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An Improved Character Recognition Algorithm for License Plate Based on BP Neural Network

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Abstract: License plate character recognition is the basis of automatic license plate recognition (LPR) and it plays an important role in LPR. In this paper, we considered the advantages and disadvantages of the neural network method and proposed an improved approach of character recognition for license plates. In our approach, firstly, license plates were segmented into character pictures by using the algorithm which combines the projection and morphology. Secondly, with a focus on each character picture, recognition results determined by the calculation of the new recognition algorithm were as a reflection of the different features of every kind of character image. Then, character image samples were classified according to different light environment and character type itself. Finally, we used extracted features vectors to train the BP (error back propagation) neural network with adding noise relatively. Due to the influence of environmental factors or character images themselves will bring font discrepancy, font slant, stroke connection and so on, compared with template matching recognition method, neural network method has relatively great space to enhance the recognition effect. In the experiment, we used 1000 license plates images that had been successfully located. Of which, 11800 character images have been successfully identified, and the identification rate of our new algorithm is 91.2%. The experiment results prove that the improved character recognition method is accurate and highly consistent.

Keywords: BP neural network, character image feature, character recognition, license plate recognition.

1. INTRODUCTION

With the increasing popularity of vehicles and the improvement of people's living standard, traffic accidents have exponentially grow in last few years. License plate character recognition plays an important role in many applications such as unattended parking lots, security control, and automatic toll collection station and so on. Therefore, satisfying driver's requirements for high efficiency and security is becoming a research topic and of great significance in both theoretical studies and practical application. Due to the nature of license plate character image and the similarity among some character images, for example, an image always contains much redundant information, traditional character recognition method is not applicable.

At present, template matching algorithm and neural network algorithm are popularly used in license plate character recognition. At the same time, these two kinds of algorithms all have their own advantages and disadvantages. The template matching algorithm has a very high speed, but it is not very effective for some character images which have font discrepancy, font slant, noise and stroke connection [1]. The neural network algorithm has a relatively high recognition rate, but it is at the cost of increasing time complexity [2].

In this paper, we pay more attention to accuracy rate than time complexity. Therefore, we proposed a new character recognition method, which is based on the BP (error back propagation) neural network algorithm. Its main advantages lie in: firstly, character images were classified according to light intensity and character type itself. Secondly, the features of character images are only few data which contains much information, compared to the original license plate images information, the required memory space is much smaller, so that the time of training the neural network is relatively small. Thus it can improve the accuracy and efficiency of character recognition.

The rest of the paper is organized as follows: in Section 2, the former related work is presented. The new character recognition algorithm is detailed in Section 3. Section 4 presents some experimental results. Final experimental conclusions and some ideas for future work are presented in Section 5.

2. RELATED WORK

In this section, the process of license plate recognition is presented. Some pre-process works should be done before recognizing the license plate character images. The pre-

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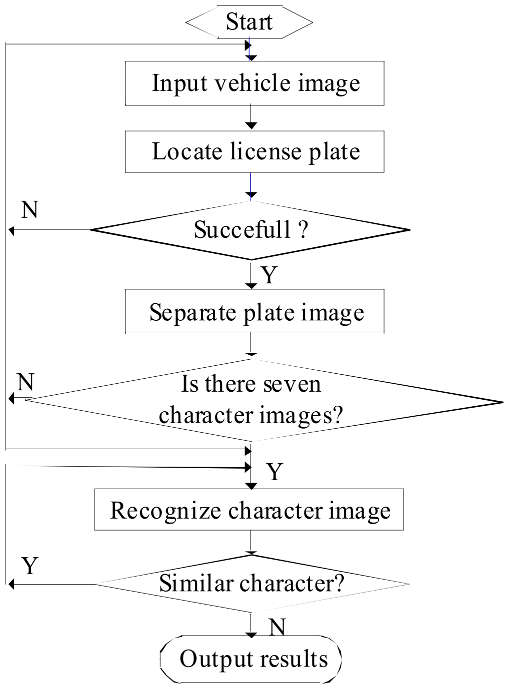


Fig. (1). Diagram of LPR.

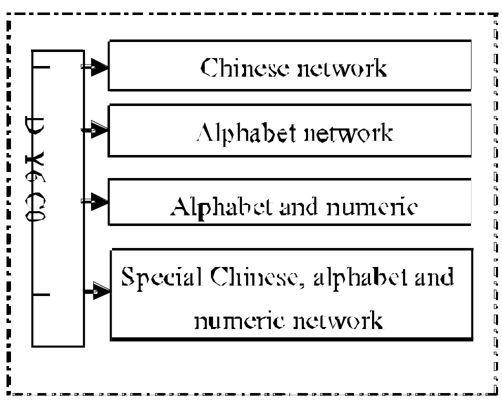


Fig. (2). Four neural networks based on hierarchical and classified method.

process works play an important role in the recognition procedure. Fig. (**1**) shows the presented LPR process.

In this paper, we assumed that license plate has been located successfully, and the character images also have been extracted from the located license plate. Through the location and segmentation of the license plate, we can acquire seven character images.

According to the compositional semantics of license plate, we designed four BP neural networks to recognize the character corresponding to the position respectively as shown in Fig. (**2**).

Generally, any image could be denoted by the three primary colors of RGB [3], which includes much information needing to be managed. So it will waste a lot of time to deal with redundant information, especially the processing of license plate characters recognition. Besides, character images extracted may be deformed, noisy and broken. In

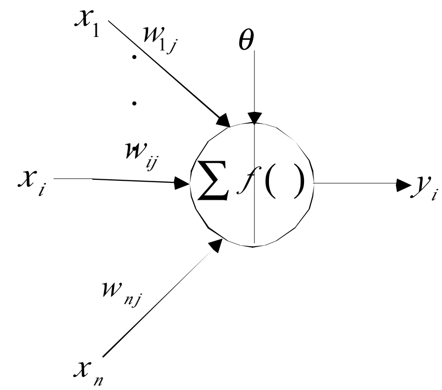


Fig. (3). Unit structure of the node.

order to retain useful data and remove the useless non-character information at the same time, we did some pre-process work. In our algorithm, the preprocessing procedure consists of five parts. They are mainly binarization, median filter, character image reversal, image normalization and features extraction. After preprocessing, we can get the character images which contain useful character information and with the size of 20×16 pixels.

3. ALGORITHM REALIZATIONS

3.1. The Pre-processing

The pre-processing mainly contains the following steps:

(1) Do binarization processing to character images by using a variable threshold [4] in order to reduce character information loss as far as possible.

(2) Do Median filter process to remove the salt and pepper noise.

(3) Invert those character images to get the images with black characters and white background, where “0” and “1” indicate white pixel and black pixel respectively.

(4) Resize the images to 20×16 pixels.

(5) Extract features which are strong enough to distinguish character.

After pre-processing, different character samples will be input to the corresponding neural network.

3.2. BP Neural Network

3.2.1. Principle of BP Neural Network

In general, BP neural network [5] includes nodes in input layer, nodes in output layer and nodes in latent layer, where latent layer can be one layer or multilayer. In this paper, we adopt the network which contains one latent layer. There are many applicable functions in the neurons of BP neural network; we adopt sigmoid functions [5, 6] in every layer. In the BP neural network, every node has the unit structure which is shown in Fig. (**3**) [7].

1111	0000	0000	0111	1111	1111	1111	1111
1111	0000	0000	1111	1111	1111	1111	1111
0111	1000	0001	1110	1111	1111	1111	1110
0011	1100	0011	1100	0000	0000	0001	1110
0011	1100	0011	1100	0000	0000	0011	1110
0001	1111	1111	1000	0000	0000	0111	1100
0000	1111	1111	0000	0000	0000	1111	1000
0000	0111	1110	0000	0000	0001	1111	0000
0000	0111	1110	0000	0000	0001	1110	0000
0000	0011	1100	0000	0000	0011	1110	0000
0000	0011	1100	0000	0000	0111	1100	0000
0000	0011	1100	0000	0000	1111	1000	0000
0000	0011	1100	0000	0000	1111	1000	0000
0000	0011	1100	0000	0001	1111	0000	0000
0000	0011	1100	0000	0011	1110	0000	0000
0000	0011	1100	0000	0111	1100	0000	0000
0000	0011	1100	0000	0111	1000	0000	0000
0000	0011	1100	0000	1111	1100	0000	0000
0000	0011	1100	0000	1111	1111	1111	1111
0000	0011	1100	0000	1111	1111	1111	1111

Fig. (4). Feature extraction about Y and Z.

0001	1111	1111	1000	0011	1111	1111	1000
0011	1111	1111	1100	0111	1111	1111	1100
1111	1000	0001	1110	1111	1000	0011	1110
1111	0000	0000	1111	1110	0000	0001	1110
1110	0000	0000	1111	0000	0000	0000	1111
1110	0000	0000	0111	0000	0000	0000	1111
1110	0000	0000	0111	0000	0000	0001	1110
1110	0000	0000	1111	0000	0000	0011	1110
1110	0000	0000	1111	0000	0000	0111	1000
1110	0000	0000	1111	0000	0000	1111	1000
1110	0000	0000	1111	0000	0001	1110	0000
1110	0000	0000	1111	0000	0011	1110	0000
1110	0000	0000	1111	0000	0111	1000	0000
1110	0000	0000	1111	0000	1111	0000	0000
1110	0000	0000	1111	0001	1110	0000	0000
1110	0000	0000	1111	0011	1110	0000	0000
1110	0000	0000	1111	0111	1100	0000	0000
1111	0000	0000	1111	0111	1100	0000	0000
1111	1110	0111	1110	1111	1111	1111	1111
0001	1111	1111	1000	1111	1111	1111	1111

Fig. (5). Feature extraction about 0 and 2.

For instance, there are training samples $x_i, (i = 1, 2, \ldots, N)$. We assume that the input value of the neuron i in the k-1 layer is y_i^{k-1}, and the output is $\cdot^{(\cdot)}$. We use θ represent the threshold of the neuron, here we make θ as 1. Then the relationship between the input value and the output value is shown in formula (1).

$$\cdot^{(\cdot)} = \cdot\left(\sum_{\cdot=1}^{\cdot}\omega^{(\cdot-1)}_{\cdot\cdot}\cdot^{-1} - \theta^{(\cdot)}\right) \qquad (1)$$

Where $\omega^{(\cdot-1)}$ stands for the weight between neuron i in k-1 layer and neuron j in k layer. denotes the number of neurons in k layer and $(\cdot)$ represents the applicable function of the neuron.

In this subsection, we develop a new character recognition approach based on traditional BP neural network to suit our particular application. The new approach consists of three steps: character categorization, the BP training and the BP recognition.

In the first step, the character images are distinguished as numeric character sets, alphabetical character sets and Chinese character sets according to the compositional semantics of license plate. In the next step, in order to improve the robustness of the recognition system, input the different feature vectors of the different character samples presorted in different light environment to train the corresponding BP neural network. In the final step, input the feature vectors of the characters which will be recognized by the BP neural network, and then output the real results.

3.2.2. Training of BP Neural Network

In this procedure, we should input the license plate character samples which need to be learned, then calculate the error between the actual output values and the expected output values and then adjust the weight between output layer and hidden layer according to the error [8]. The above two processes are repeated until the error achieves the desired result [9].

We trained the four neural networks respectively according to the different character type, in order to improve the recognition accuracy, different feature vectors are extracted according to different character sample sets presorted. In the Chinese characters network, we extracted all pixel values of the character samples as feature vectors. And considering the simplicity of alphabet and numeric character sets, we extract some key features as the feature vectors of alphabet and numeric character sets.

In the alphabet network and numeric network, the feature extraction method is mainly based on the shape of characters. For example, the feature of character "Y" and character "Z" is shown in Fig. (**4**), and the feature of character "0" and character "2" is shown in Fig. (**5**).

The feature extraction method mainly contains the following steps:

(1) The feature vector is generated by dividing the binary character image into 16 sub-blocks of 4×5 pixels.

(2) Count the number of black pixels in every sub-block.

(3) The 16 data recorded will be used as the input of the neural network.

In our new algorithm, in order to make the character sample sets whose resolution is not high can have recognition results, we added noise into the character sample sets artificially, and then carry out the training of every network.

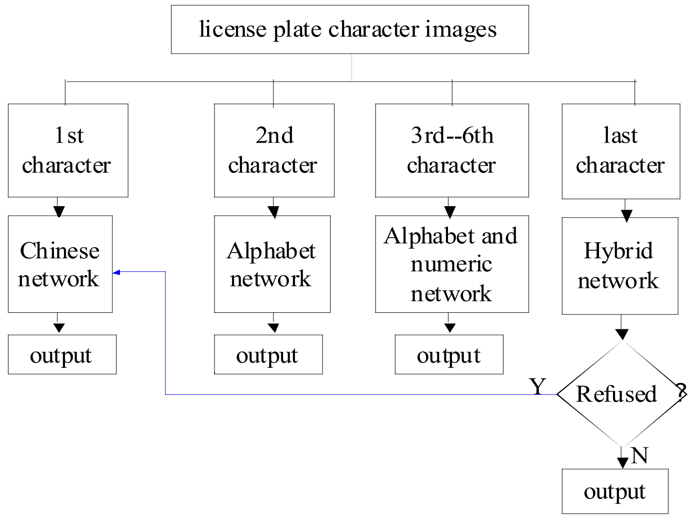


Fig. (6). The procedure of the improved algorithm.

Table 1. The recognition results of the improved algorithm.

Name		Sum	Recognized Number	Refused Number	Correct Number	Recognition Rate (%)
Chinese network	training without noise added	1018	955	63	825	81.04%
	training with noise added		998	20	914	91.58%
Alphabet network	training without noise added	1575	1352	223	1144	84.62%
	training with noise added		1524	51	1432	93.96%
Numeric network	training without noise added	4407	4210	197	3659	86.91%
	training with noise added		4327	80	3997	92.37%

3.2.3. Combinational Structure of Multiple BP Neural Networks

After training, the BP neural networks would be used to recognize characters precisely. In our new algorithm, the recognition process is as shown in Fig. (**6**).

The recognition process mainly contains the following steps:

(1) According to the characteristics of the license plate format, four neural networks are divided: Chinese characters network, Alphabet characters network, Alphabet and numeric characters network, and Hybrid network.

(2) The input of the Chinese characters network is the feature vector of first character. And the input of the Alphabet characters network is the feature vector of the second character. The feature vectors of the characters from the 3rd character to the 6th character will be input of the Alphabet and numeric characters network. Then the feature vector of the last character will be of input of the Hybrid network.

(3) Chinese characters network, Alphabet characters network, Alphabet and numeric characters network output the recognition results respectively. For the last character, if the recognition result is refused, the feature vector of the last character will be input in the Chinese characters network to be recognized again. If not, output the recognition result directly.

4. SIMULATION EXPERIMENTS AND ANALYSIS

Considering the extensiveness and generality of vehicle images, we selected 1000 images, whose resolution is not high from the environment of the daytime, evening, cloudy day and rainy day. We assess the performance of our improved license plate character recognition method by using the recognition accuracy. Its definition is shown as the formula (2).

$$ = \frac{}{\quad + \quad + \quad} \times 100\% \qquad (2)$$

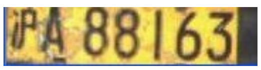
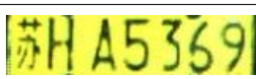
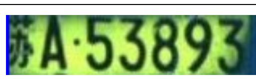
Where , and denote the recognized correct character, the refused character and the false character respectively.

In order to detect the recognition effects of our improved method, we took 1000 typical license plate images as the test

Table 2. The contrast to recognition rate of the two methods.

Method	License Plate Images	Correct Number of License Plate Recognized	Recognition Rate of License Plate
The original character recognition algorithm without noise added when training	1000	807	80.7%
The new character recognition algorithm in this paper	1000	912	91.2%

Table 3. Recognition results of some typical license plate.

License plate located	The Original Character Recognition Algorithm without Noise Added when Training	The New Character Recognition Algorithm in this Paper
	(Su)苏M.A99B0	(Su)苏N.A9980
	?A.B8163	(Hu)□A.88163
	?L.09815	(Hu)□E.09815
	(Su)□?.0??85	(Su)□H.07985
	??.???38	(Yu)□N.NN938
	?N.??081	(Su)□N.C3081
	?H.A3?69	(Su)□H.A5369
	(Su)□A.3?2C?	(Su)□A.372C7
	?A.5389?	(Su)□A.53893
	(Su)□G.F57?0	(Su)□G.F5720

images. Each character image has 320 pixels and its resolution is 20×16 pixels. The recognition results of the improved algorithm are shown in Table **1**.

From the statistics of the above Table **1**, we can see that our improved BP neural network-based license plate character recognition method has higher accuracy rate for almost all the extracted character images. With regard to the character images recognized falsely, it is because the similarity among some character images. However, our improved method has a simple principle and easy to realize, and at the same time, it has a low computational complexity.

The recognition rate of the two methods is shown in Table **2**. In this experiment, we tested for the 1000 typical license plate images, the improved method can recognize 912 images correctly, and then we got the identification rate as 91.2%, which is much higher than 80.7% of the original method.

Recognition results of some typical license plates are shown in Table **3** where "?" stands for the character which was refused by recognition system.

From the above experiment results, we can know that the new character recognition algorithm is more effective than traditional method. On the whole, our improved character recognition method could fulfill the tasks of feature vector extraction, BP training and character recognition better. As it is combined with combinational structure of multiple BP neural network method, so the improved method has high recognition precision.

CONCLUSION

In the paper, we present an improved algorithm of license plate character recognition based on BP neural network. In order to decrease the training time and recognition time, we extract different feature vectors from different character sets. In the process of training the BP neural network, we improved the traditional training of BP neural network for normal license plate character library, which is combined with hierarchical and classified Method. Moreover, we used four different BP neural networks to improve the recognition rate. Simulation results show that compared to traditional license plate character recognition method, the improved algorithm improves the accuracy rate.

In the future, we will consider the influence of light and train each neural network under the strong and weak condition of the light.

CONFLICT OF INTEREST

The authors confirm that this article content has no conflict of interest.

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