

A Novel Approach for License Plate Slant Correction, Character Segmentation and Chinese Character Recognition

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Abstract

In this paper, the methods of correcting skew vehicle license plate and segmenting characters in plate are discussed first. An approach making use of self-organizing map (SOM) is introduced to find the tilt angle of plate which simultaneously reduces seven important points with coordinates being elements of weight matrix. After necessary processing to corrected plate, a character segmentation algorithm based on the shortest distance classification is presented, which takes advantage of exactly seven points gained from SOM as class centers. In the next place, a hybrid algorithm cascading two steps of template matching is utilized to recognize Chinese characters segmented from the license plates, which is based on the connected region feature and standard deviation feature extracted from sample corresponding to each template. Experimental results show that the proposed method can be implemented efficiently.

Keywords: *license plate slant correction, character segmentation, character recognition, self-organizing map, template matching*

1. Introduction

Nowadays automatic license plate recognition (ALPR) plays an important role in many automated transport systems such as road traffic monitoring, automatic payment of tolls on highways or bridges and parking lots access control. Prior to the character recognition, characters in license plate image which is located from vehicle picture captured by the CCD camera should be segmented one by one. And by reason of the impact of the distance between the lens and the plates, cars driving speed, license plate position and so on, the plate images got from pictures are not always horizontal, which brings difficulties for separating the characters and recognizing them.

Lots of studies have been done on the plate slant correction. Y. J. Hao and W. Y. Liu [1] utilized Hough transformation to detect the line of frames in plate images, and determined the tilt angle of the plate. This method works efficiently when dealing with the plate with obvious frames. However, the frames in the located plates that are abrasion or not obvious will make this correction method failure. M. Wang and G. H. Wang [2] projected the license plate image at different angles and searched for the angle at which the projection width was the narrowest. Then the obtained angle was regarded as the tilt angle of the plate. But because the projection shape of each slant angle must be analyzed, the calculation amount is very great. D. H. Wu and C. H. Zhu [3] presented a method based on principal component analysis (PCA). In this method, the image data coordinate matrix is transformed to two-dimension covariance matrix by centering. Then by the singular value decomposition, the matrix is refold to the bi-diagonal

matrix and coordinate transform matrix, which are consistent with the main slant direction of the license image. But this algorithm highly relies on the accuracy of binary image.

Character segmentation is the necessary procedure after plate location and slant correction. Its accuracy relates to the efficiency of character recognition. The most common segmentation methods of Chinese plate is based on the projection information of plate characters (see, for example, Y. P. Bai *et al.*, [4] and H. D. Xia *et al.*, [5]), template matching (W. J. Li *et al.*, [6] and W. Q. Yuan *et al.*, [7]) and clustering (L. Chen *et al.*, [8] and J. Yu *et al.*, [9]). The first method is easy to understand and perform. But when there are joints of different characters or disconnected domain of Chinese characters, the segmentation result is unsatisfactory. Another two segmentation methods perform better in these cases but are more complicated in procedure. All these methods are almost independently designed corresponding to the previous processes.

Many researchers have been making great efforts on character recognition (see, for example, Y. P. Bai *et al.*, [4], P. Foggia *et al.*, [10], V. Koval *et al.*, [11] and O. D. Trier *et al.*, [12]). As to the recognition of license plate character, there are two important aspects: feature extraction and classification method. There have been a lot of methods on the feature extraction of characters, which are based on the projections, strokes, counters, skeletons, pixels number in grids, Zernike moment and wavelet moment etc. All these features can be used alone or associatively. The most commonly used classification methods are template matching and neural network. The former is based on the different between sample and template, and the latter is based on the generalization ability of the network.

In this paper, we first present a new approach concerning the slant correction and character segmentation. On the one hand of correction, after necessary management to plate image deduced from location, self-organizing map (SOM) is used to detect the tilt angle of plate which simultaneously educes seven important points with coordinates being elements of weight matrix. Then rotation process can be performed to plate image. On the other hand of character segmentation, an algorithm based on the shortest distance classification is proposed. In terms of the prominent clustering efficacy of SOM, the seven points gained from SOM can exactly be taken as the class centers. Secondly, a hybrid algorithm cascading two steps of template matching is utilized to recognize Chinese characters segmented from the license plates, which is based on the connected region feature and standard deviation feature extracted from sample corresponding to each template.

The rest of the study is organized as follows. Section 2 briefly introduces the theory of SOM and details the method of slant correction of license plate based on SOM. Section 3 describes the approach of character segmentation or classification based on the result of SOM. Section 4 presents the process of Chinese character recognition based on template matching. Experimental results illustrate the efficiency of the algorithms. Conclusions are drawn in Section 5.

2. Slant Correction of License Plate

Due to the impact of the camera station, license plate position, cars' driving speed and so on, the plate images got from pictures are not always horizontal, which brings difficulties for separating the characters and recognizing them. Therefore, in this section we consider slant correction to the binary plate images aided by the self-organizing map (SOM) and all samples here are plate images extracted from practical experiments.

2.1. A brief introduction of SOM

A self-organizing map (SOM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. The model was first described as an artificial neural network by Teuvo Kohonen [13], and is sometimes called a Kohonen map. Figure 1 shows a Kohonen network connected to the input layer representing a n dimensional vector.

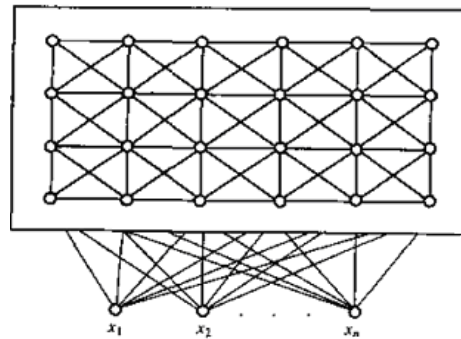


Figure 1. A Kohonen Network

The goal of learning in the self-organizing map is to cause different parts of the network to respond similarly to certain input patterns. This is partly motivated by how visual, auditory or other sensory information is handled in separate parts of the cerebral cortex in the human brain.

The training algorithm utilizes competitive learning. Detailed approach is as follows.

1. Randomize the map's nodes' weight vectors W_v s.
2. Grab an input vector D .
3. Traverse each node in the map
 - (i) Use Euclidean distance formula to find similarity between the input vector and the map's node's weight vector.
 - (ii) Track the node that produces the smallest distance (this node is the best matching unit, BMU).
4. Update the nodes in the neighborhood of BMU by pulling them closer to the input vector as

$$W_v(t+1) = W_v(t) + \theta(v,t)\alpha(t)(D(t) - W_v(t))$$

Here $\alpha(t)$ is a monotonically decreasing learning coefficient. The neighborhood function $\theta(v,t)$, usually takes Gaussian function form, depends on the lattice distance between the BMU and neuron v , and shrinks with time.

5. Increase t and repeat from step2 while $t < \lambda$, where λ is the limit on time iteration.

2.2. Skew Plate Correction Approach based on SOM

In this section, we detail the algorithm of correcting slant plate which finds the tilt angle of plate by SOM. This approach is close related to the latter character segmentation step, providing the basis for classification of characters.

Step1. Create a self-organizing map. Regarding the aim of correcting the skew plate and segmenting 7 characters subsequently, we choose an SOM network with 7 output points and take the coordinates of white pixels as the input vectors.

Step2. Initialize the weight matrix. In order to speed the convergence of the network, weight matrix is initialized as

$$W = \begin{bmatrix} M/2 & M/2 & M/2 & M/2 & M/2 & M/2 & M/2 \\ N/14 & 3N/14 & 5N/14 & 7N/14 & 9N/14 & 11N/14 & 13N/14 \end{bmatrix}'$$

Here M and N are the number of rows and columns of plate image respectively.

Step3. Train the self-organizing map. After carrying out the competition algorithm described in Section 2.2.1, white pixels are classified and new weight vectors are got. For reducing the time consumption, number of cycles is set as 5 in our experiment. More cycles bring little improvement in accuracy but much more running times here.

Step4. Find the tilt angle of the characters. With the purpose of convenience, we exchange the columns of weight matrix in SOM after competition learning. Determine the polynomial of degree 1 ($y = p(x) = kx + b$) that fits the 7 points with coordinates as the row elements in weight matrix in a least squares sense. The tilt angle θ can be obtained by

$$\theta = -\arctan(k) \quad (1)$$

Step5. Rotate images. Rotate the plate images following the familiar formula:

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (2)$$

2.3. Slant correction experiment

In our experiment, we take 200 plate images extracted from practical vehicle pictures as samples to demonstrate the efficiency of the method. Most of them can be corrected satisfactorily. Some examples are listed in Figure 2 (b1)-(b4) are original plate images; (a1)-(a4) are the plots of points described in step3 of Section 2.2 and lines that fit these points in a least squares sense; (c1)-(c4) shows the results of slant correction corresponding to (b1)-(b4).

Remark: The experimental results shows that the method based on SOM are robust to a certain extent when some interference signal exists in the plate image (as seen in Figure 2. (c2)- (c4)). And it is also robust to the plates that are almost horizontal (as seen in Figure 2. (b4), (c4)).

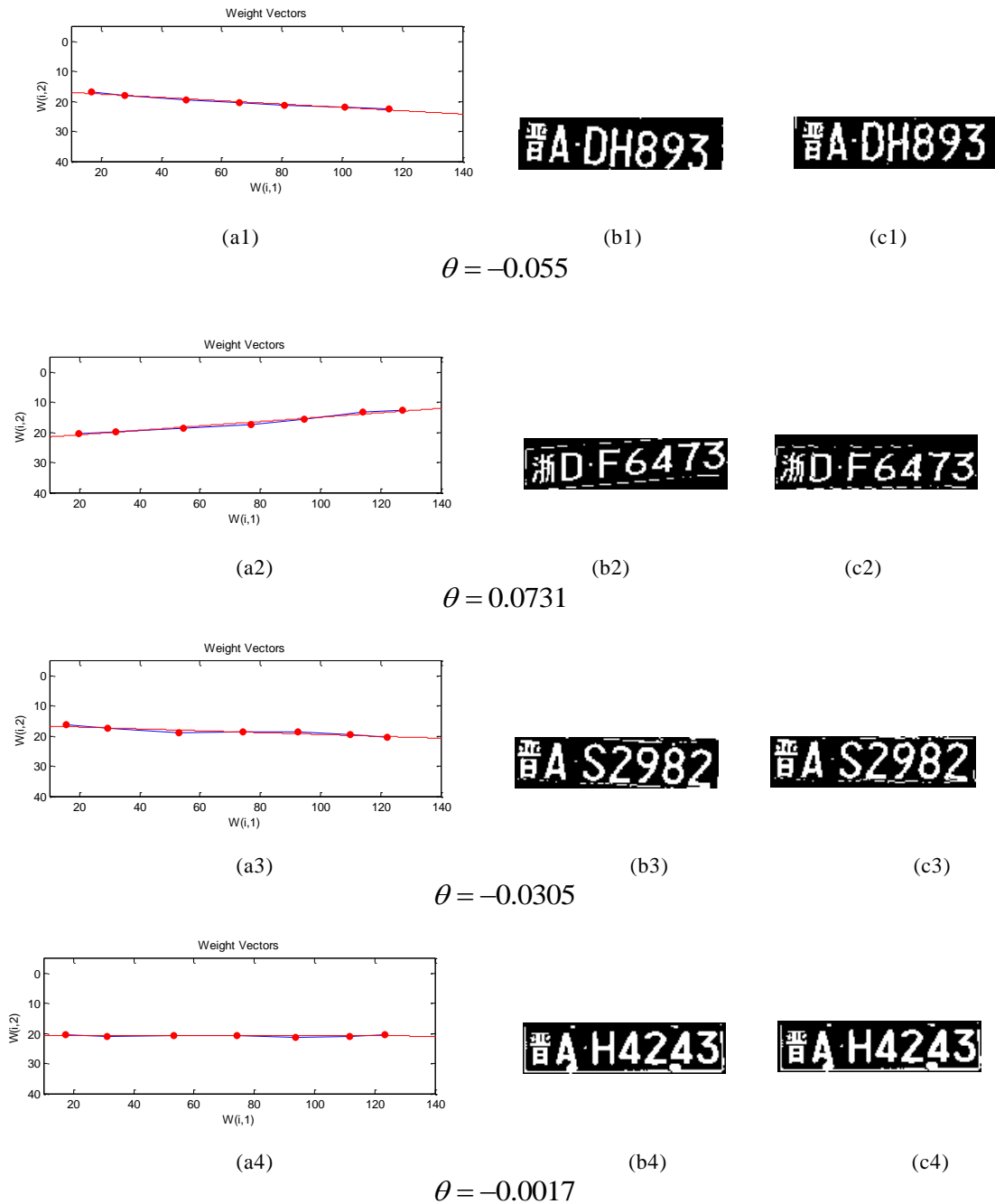


Figure 2. Some Examples of Slant Plate Correction

3. Segmentation of Characters in Plate

Familiar methods used to segmenting plate characters are almost independently designed relative to the previous processes. In view of the theory of SOM, the learning process in Section 2.2 corresponds to the clustering process of white pixels as input patterns. Certain classes of pixels are “mapped” to 7 output neurons respectively, with synaptic weights “similar” to corresponding class patterns. In this section, we propose the character

segmentation approach after SOM based slant correction, which is based on the shortest distant classification, taking advantage of the points from weight matrix as class centers.

3.1. Preparation

Before segmenting the characters, we need to wipe off some insignificant part of the picture. As seen in Figure 2 (b3) (b4), due to the characteristic of Chinese vehicle plates, many plate images located from vehicle pictures contain the rivets that fix the plates and the thin white rectangle frames draw in plates. In order to make a more accurate segmentation of characters, we take a management to the corrected images to take out these points. The algorithm only takes in to account the unwanted information above and below the character pixels, because the vertical frames can be removed from after segmentation of characters by vertical projection.

Here we briefly describe the algorithm. First, set a corresponding interval that helping identify whether it is a row in characters or not and count the number of white pixels in every row. Second, set an initial row (*e.g.*, the k th row) to check whether it is a character row. If it is, set $k = k - 1$ and continue the process until $k = 1$; if it isn't, cut 1st~ k th rows out of the image. Here we choose k is the nearest integer of $0.2 \times M$ and the interval of white pixels number identifying character rows is $(0.15 \times N, 0.6 \times N)$. We also can set $l = M - k$, and check rows following $l \rightarrow l + 1 \rightarrow l + 2 \rightarrow \dots$ to cut insignificant rows below characters. Managed images corresponding to the corrected plates in Figure 2 are show in Figure 3.

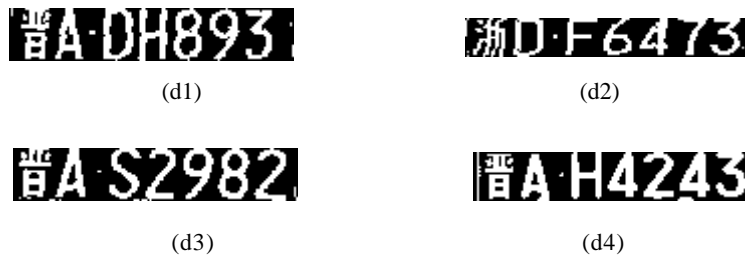


Figure 3. Results of Management of Figure 2 (c1)-(c4)

3.2. Character Segmentation

Here we segment the characters in the shortest distance sense and choose the class centers being exactly the rotated 7 points derived from SOM weight matrix.

Step1. Register the coordinates of all white pixels.

Step2. Calculate the final coordinates of 7 points after rotation and image cutting, and denote them as $P_i(x_i, y_i)$ ($i = 1, 2, \dots, 7$).

Step3. Classify all white pixels to 7 classes in terms of

$Class\ i = \{Q(x, y) \mid \|Q - P_i\|^2 = \min(\|Q - P_1\|^2, \dots, \|Q - P_{i-1}\|^2, \|Q - P_{i+1}\|^2, \dots, \|Q - P_7\|^2)\}$
 $i = 1, 2, \dots, 7$, $Q(x, y)$ denotes the white pixels, and $\|Q - P_i\|^2 = (x - x_i)^2 + (y - y_i)^2$. One class consists of white pixels belonging to a character.

Step4. Segment the characters using the second coordinate of points in each class.

Step5. Move the irrelative part in each character matrix. Considering the same distance condition, the white dot between the second and third characters and the classification error,

there may be some irrelative part in the character matrices. As the last of segmentation steps, we move the irrelative part in each character matrix by the method of vertical projection.

Figure 4 shows the position of modified weight vectors points and the corresponding plate image after slant correction and cutting process. The figure testifies again that the weight vectors can represent the corresponding character class well. The final results of segmentation process described above are listed in Figure 5.

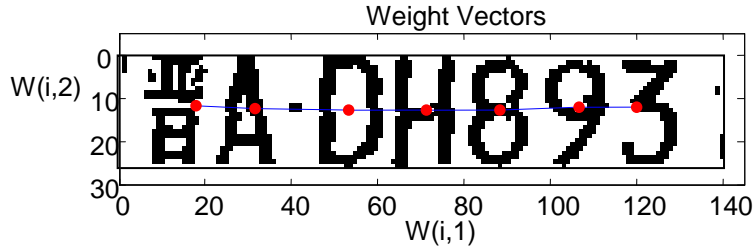


Figure 4. Modified Weight Vectors Points and the Corresponding Processed Plate Image



Figure 5. Results of segmentation process of Figure 3 (d1)-(d4)

4. Chinese Character Recognition

Chinese license plate is composed of seven characters in which the first one is a Chinese character, the second one is an English letter and the remaining ones are numbers or English letters. There has been a lot of works on the recognition of numbers and English letters. In this section, we pursue the method of recognizing Chinese characters, which indicate the province that a vehicle is registered. Considering the fallibility of character's skeletons got by thinning process, and the contaminated contour going with blurring plates, the proposed algorithm is based on the whole matrix of character sample, which finding the most matched template utilizing the connected region feature and standard deviation feature.

4.1. Connected Domains in Binary Image

A binary character image is a matrix containing white and black pixels, whose positions decide which character the image related to. In this part, we give an improved algorithm to get the number of connected domains with 8 directions. The detailed algorithm is as follows.

Step1. Define an empty matrix res , real number $N=0$, and two zero matrixes A , B , whose sizes are same as character image I .

Step2. Scan image I pixel by pixel along the rows, until find the first non-zero element $I(i, j)$, let $A(i, j)=1$.

Step3. Let $B=A$; Find the non-zero element $A(i, j)$ in A and give the values of elements in 8-neighborhood of $I(i, j)$ to the elements in 8-neighborhood of $A(i, j)$.

- Step4. If it's true that $B = A$, go to step5; else, go to step3.
 Step5. $res(N + 1, :, :) = A$.
 Step6. $N = N + 1$.
 Step7. If $A(i, j) = 1$, take the corresponding element $I(i, j) = 1$.
 Step8. Take all elements in A be 0.
 Step9. Determine whether I is a zero matrix. If it's true, the operation finish; else, go to step 2.

The matrix res contains all connected domains of I , and N is the number of these domains. Figure 6 shows the results of detecting connected domains of two characters '吉' and '辽'.

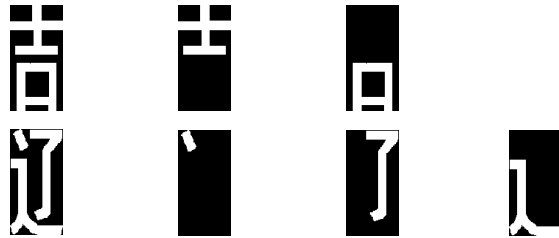


Figure 6. Characters '吉', '辽' and their Connected Domains

4.2. Feature Extraction based on Templates

4.2.1. Connected Domain Feature (CDF): Suppose $r \times q$ is the size of character sample matrix X and template matrix A , and matrix $I = X \wedge A$ (logical AND of X and A). I actually indicates the information belonging to both X and A , as example in Table 1. Count the number of 8-connected domains of character in I and A respectively. We denote them as d_1 for I , and d_2 for A .

Define the connected domain feature (CRF) relative to template A of character sample X as

$$d = |d_1 - d_2|. \quad (3)$$

From the results of experiments implemented on character samples from practical license plates, it's easy to find that the similarity between sample and template is correlative to the value of CDF. In specific, ideally, CDF relative to the template with correct character should be 0 and others may be more than 0 except some particular cases (see in Table 2).

In practical cases, because of the illuminant condition and binarization process carried to plate images, the strokes of character may not distinct as ideal cases and the number of connected domains of same characters may differ. But CDF of samples relative to correct template also is smaller than most of other templates, as example in Table 3. Based on this fact, the CDF of samples can be used to coarsely recognize characters, choosing the most resemble ones as the matched templates for the next step.

Table 1. Character sample X (image in 2nd row and 1st column), template A^i (1st row), $I^i = X \wedge A^i$ (2nd row) and connected domain feature (CDF) d (3rd row). In our experiment, $r = 32, q = 16$

d		3	0	4	4	8	5	10	3	8	10	8	6

Table 2. Particular Cases with Different Characters in Sample and Template when $d=0$ in Ideal Cases

Ideal char	‘吉’	‘吉’	‘青’	‘湘’	‘浙’	‘宁’	‘宁’
Template char	‘鲁’	‘青’	‘吉’	‘浙’	‘湘’	‘京’	‘渝’
d	0	0	0	0	0	0	0

Table 3. 4 Examples of CDFs Relative to some Templates. The First Row Consists of Some Templates and the First Column Shows Some Samples of Character Images

	1	0	2	0	2	4	2	2	4	2	5	2
	0	0	1	1	1	4	5	0	3	3	3	1
	4	2	3	2	1	1	0	0	4	5	2	0
	7	8	9	4	3	6	9	5	9	3	14	3

4.2.2. Standard Deviation Feature (SDF): We define the standard deviation feature (SDF) of sample X corresponding to template A as

$$S = \sqrt{\frac{(\text{sum}(X) - U)^2 + (\text{sum}(A) - U)^2 + (\text{sum}(I) - U)^2}{2}} \quad (4)$$

Where $\text{sum}(\cdot)$ refers to summing up the elements of binary matrix, matrix $I = X \wedge A$, and real number $U = \frac{\text{sum}(X) + \text{sum}(A) + \text{sum}(I)}{3}$.

As in formula (4), SDF of sample X is based on the number of sample character pixels, the number of template character pixels and the number of both pixels. Ideally, the more similar between the sample and template are, the smaller SDF is. But in practical cases, the situation is more complicated. We choose the SDF as the second step after coarsely classification to decide which character does the sample really represents.

4.3. The Approach of Character Recognition

Our method is the cascade by two step template matching based on CDF and SDF respectively. In the experiment, the templates used are a sequence of 32 matrices of size 32×16 , which represent 32 Chinese characters that appear in civilian vehicles plates.

Step1. Normalize the binary character image sample by 32×16 , with white pixels belong to the character and black pixels belong to the background.

Step2. Extract the connected domain feature (CDF) relative to the templates one by one. Sort them in ascending order $D = \{d^i\}$, ($i = 1, \dots, 32$). Taking into account the unpredictable cases of sample, we first pick out 3 elements d^1, d^2, d^3 , then check whether $d^4 = d^3$. If it's true, check whether $d^5 = d^4, \dots$, until $d^{n+1} \neq d^n$. Record the templates corresponding to CDFs d^1, \dots, d^n .

Step3. Extract the Standard deviation feature (SDF) of sample relative to templates picked out from step2. Sort them in ascending order and find the smallest one. The template corresponding to this SDF is regarded as the most suited one, and the corresponding character of this template is the final result of recognition.

4.4. Experimental Results

In this part, we extract 322 Chinese character images from plate pictures in different conditions. The experiment is implemented with MATLAB and the results in Table 4 show that the success recognition rate of characters is up to 96%.

Table 4. Experimental Results

Number of samples	Number of Correct recognition	Number of false recognition	Correct recognition rate	False recognition rate
322	309	13	95.96%	4.04%

5. Conclusions

In this paper, a novel approach of correcting slant plate and segmenting characters is proposed at first. In terms of the theory of self-organizing map, the algorithm based on SOM is utilized to decide the tilt angle of plate images. And the seven points with coordinates being elements of weight matrix got from SOM are used in character segmentation approach, which takes advantage of them as class centers. Secondly, a method of Chinese character recognition based on cascading template matching is introduced which utilizes the connected domain feature and standard derivation feature respectively. Experimental results show that success recognition rate of characters is up to 96%.

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References

- [1] Y. J. Hao, W. Y. Liu and S. Lu, "Spatial correction of the distorted license plate image of automobiles", *Journal of Southwest Jiaotong University, China*, vol. 4, no. 37, (2002).
- [2] M. Wang and G. H. Wang, "Method of vehicle license plate correction based on characters projection minimum distance", *Computer Engineering, China*, vol. 6, no. 34, (2008).
- [3] D. H. Wu and C. H. Zhu, "A novel license plate slant correction method based on principal component analysis", *Journal of Highway and Transportation Research and Development, China*, vol. 8, no. 23, (2006).
- [4] Y. P. Bai, H. P. Hu, F. Li, W. Shuang and L. X. Gong, "A recognition system of China-style license plates based on mathematical morphology and neural network", *International Journal of Mathematical Models and Methods in Applied Sciences*, vol. 1, no. 4, (2010).
- [5] H. D. Xia and D. C. Liao, "The study of license plate character segmentation algorithm based on vertical projection", *Proceedings of 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet)*, (2011).
- [6] W. J. Li and D. Q. Liang, "Character segmentation for degraded license plate", *Journal of Computer Aided Design & Computer Graphics*, vol. 5, no. 16, (2004).
- [7] W. Q. Yuan, C. J. Mu and D. S. Li, "A vehicle plate character segmentation method based on the Chinese character characteristic", *Chinese Journal of Scientific Instrument. S2*, vol. 24, (2003).
- [8] L. Chen, X. H. Huang and M. Wang, "Cluster-based method of characters' segmentation of license plate", *Computer Engineering and Applications*, vol. 6, no. 38, (2002).
- [9] J. Yu, H. X. Huang and Z. J. Liu, "Segmentation and feature extraction of license-plate character in complex background", *Ordnance Industry Automation*, vol. 4, no. 24, (2005).
- [10] P. Foggia, C. Sansone and F. Tortorella, "Character recognition by geometrical moments on structural decomposition", *Proceedings of Fourth International Conference Document Analysis and Recognition (ICDAR'97)*, Ulm, Germany, (1997).
- [11] V. Koval, V. Turchenko and V. Kochan, "Smart license plate recognition system based on image processing using neural network", *Proceedings of the Second IEEE International Workshop on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Application*, (2003).
- [12] O. D. Trier and A. K. Jain, "Feature extraction methods for character recognition—a survey", *Pattern Recognition*, vol. 4, no. 29, (1996).
- [13] T. Kohonen and T. Honkela, *Kohonen network*, Scholarpedia, (2007).

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