Chinese License Plates Recognition Method Based on A Robust and Efficient Feature Extraction and BPNN Algorithm

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Abstract. The prosperity of license plate recognition technology has made great contribution to the development of Intelligent Transport System (ITS). In this paper, a robust and efficient license plate recognition method is proposed which is based on a combined feature extraction model and BPNN (Back Propagation Neural Network) algorithm. Firstly, the candidate region of the license plate detection and segmentation method is developed. Secondly, a new feature extraction model is designed considering three sets of features combination. Thirdly, the license plates classification and recognition method using the combined feature model and BPNN algorithm is presented. Finally, the experimental results indicate that the license plate segmentation and recognition both can be achieved effectively by the proposed algorithm. Compared with three traditional methods, the recognition accuracy of the proposed method has increased to 95.7% and the consuming time has decreased to 51.4ms.

1. Introduction

Vehicle plate license recognition (VPLR) plays a significant role in the fields of traffic management, vehicle monitoring and suspect vehicle tracking these days. For example, in some cities in China, a new VPLR technology which enables drives to pay parking fee using electronic wallet in a short time automatically without leaving cars has received widely favourable reception. Due to the increasing demand of human society, it’s of great significance to enhance the result of license plate location and recognition in terms of improving vehicle management and alleviating traffic congestion. However, because the license plates can be easily affected by external factors such as lightning conditions, weather and backgrounds, locating and detecting the license plate from original images accurately and efficiently is still the main obstruction for successful license plate recognition.
In the past several years, many researchers have developed various methods to extract features from specific characters [1-4]. In [5], the researchers find that a vertical traverse density (VTD) vector and horizontal traverse density (HTD) vector can be used to describe each character object. However, due to the similar structures in different characters, the presented algorithm has difficulty distinguishing between Z and E, T and L, and some other groups.

In this paper, a robust license plate detection and character recognition method based on a novel combined feature extraction model and BPNN algorithm is presented. The combined feature extraction method uses VTD, HTD features and edge distance features as training samples of the VPLR classifier. It means that the method which contains more useful information for network training has a good recognition accuracy.

2. License plate location and segmentation of characters before recognition

2.1. Pre-processing of original image and license plate detection

Considering practical conditions, there exists much interference in original images such as lighting condition and image quality, which cause damaging influence to the recognition performance. So a pre-processing of the original image is important to locate the license plate quickly and accurately. Figure 1 shows the original vehicle image and the gray-scale image respectively.

![Figure 1. Original image and the gray-scale image of the vehicle](image)

The whole steps of the original image pre-processing are described as follows: Firstly, a grey level stretch processing is applied to enhance the contrast between the license plate area and the other parts of image. Then, detecting edge using Roberts operator to highlight the difference between the license plate frontier and the background. After this, a set of candidate regions are extracted after image erosion and morphological closed operation, excluding the small parts which are certainly not parts of the license plate region. According to empirical experience [6], the true region of the license plate parts is verified while the other candidate regions are all removed from the image.

2.2. Accurate positioning of the license plate image and character segmentation

The horizontal integral projection which is used to locate the license plate accurately in vertical direction can be depicted by the following equations:

\[ r(i, j) = |f(i, j) - f(i, j - 1)|, \quad i = 1, 2, 3, 4, \ldots, n \]

Where, \( r(i, j) \) is the pixel value of the image \( r \), \( f(i, j) \) is the pixel value of the image \( f \), \( m \) and \( n \) are the height and the width of the image \( f \) respectively. Then the projection value of the row \( i \) named \( T_r(i) \) can be obtained by accumulating the pixel value of image \( r \) per row, which can be depicted as

\[ T_r(i) = \sum_{j=2}^{n} r(i, j) \]

Similarly, applying the vertical integral projection to locate the license plate accurately in horizontal direction. The difference in coarse image, vertical direction processed image and accurately poisoning image of the license plate is shown in figure 2 respectively.
Figure 2. Coarse image, vertical direction processed image and accurately poisoning image

The license plate image consists of seven characters, a dot and the space between them. To get the images only contains each character, it’s natural to seek for the starting and ending points of each character. Thus, an algorithm based on calculating the times of white and black transformations in each column is presented. The histogram of transformation projection is shown in figure 3.

Figure 3. Histogram of transformation projection

Thus, the first character can be divided ranging from column 1 to column A from the image. The second character begins with point B and ends with point C. Due to the fact that the point D represents for the dot which need to be removed, the remaining image should start at the ending point of the dot. In this way, the rest five characters can be segmented one after another. The final segmentation result is shown in the figure 4.

3. Character recognition based on a novel combined feature extraction

3.1. Features extraction algorithm based on VTD and HTD methods

The traditional traverse dense features consist of HTD and VTD features. Choosing a character object "N" to explain the extraction algorithm clearly. As is shown in figure 5, the character N is selected after the binary operation. Scanning the column and row one by one of the image pixels and recording the number of changes in black and white pixels. The algorithm can be described as follows:

\[ \text{feature value} = \begin{cases} 1, & \text{while the first pixel of the row or column is white} \\ \text{feature value} + 1, & \text{while } r(i,j) = 0 \& \& r(i,j+1) = 1 \text{ in row} \\ \text{feature value} + 1, & \text{while } r(i,j) = 0 \& \& r(i+1,j) = 1 \text{ in column} \end{cases} \] (3)

Where, the initial feature value is 0 and \( r(i,j) \) is the pixel value of the image. In the column scan of the character "N", the most number of alternating black and white pixels is one. These characteristic values are remarked as small black squares shown in figure 6, the number of squares means the feature value of the column. A series of feature values are obtained from left to right, recorded as VTD features. In the same way, scanning the object from top to bottom, the image has altered form black to white twice in side parts and three times in the intermediate part, describing the HTD features clearly.

Figure 5. The processing of character N

Figure 6. The VTD features of character “N”

\[ \text{VTD (N)} = 11111111112211111111 \]
The dimension of the VTD and HTD features are the width and height of the processed character image. According to the experimental results, the final optimal license plate size is 35×20, that is to say, the dimension of the two feature vectors are 35 and 20 respectively.

3.2. Improved features extraction algorithm using edge distance features

The algorithm mentioned above uses VTD and HTD features as two sets of characteristic vectors. However, it may cause incorrect results in recognition when handling with some words which have similar traverse density structure like the letter “E” and “Z”, the letter “T” and “L”. As shown in figure 7, the character “E” and “Z” have the almost identical VTD and HTD feature vectors which is indistinguishable.

![Figure 7. The character “E” and “Z”](image)

![Figure 8. Extraction processing of edge distance feature](image)

In order to solve this problem, another set of features based on edge distance is presented to compensate for the deficiency in traditional feature extraction algorithm. The proposed method of extracting the edge distance features can be described as followings:

From the up to the bottom, searching the each pixel of row from the left to the right of the character image. Then, finding the first pixel of the row \(i\) whose value is 1 (white), recording the index of the pixel, setting as \(d[i]\), where, \(i=1,2,...,n\), \(n\) is the height of the character image. Finally, we obtain the array \(d[i]\), the elements in which consist of the feature vector. As shown in figure 8, the edge distance feature values of the character “Z” are changing from the row 1 to row \(n\), while the most edge distance feature values of the character “E” are identical. The feature values of these two characters is obvious different when adding this set of features.

Thus, three different sets of features have been defined in the improved features extraction algorithm: the vertical traverse density, the horizontal traverse density and the edge distance features.

3.3. Characters classification and recognition using Back-propagation Neural Network

In order to recognize the numbers 0-9 and the English letters A-Z of the license plate, choosing BPNN as a training model to utilize the specific learning process of the neural network [7-8].

Since the dimension of the HTD features, VTD features and the edge distance features of a specific character are 35, 20 and 35 respectively, connecting three sets of features into one feature vector, so the number of input layer nodes is 90. There are 26 English letters, 10 digital numbers, 36 alphanumeric characters waited to be recognized in the system, so the output layers has 26 nodes, 10 nodes and 36 nodes corresponding to the English letters classifiers, digital numbers classifiers and mixed classifiers respectively. According to the experimental results and empirical formula, the node number of hidden layers in English letters classifier, digital numbers classifier and mixed classifier are 48, 27 and 64 respectively. The error of the training processing of letters and numbers mixed classifier is plotted in the figure 9.
4. Experiment and analysis
The experimental results of image pre-processing and license plate detection are shown on figure 10.

Figure 10. The results of each step in the pre-processing and license plate detection
As seen from the above figure, the edge is detected by Roberts operator in figure 10(a), then after erosion operation and morphological closed operation, there are five candidate regions of license plate waiting to be checked shown in figure 10(b). Then the license plate region is determined which is marked white colour shown in figure 10(c) while the other candidate regions are all removed. Finally, the license plate region is successfully located in the original grey-scale image shown in figure 10(d). The figure 11 shows the entire recognition processing of the original image applying the VPLR system.

Figure 11. The entire recognition processing of the original image using the VPLR system
Table 1. Identification function of each classifier

| Classifier | Parameter          | Value |
|------------|--------------------|-------|
| Letters    | Recognition Rate (%) | 94.8  |
|            | Recognition Times (ms) | 55.2  |
| Numbers    | Recognition Rate (%) | 96.3  |
|            | Recognition Times (ms) | 46.3  |
| Mixed      | Recognition Rate (%) | 95.7  |
|            | Recognition Times (ms) | 51.4  |

Table 2. Comparison of the proposed method and conventional methods of two factors

| Method                        | Precision (%) | Computational time (ms) |
|-------------------------------|---------------|-------------------------|
| Proposed method               | 95.7          | 51.4                    |
| Line processing[1]            | 94.3          | 70.4                    |
| Peak position[2]              | 95.2          | 66.7                    |
| Pixel density[3]              | 94.9          | 59.9                    |

Finally, 35 license plates collected in different backgrounds and illumination condition are used. As a result, 28 license plates are completely correct identified and the license plate recognition accuracy is 80 percent. There are total 201 of 210 valid characters are correctly recognized and the character recognition accuracy is 95.7 percent. The recognition rate of each classifier and the consuming time of single character are shown in table 1. Compared with the traditional methods, the proposed algorithm occupies a dominant position in the precision and the computation time. Experimental results are summarized in table 2.

5. Conclusion
A novel combined feature extraction model with BPNN algorithm is proposed to realize license plate recognition in this paper. The advantages of proposed method are higher accuracy and can be applied efficiently under complicated backgrounds. In the future, the algorithm would be further studied to implement on hardware in order to fit more complex conditions and reduce time-cost.

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