A Hybrid Method for Robust Car Plate Character Recognition *

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Abstract - *Image based car plate recognition is an indispensable part of intelligent traffic system. The quality of the images taken for car plates, especially for Chinese car plates, however, may sometimes be very poor, due to the operating conditions. Furthermore, there exist some "similar" characters, such as "8" and "B","7" and "T" and so on. They are less distinguishable because of noises and/or distortions. To achieve robust and high recognition performance, in this paper, a two-stage hybrid recognition system combining statistical and structural recognition method is proposed. Car plate image are skew corrected and normalized before recognition. In the first stage, four statistical sub-classifiers recognize the input character independently, and the recognition results are combined using the Bayes method. If the output of the first stage contains characters that belong to prescribed sets of similarity characters, structure recognition method is used to further classify these character images. Experiments show that our recognition system is very efficient and robust. As part of an intelligent traffic system, the system has been in successful commercial use.*

Keywords: Car plate character recognition, similar character recognition, statistical recognition, structural recognition.

1 Introduction

In recent years, intelligent traffic control systems have been widely used in toll-pay, real-time monitoring and parking systems[1]. Image based car plate recognition is an indispensable part of such systems.

In general, image based car plate recognition systems are composed of the following three major steps: location of car plate regions, segmentation of characters from the plate regions and recognition of each character[2]. A number of methods have been developed to locate car plate regions from the images and to segment each character[3-4]. However, few aimed at the recognition of car plate characters. Neural network method is employed to recognize car plate characters[5]. The method can achieve promising performance if the quality of the given car plate image is well. However, the quality of image taken for car plates, especially for Chinese car plates, is not always well. This is due to the operating conditions (e.g., dusts on the car plates) and distortion and/or degraded because of poor photographical environments. Furthermore, there exist some "similar" characters, such as "8" and "B","7" and "T" and so on. They are less distinguishable because of noises and/or distortions. Experiments have shown that it's difficult to achieve high car plate recognition rates only by neural networks method.

Recently, many methods have been developed to improve the character recognition rates, noticeably multiple classifiers combination methods, such as multistage classification schemes[6], "parallel" combination of multiple classifiers[7]. In addition, many researchers turned their attention to integrate two kinds of schemes [8]. Different classifiers with different features can complement each other, and group decision can reduce errors drastically and achieve higher recognition rates[9].

In combining multiple classifiers, a main problem is that how to integrate statistical methods and structural methods due to their strong complement. This paper proposes a two-stage car plate character recognition system combining statistical and structural methods. Car plate image is skew corrected and normalized before recognition. In the first stage, four statistical sub-classifiers recognize the character images independently, and the recognition results are combined using the Bayes method. If the output of the first stage contains characters that belong to prescribed sets of similarity characters, structure recognition method is used to further classify: the character image is preprocessed once more, structure features are obtained and fed into a decision tree classifier. The proposed method has been integrated into a commercial car plate recognition system and replaces the BP neural network method originally used in the system. The method has proven to be very efficient and robust.

The paper is organized as follows: In Section 2, methods for recognizing characters by statistical approaches are described. In Section 3, structural methods are used to recognize similarity sets of characters. Section

4 shows some experiment results by the proposed methods and comparison with the results by original BP neural network schema is presented. Section 5 concludes the paper and gives some future work.

2 Preprocessing

In order to recognize characters accurately, preprocessing to the images, such as skew correction and normalization, has to be performed. In this section, we briefly introduce skew correction and normalization operations.

2.1 Skew correction

Character recognitions are generally very sensitive to skew. Therefore, skew detection and correction are critical. We propose here a least-square based skew detection method. Suppose the binary image $F = \{F(i,j), i = 1,2,\cdots I, j = 1,2,\cdots J\}$ is defined as follows:

$$F(i,j) = \begin{cases} 0 & white \\ 1 & black \end{cases}$$

Step 1: Find out all the connected regions. Let the connected region sets be $\{C_1, C_2, \cdots C_N\}$, and C_i has a height H_i and width W_i.

Step 2: For each connected region, check if it is a "valid" region. A connected region C_i is said to be "valid" if $T_{\min} < Wi / H_i < T_{\max}$, where $T_{\min}$ and $T_{\max}$ are predefined values. As for a standard, the rate between width and height of each character ranges from 0.4-0.8 in a given Chinese car plate. Therefore, in our implementation, $T_{\min}$ and $T_{\max}$ are set to 0.3 and 1.0 respectively.

Step 3: For each "valid" connected region, calculate its centroid (G_{ix}, G_{iy}):

$$G_{ix} = \frac{\sum_{(x,y)\in C_i} x \cdot C_i(x,y)}{\sum_{(x,y)\in C_i} C_i(x,y)} \qquad G_{iy} = \frac{\sum_{(x,y)\in C_i} y \cdot C_i(x,y)}{\sum_{(x,y)\in C_i} C_i(x,y)}$$

Step 4: Perform the skew correction by least-squares based on the centroid (G_{ix}, G_{iy}). Approximate sets (G_{ix}, G_{iy}) by least-square, and compute the skew angle θ. Given that $F(x,y)$ is the skew image and $F(x',y')$ the corrected image, the skew correction equation is defined as follows:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$$

Figure 1 gives some images before and after skew correction.

Figure 1: Some images before(upper) and after(lower) skew correction

After skew correction of the character images, characters are segmented from the corrected images.

2.2 Size Normalization

Characters segmented from different car plates have different sizes. A linear normalization algorithm is applied to the input image to adjust to a uniform size (in our implementation, 32×16). Assume the horizontal and vertical projections of the original image F be H and V, respectively. The normalization position (m,n) of (i,j) is obtained by

$$m = \sum_{k=1}^{i} H(k) \times \frac{M}{\sum_{k=1}^{I} H(k)}$$

$$n = \sum_{k=1}^{j} V(k) \times \frac{M}{\sum_{k=1}^{J} V(k)}$$

where M, N is the height and width of normalized image.

Figure 2 shows some normalization results:

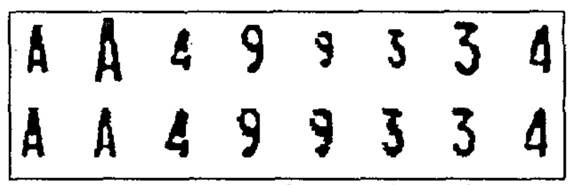

Figure 2: Character images before (upper) and after (lower) size normalization.

3 Recognizing characters by statistical methods

After preprocessing, the input character image is first recognized by statistical methods. In our approach, four sub-classifiers recognize the character independently, and their recognition results are combined using the Bayes method.

Four sub-classifiers are designed independently, and different features are utilized. The recognize method for sub-classifiers is template matching due to its simplicity and stability. We give a brief description about these features used in the system.

Sub-Classifier 1

Sub-Classifier 1 uses the zoning density[10]. To calculate the zoning density, the input image is divided into $n \times m(n=4, m=4)$ zones. In each zone, the density of black points is calculated. Thus the feature has 32 components for the input character image.

Sub-Classifier 2

The input feature is the vertical projection $\{y(i) \mid i=1,2,\cdots\cdots,16\}$, where $y(i)$ is the number of black pixels of the i-th column.

Sub-Classifier 3

The input feature of this sub-classifier is the left-right contour feature. The contour feature can be obtained as follows: in k-th row, scan the image from left to right boundary. Whenever the pixel turns out to be black, compute the width LP_k between the pixel and left boundary. The width RP_k between the pixel and right boundary can be similarly calculated. There exist 64 dimension left-right contour features.

Sub-Classifier 4

In sub-classifier 4, we extract line segment features of the input character. For each row, we count the number of line segment. The same operation is performed for each column. Therefore, the line segment features have 48 dimension(the image size is 32*16).

To achieve robustness and high recognition rates in the recognition system, the recognition results from the above four sub-classifiers are combined by the Bayes method[7]. After combination, we obtain recognition result P_1. If the result doesn't belong to the prescribed sets of similarity characters, the class P_1 is taken as the final recognition result. Otherwise, the character is further recognized by the structural methods described below in Section 3.

4 Recognizing similar characters by Structural methods

To recognize similar characters in our car plate character recognition system, it is important to extract stable and representative structure features. Fortunately, different similarity sets have different structural features. Taken for example, we will discuss in this section how to distinguish most frequently occurring similarities: "8" and "B" by using left edge contour feature.

First, we give the definition of edge point.

Definition 1: A point (i, j) with $F(i,j) \cap \left[\bigcup_{0 \le u \le 1, 0 \le v \le 1} \overline{F(i+u, j+v)} \right] = 1$ is called an edge point.

The left edge sequence of the input image F is defined, which is a left edge point set $\{F(i,k_i) \mid i=1,2,\cdots\cdots,M\}$. For point $F(i,k_i)$, the value k_i can be obtained by the following process: In the i-th row, the column index j moves from left to right until $F(i,j)$ is a left edge point, and $k_i = j$ (the last value). Then the curve direction of edge point (i,j) is defined as follows:

$$dir_i = \begin{cases} 1 & f(i,j) - f(i-1,j) > 0 \\ 0 & f(i,j) - f(i-1,j) = 0 \\ -1 & f(i,j) - f(i-1,j) < 0 \end{cases} \tag{7}$$

Let the curve direction sequence be $\{dir_i \mid i=1,\cdots\cdots,M\}$, if dir_i *and* dir_k satisfy the following conditions:

$$dir_i \times dir_k > 0, dir_t = 0 \mid t =_{t=i+1,\cdots,k-1}; \| i-k \| < W \tag{8}$$

Then the sequence is said to contain **a curve point,** where W is a predefined threshold.

The left edge contour feature is calculated as follows:

Step 1: Obtain the left edge sequence $\{F(i,k_i) \mid i=1,2,\cdots\cdots,M\}$ of the input image F.

Step 2: Compute the curve direction of the left edge sequence $\{dir_i \mid i=1,\cdots\cdots,M\}$.

Step 3: Compute the total of the curve point set (denoted by ***totalcurve***) from the direction of the left edge sequence.

Step 4: Approximate the left edge sequence by using a least-square method. Compute the approximate error (denoted by ***error***).

The two types of structural features are feed into a binary decision tree to distinguish "8" and "B". The decision tree doesn't always give the precise result. If the decision rejects the character, the final recognize result is set back to P_1 (refer to Section 2). In our system, several parameters(such as W) and decision parameters used in binary decision tree need to be predefined, and they can be obtained by some optimization algorithm, and we use genetic algorithm for optimization parameters.

5 Experimental Results

To test the performance of the hybrid method, we compare the results from our method with the Bp neural network(Multi Layer Perception with back propagation training algorithm) which had been already implemented in the original car plate recognition system and had been already in commercial use. The recognition rates listed in the following table (without considering the rejected characters for which no decisions will be made for the characters). It is a three-layer structure, and both hidden layer have 50 nodes.

Table 1: The recognition rates of our hybrid method v.s. the Bp neural network method

Method	Training set	Testing set
Bp neural netowrk	95.68%	91.03%
Our hybrid method	97.46%	95.41%

It can be seen from Table 1 that our method has small improvement on the recognition rate over the Bp neural network method. However, the difference for testing character set is very obvious.

To further prove the robustness and efficiency of our hybrid method, we tested more than 10000 car plate images taken from real world application. As show in the graph in Figure 1, the recognition rates differ greatly with the road conditions, illumination and cleanness of cars. Compared with Bp neural, our hybrid method can always achieve a drastic improvement in the recognition performance.

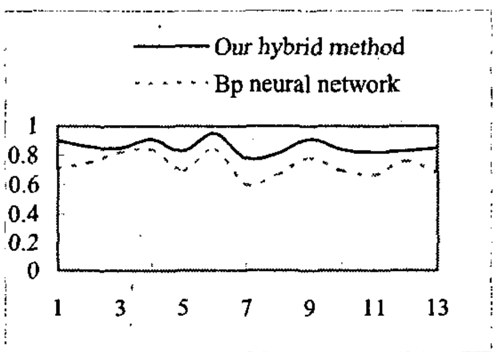

Figure 3: Comparison of recognition rates of our hybrid method and the Bp neural network for more than 10000 car plate character images in 13 Chinese geographical provinces.

Figure 4 shows some typical car plate images recognized incorrectly by Bp neural network(characters recognized incorrectly are flagged with frames). However, these car plate images can be recognized correctly by our hybrid method.

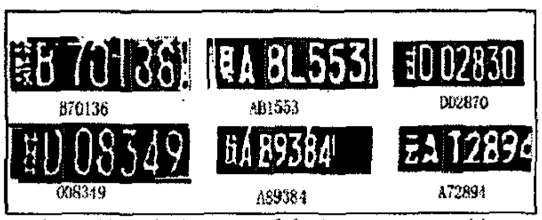

Figure 4(a): The images and the incorrect recognition results by Bp neural networks

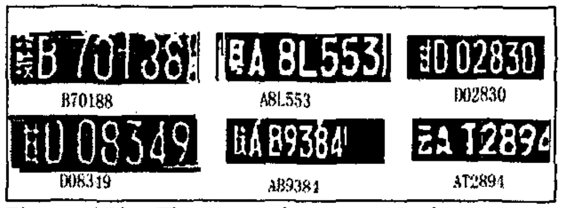

Figure 4(b): The same images and the correct recognition results by our hybrid method

Figure 4: Improved recognition results by our hybrid method over the Bp neural network.

6 Conclusion and Future Work

In this paper, we propose a two-stage hybrid method for car plate character recognition. The main contributions of our work include (1) Distinguishing similar characters by local structural features. (2) Developing a system architecture combining statistical and structural recognition methods. We tested the method with huge number of plate images captured in different environments from real applications, and proven to be successfully in commercial car plate recognition. Compared with Bp neural network, our hybrid method is more effective and robust. We believe that our method can be extended to other OCR application fields.

The first character of Chinese car plates is always a Chinese character, which sometimes may be very illegible even by human beings. How to recognize it is a challenging research topic.

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