network, a plate positioning system is constructed. On this basis, combined 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*

1. Introduction

The vehicle license plate recognition system is an important part of the intelligent transportation systems. It is based on a computer vision system on vehicle license for a specific target, 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 system 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 to find the location of the vehicle license from the intake of car images, and accurately segments the license plate from the region for character segmentation use. Therefore, the determination of the license area is one of the important factors that affect system performance. The accurate positioning of a license or not 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, which the imaging conditions of the license

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plate and the background in the natural environment in general is not controlled, especially lighting conditions and complex background information brought great difficulties to the target search, coupled with the shooting different distances, angles, the plate area is very difficult to distinguish from the various interferences. And the special nature of application, requires completing license plate location 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, is a key technology in the license plate recognition technology.

According to 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 methods based on edge detection and Hough transform [1], based on morphological processing and window searching [2], based on neural network [3], based on the license plate of the scan line positioning, as well as texture-based license plate location method [4]. This paper combines rough set knowledge acquisition capability with neural network classification, study and implementation of automatic positioning system for license plate image, 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, The vehicle detection in the past are mostly acquired by pressure sensitive coil embedded in a fixed location of the road, the disadvantage of this approach is the complexity of the installation process, easy to damage, and damage to the road surface, a relatively high maintenance costs. The detection based on laser sensor and red sensor, human interference is relatively large. Relatively speaking, with a wide detection range, flexible installation, low maintenance costs, application process, the video-based road traffic monitoring system does not destroy the road surface, even though there are some defects, such as vulnerable to the impact of the external environment interference, and a low detection accuracy, with the continuous development of computer hardware and software technology, however, it has gradually become an emerging technology in traffic parameter detection [5].

In dynamic vehicle license plate recognition, image acquisition and subsequent identification is closely linked to be able to reflect the real-time, without a long delay, otherwise, there is not much practical value. The sense coil and capture card as the core of license plate collection system consists of the lane before coil sensors capture controller, CCD camera, a frame grabber, auxiliary lighting equipment and industrial computer equipment. The lane before coil sensors uses the coil sensors, it will send signals to capture controller, the capture controller will control the image acquisition card vehicle images and digitize into the computer, in order to gain information on its 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 paper mainly conducts low-pass filtering and gray-scale expansion treatment on these images [6]. We first make the segmented color car brand image grayed, then use Wiener filtering to remove noise from grayscale images, at last we make license clear through histogram equalization.

3.1 Grayscale Conversion

Through the license plate image acquisition technology, the original images we get are all color images. Color image contains a large amount of color information, so it requires a large storage space, and it will spend a lot of system resources when processing, and will reduce the speed of system execution. So, we use grayscale image, with a 256 luminance value, to do color image processing. The vehicle images captured default is 24-bit true color image, first, the original image is transformed from RGB space to YCbCr space, and then extracts only the Y component, thus grayscale images are generated.

3.2 Wiener Filter

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

Step1: Digitized samples on input signal s(t).

Step2: Seeking the autocorrelation function of the input sample, thereby obtaining an estimate $R_x(\tau)$.

Step3: Calculated the Fourier transform of $R_x(\tau)$, to obtain $P_x(s)$;

Step4: Digitized a sample of the input signal in the case of no noise;

Step5: Requirements for the cross-correlation function of the signal samples and input samples, thereby estimating $R_{xs}(\tau)$;

Step6: Computing the Fourier transform of $R_{xs}(\tau)$, to draw the $P_{xs}(s)$;

Step7: Calculating the Wiener filter transfer function $H_0(s)$ with the formula.

3.3 Gray-scale Transformation Enhancement

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

Gray-scale Transformation. The gray transform method can enhance grayscale range, 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]. If the original image f (x, y), most of the pixels within a relatively small range of gray levels, or if we only have interest on the gray level in a certain range of the pixel, we set this grayscale range as [a, b]. After linear gradation transformation, it can be extended the grayscale range [a, b] to the image g (x, y) in a relatively large gradation range [c, d], where g (x, y,) image is after gradation conversion, and | d-c |> | b-a |. 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 concentrated in a narrow range, will cause the image detail fuzzy, in order to make image detail clear and some objectives prominent to achieve the purpose of enhancing the image, we improve the ratio between the brightness of each part, it can implement on histogram adjustment method. Set the original total number of pixels N, then, the histogram equalization calculation steps are as follows:

Step1: List of the original image gradation r_i, i=0,1, ..., L-1, where L is the number of gray level;

Step2: Statistics of the gradation number of pixels n (r_i), i = 0,1, ..., L-1;

Step3: Computing respective gray level frequency of the original image histogram P(r_i);

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

Step4: Calculated for gray-scale transformation function $T(r_i)$

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

Step5:Calculate the gradation of the output image after mapping s_j:

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

Step6: Count each grayscale pixel number after statistical mapping n (s_i)

Step7: Calculate the output image histogram $Q(r_i)$:

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

Step8: Use r_i and s_i mapping relationship to adjust the gradation of the original image histogram, obtain an approximately uniform output image distribution.

4. Plate Location Based on Rough Set and Neural Network

With a computational complexity in the neural network, and a long time training, in order to accelerate the learning process of the network, using the rough set method to train data preprocessing, reduction information table, eliminating redundant data input value, decreased input in the number of nodes and the right value, so you can shorten the learning time. To use the knowledge of rough set reduction capability for the training data analysis to obtain an outline of decision rules, then mapped the rules to the corresponding fuzzy neural network model, to use self-learning neural network and global approximation ability to optimize the rule parameters, eventually get to solve the problem of optimal control rules [8]. BP model is of great significance in every respect, and the application is very broad, but it also has some disadvantages. So 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 license plate positioning algorithm based on neural network.

First to improve the neural network appropriately, generally the output dynamic range, on the S-type compression function (0,1), which are not necessarily superior. Seen from the weight adjustment formula, we know the changes in the value of the weights is 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 lengthened training time. To solve this problem, this paper 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 rough set theory and BP neural network deal with the problem in two different methods, they have a strong complementarity. Therefore, combine the two to deal with the technology of intelligent transportation systems in the complex environment license plate positioning is of positive significance. So this paper presents a license plate positioning system based on rough sets and neural network theory, the model is shown in Figure 1.

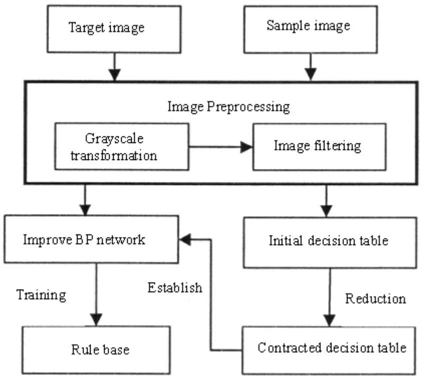

Figure 1. RS-BP Network Model

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

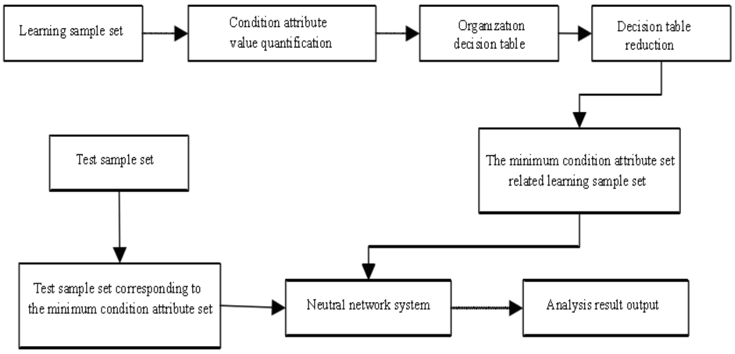

Figure 2. Learning and Testing Processes of RS-BP

4.1. Neural Network Learning Algorithm

In this paper, 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 pre-determined number of hidden layer unit, the network obtained by clustering is optimal, and this algorithm is available 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 vector, a counter B(l) to count the number of various samples for statistical.

Step 2: From the start of the first data (x^1, y^1), to establish a cluster center, so $c_1=x^1$, A(l) =y1, B(l)=1.

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

If $|x^2-c_1|\leq r$, c1 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)=l.

Step 4: If we consider the No.k sample data (x^k,y^k), k=3,4,…,N, there are m cluster centers, its center is $c_1,c_2,\ldots,c_M$. Then make out the distance from xk to m cluster centers respectively: $| x^k-c_i |$,i=1,2,…M.

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

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 $A(i),B(i)$ 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 RS-BP model car license locator, which working style is: using an M × N sliding window to traverse the preprocessed image pixel by pixel, data of the sub-image within the window after normalized input end to the neural network as the input vector, if the neural network output is high, you can determine the location of the sliding windows with a license plate, otherwise no license plate.

Sliding Window Select. Based on the license plate characteristics, sliding window should be a long strip, and its size is not too large, or the neural network scale is too large, the positioning accuracy is not high at the same time it can not be too small, or not enough to make the network extraction license plate features to 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 is, 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 more superior.

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

$$\overline{f_d(x,y)} = \frac{f_d(x,y) - \min_{i,j}\{f_d(x,y)\}}{\max_{i,j}\{f_d(x,y)\} - \min_{i,j}\{f_d(x,y)\}} \tag{7}$$

License Plate Coarse Positioning. Normalized sub-image is input to the neural network, if the output is high, it indicates that this region may have plates, mark down the coordinates of the upper left corner of this region, and neural network output values of this position. After the sliding window traversing the entire vehicle image, it may get some coordinates of license plate image area, as well as the neural network output values, remove the difference between the output value and a desired value, and to sort them. Fetch the minimum coordinates of some locations, for statistical processing, and it 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

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

Table 1. Experimental Results of License Plate Positioning

collect environment	total of positioning	accurate positioning	positioning accuracy
general situation	148	136	91.9%
rainy day or night	65	55	84.6%
comprehensive	213	191	89.4%

Input color vehicle positioning, through algorithm processing, the final positioning of the license plate is shown in Figure 3.

Figure 3. License Plate Positioning Result. (a) is Original Car License Image.(b) is Image after the Positioning

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 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 paper discussed the basic principles of neural network, proposed the license plate positioning algorithm based on rough sets and neural networks combined. The experiments show that the license plate positioning achieved by using the method is of high accuracy. Use the shape of the plate region, the proportion of features and gray transition characteristics to achieve the precise positioning of the license plate.

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