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License Plate State Recognition based on Logo Matching and State Name String Classification

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Abstract: In most countries, vehicle license plates contain both alphanumeric characters and the state/province of origin. State/province recognition of the license plate provides additional information to the traffic management agency and guidance information, aiding in character segmentation and in recognition. Existing methods use the character string of the state name only. Unfortunately, in some countries, the state name is too small to be captured clearly by a low-definition video camera and may also be obstructed by the license plate frame. In this study, we analyze the characteristics of license plates and propose an issuing state recognition method based on adaptive unique logo matching (AULM) and state name string recognition (SNSR). First, the AULM approach utilizes template matching to recognize the distinguishable logos. Second, if the logo is not located, the SNSR method is applied. The new method is compared with existing practices, and the experimental results show that the proposed method achieves higher accuracy and is more suitable when using high- or low-definition video images.

Keywords: state recognition, state name recognition, support vector machines, template matching

1 Introduction

Recognition of the issuing state is the identification of the attribute state using the information shown on the license plate [1]. Generally, the license plates contain cultural references or slogans associated with the issuing state in addition to the alphanumeric characters [2]. Usually, the state name string is shown along the top or bottom of the plate face. It may be difficult to recognize the issuing state by the state name string alone, because of the size of the license plate frame, including advertisements inserted by the vehicle service center or the dealership [3], or the poor definition of the video cameras used to capture images. Moreover, the plate styles are not uniform. Most license plate recognition systems only report the license plate letters and numbers, without including the state information.

Researchers have studied a similar problem in some countries, i.e., attribution/address recognition. Because the format of license plate is different, the approaches to different countries are different. For example, in China, the first Chinese character and English letter represent the province and city information, respectively. The license plate recognition (LPR) system can report attributes by reading the main characters [4][5][6]. Similarly, in Germany, the 2 - 3 letter combination represents the region or city of registration [7]. For Japanese and Korean license plates, the address string can be used to recognize an attribute [1].

Nevertheless, if the license plates are partially obstructed by its frame, the state name string will not be legible. Exactly extracting the name string from personalized license plates remains challenging (Fig. 1).

The license plates used in this paper are captured mainly in the United States (US). By analyzing the characteristics of license plates, some standard patterns, including the color schemes and logos, can be used to differentiate the license plates of different states or even different categories, such as a university, the army, or the navy [8] (Fig. 2). We use an adaptive template-matching method to recognize the logos first. If we cannot identify the issuing state by the logo, the support vector machine (SVM) classifier [9][10], using a principal component analysis (PCA) [11][12] feature, is applied.

The remainder of this paper is organized as follows: Section 2 presents a detailed description of the proposed

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Fig. 1: Samples of some standard issued license plates in various states: (a) low-resolution images where it is difficult to recognize the state name string because of poor quality and/or parts of the images are influenced by the license plate frames and (b) high-resolution images.

Fig. 2: Some standard issues in the US, including license plates, logos, and state name abbreviations.

method, Section 3 presents the experimental results and discussions, and the conclusions are discussed in Section 4.

2 The proposed method

2.1 Overview

We assume that the license plate image has been extracted and define three regions of the license plate, as shown in Fig. 3: the upper region, the main character region, and the lower region. We adjust the image of the license plate carefully after its extraction, e.g., correct the rotation (horizontal slant and vertical slant) and refine the crop of the main character region. The overall flowchart of the proposed method is shown in Fig. 4.

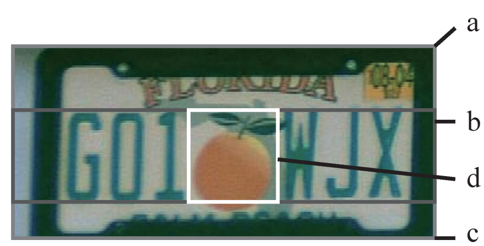

Fig. 3: Illustration of the license plate regions: (a) the upper region, (b) the main character region, (c) the lower region, and (d) the logo template, the height of which is the same as the main character region.

2.2 Main character region extraction

We extract the main characters using the similar character heights feature. The Gaussian minus C adaptive thresholding approach [13] is applied to obtain the binarized images.

Step 1. The connected component analysis is used to extract the bounding boxes, which satisfy the following requirements:

$$\begin{cases} h \cdot w > \alpha \\ h \in (\beta_1 H, \beta_2 H) \\ \frac{w}{h} \in (\eta_1, \eta_2) \end{cases} \tag{1}$$

where h and w are the height and width, respectively, of the corresponding bounding box, H is the height of the extracted license plate, and $\alpha \in \mathbb{R}^+$, $0 < \beta_1 < 1$, $0 < \beta_2 < 1$, $\eta_1 \in \mathbb{R}^+$, and $\eta_2 \in \mathbb{R}^+$ are the thresholds of the area,

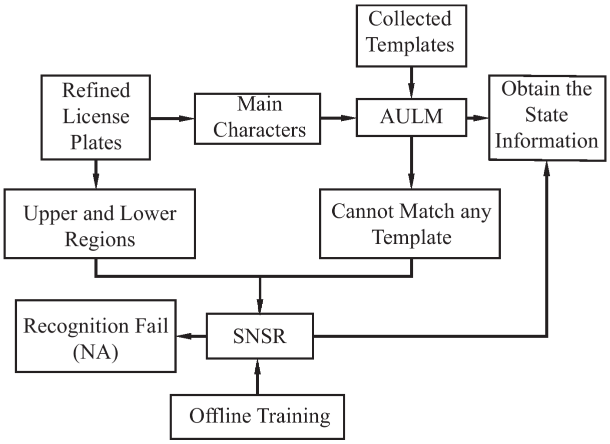

Fig. 4: The overall flowchart of the proposed method.

height, and aspect ratio, respectively. In these experiments, $\beta_1 = 0.15$ and $\beta_2 = 0.75$.

The boxes are then divided into the following groups according to $h \in \Phi = \{[0.75H, H], [0.65H, 0.8H], [0.55H, 0.7H], [0.45H, 0.6H], [0.35H, 0.5H], [0.25H, 0.4H], [0.15H, 0.3H]\}$.

We add up the number of boxes (N_{box}) in each group (interval), and select the group containing maximum N_{box} as the interval of the candidate character region.

Step 2. The upper left and the lower left foreground pixels in each bounding box are selected as the top and bottom fitted points, respectively, which are used to fit the top and bottom lines.

Line fitting is used to minimize the formula (2):

$$\min \sum_i \rho(r_i) \tag{2}$$

where r_i is the distance between the i-th point and the fitted line, and $\rho(r)$ is a distance function. In our experiments, the Welschs function is applied as follows:

$$\rho(r) = \frac{C^2}{2} \cdot (1 - \exp(-\frac{r}{C}^2)) \tag{3}$$

where $C = 2.9846$.

Step 3. If θ_X (the angle of the corresponding line) and $r_{Xi}, X \in \{T, B\}$, (T and B denote the top and bottom point group, respectively) satisfy the formula (4), the fitted lines are approximately parallel, and go to step 6; otherwise, go to step 4:

$$\begin{cases} |\theta_T - \theta_B| < \delta \\ \overline{r}_X = \frac{\sum_{i=1}^{N} r_{Xi}}{N} < d_X, X \in \{T, B\} \end{cases} \tag{4}$$

where N is the number of bounding boxes, and δ and d_X denote the threshold angle and distance, respectively.

Step 4. If the fitted lines are not parallel, the points with max(r_{Xi}) in each group are removed. The remaining points are re-fitted and re-checked using formula (4), until the lines are parallel or the number of remaining points is less than or equal to 2, which is too few points to fit a line. This procedure is illustrated in Fig. 5.

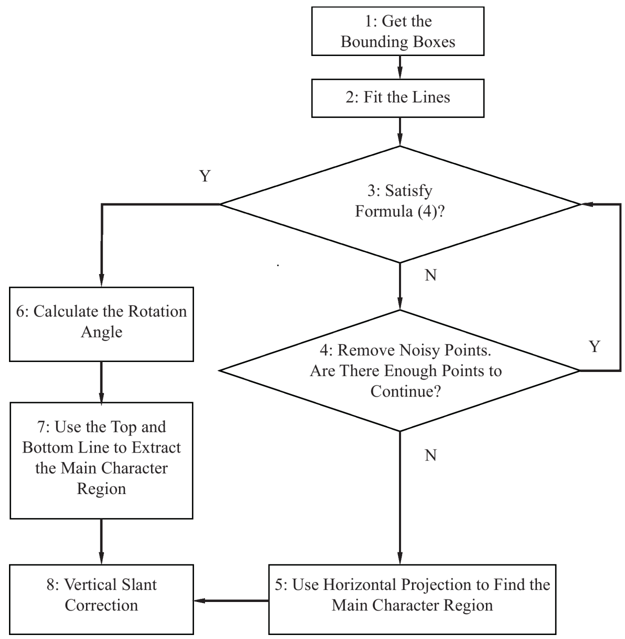

Fig. 5: The procedure of the license plate rotation and main character extraction algorithm.

Step 5. If we do not find an angle via the above algorithm, a horizontal projection is used to locate the main character region. The same method illustrated in the following state name string extraction section is employed. Then, go to step 8.

Step 6. The horizontal slant angle is calculated as follows:

$$\theta = (\theta_T + \theta_B)/2 \tag{5}$$

Step 7. The rotated fitted lines are the upper and lower boundary of the main characters (Fig. 6).

Step 8. We use the affine transformation at each angle and add up the zero values of the binary vertical projection image of the main character region. Because the characters contain many vertical edges, Sobel's operator [20] is used for the extraction. The binary image is obtained using Otsu's method [17]. The vertical projection is then calculated, and the angle corresponding to the maximum zero value is selected as the vertical slant correction angle. In our experiments, the correct vertical slant range in degrees is [-15, 15], and 0 indicates no vertical slant. To avoid the influence of the license plate frames, we calculate only the center region. The slant-corrected results are shown in Fig. 6f. The new coordinates are calculated as follows:

$$\begin{cases} x' = x - y \cdot \tan\varphi \\ y' = y \end{cases} \tag{6}$$

The steps of the vertical slant correction are shown in Fig. 7.

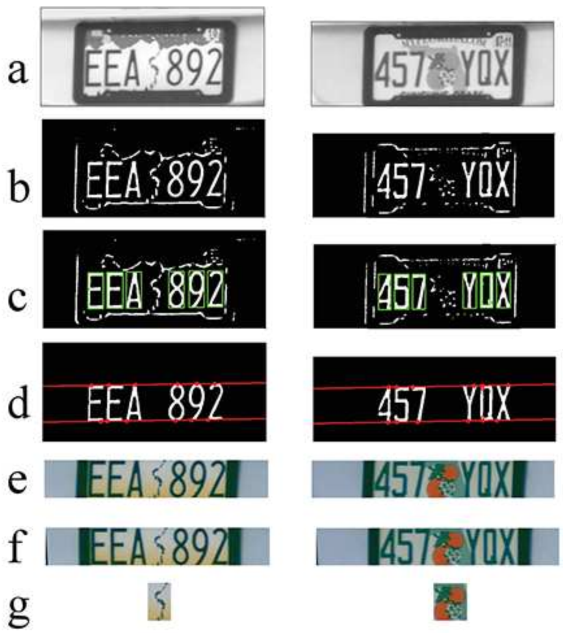

Fig. 6: The procedure of logo recognition: (a) gray scale images, (b) binarization results, (c) the remaining bounding boxes selected using the similar height strategy, (d) fitted lines, (e) the results of horizontal slant correction and removing the upper and lower boundaries, (f) the results of vertical slant correction, and (g) the regions matched by templates.

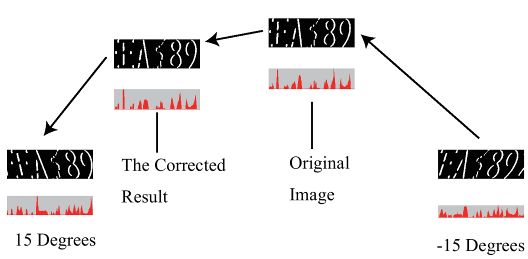

Fig. 7: The procedure of the vertical slant correction.

2.3 Adaptive Unique Logo Matching

To match the templates for the standard patterns of all 50 states and the District of Columbia (D.C.), logos are collected and extracted manually, according to the height of the main character region. The template must be unique, and must also be adequately wide without touching any character (see, e.g., Figs. 2, 3 and 6). In the matching phase, the template size is recalculated to maintain the aspect ratio, and the height is set equal to the height of the main characters.

The normalized coefficient method is then applied to calculate the best matching point. This method works well, even in cases with varying illumination, brightness and contrast [14], linear intensity distortions [15], varying sizes of the feature, and changes in the image amplitude. The formula (7) [16] is used to calculate the normalized coefficient:

$$R(x,y) = \frac{\sum_{u,v}[f(x+u,y+v) - \overline{f}_{x,y}][t(u,v) - \overline{t}]}{\sqrt{\sum_{u,v}[f(x+u,y+v) - \overline{f}_{x,y}]^2 \sum_{u,v}[t(u,v) - \overline{t}]^2}} \tag{7}$$

where f is the image, t is the template, $\overline{t}$ is the mean of the template, $\overline{f}_{x,y}$ is the mean of the image in the region under the feature, and u and v are the coordinates of the template region. $R(x,y)$ represents the map of the comparison results between the template and the image.

For color images, the template summation in the numerator and each sum in the denominator are performed for all of the channels, and separate mean values are used for each channel. The results will still be single-channel images [13]. A fast Fourier transform (FFT) and an integral of the image is used to accelerate the computation [16].

All the extracted templates for each license plate must be matched, and the response with the maximum $R(x,y)$ is chosen. If the maximum value does not satisfy the formula (8), no identifiable logo in the license plate exists:

$$R_{max} = \max\{R_1(x_1,y_1), R_2(x_2,y_2), \cdots, R_m(x_m,y_m)\} > \tau \tag{8}$$

where m is the number of templates, $R_k(x_k,y_k)$ is the maximum value in each R_k, $1 \le k \le m$, and τ is selected with the experiment. Some of the templates used are shown in Fig. 8. The position of R_{max} is the top-left point of the matched region.

2.4 State name string extraction

In some cases, distinguishing license plates using the template matching alone is difficult, primarily because their logos are similar, such as the dots and dashes of Rhode Island (RI), Massachusetts (MA), Virginia (VA), and Wisconsin (WI), as shown in Fig. 8. If the logo is

Fig. 8: The templates used for AULM and corresponding state name abbreviation.

easily confused, or no logo is present, the state name string is used to identify the issuing state.

In the previous steps, the main character region has been extracted; now the remaining upper and lower regions of the license plate can be segmented.

First, Sobel's operator [17] is applied to extract the vertical edges, and Otsu's [18] method is used to binarize the image.

Second, the morphology closing operation is applied to connect the state name characters. The morphology kernel should be selected according to the number of pixels, such as a 15×7 rectangular structuring element. Because of the direction in which the state name is written, the region selected by the connected contour analysis is rectangular, with a width greater than the height. The region ratio and area satisfy the following conditions:

$$\begin{cases} r_0 < r < r_1 \\ A_0 < A < A_1 \end{cases} \tag{9}$$

where (r_0, r_1) is the range of the aspect ratio (r), and (A_0, A_1) is the range of the area (A) of the region.

Finally, the horizontal and vertical projections are applied to determine the state name boundaries. Fig. 9 shows the analysis procedure.

2.5 State name string recognition

The following steps are applied to obtain the normalized image features:

1) Convert the state name image to a gray image, resize the image to a standard size, such as 120×20 (px), and apply the histogram equalization;

2) Apply PCA to reduce the dimensionality, such as 200, which can retain 90% energy; and

3) Normalize the features in a specific range, usually [-1, 1].

Fig. 9: The state name refinement procedure: (a) an original license plate, (b) the upper and lower region, (c) the Sobel and binarized results, (d) the morphology results, (e) the bounding box satisfying formula (9), (f) the horizontal projection, (g) the vertical projection, and (h) the refinement result.

The state name strings are manually divided into categories, according to the corresponding state. For the multi-class (50 states, D.C., and a negative class) problem, the radial basis function (RBF) kernel and the one-versus-one strategy are used. The optimal parameters are selected using a cross-validation approach [10][19]. SVM, using the RBF kernel, has been shown to perform better than the polynomial method [1].

The AULM results can also be further analyzed using these methods. For example, if the license plates that include a dash are matched, the state name must be North Carolina (NC), Nebraska (NE), RI, Tennessee (TN), VA, WI, or another state that includes a dash on its license plate.

Two classification results are also possible, C_u and C_d, corresponding to the results of the upper and lower regions, respectively. If $C_u \neq C_d$, we select the result of

C_u because the state name is shown in the upper region, as in most cases. If C_u = NA $\neq C_d$, which is classified as unknown or does not satisfy formula (8), C_d is chosen. If $C_u = C_d$ = NA, the recognition fails.

3 Experimental results and discussion

3.1 Experimental results

To test the algorithm on both high- and low-definition images, video cameras are used to capture low-and high-definition images, which are then divided into two sets as follows:

Set 1: High-definition images, with a resolution of 1280×960 (px, the same below). The sizes of the resulting license plate images approximately range from 300×150 to 400×200 (Fig. 1b).

Set 2: Low-definition images, with a resolution of 720×480. The sizes of the resulting license plate images approximately range from 100×50 to 160×80, and the state name is fuzzy (Fig. 1a).

Set 1 includes license plates of 50 states and the D.C. with approximately 50 images per category. Set 2 includes 8000 images, all of which consist of a logo for testing the AULM method on the low-definition images. The SNSR methods cannot be used for these images because of the fuzzy state names (Fig. 10-11). The SNSR methods are a category of algorithms that only use the state name string to recognize the address (issuing state).

We compared the proposed method with an SNSR method using the contour features, which is optimal for English characters in [1], the multi-layer perceptron using the back-propagation (MLP-BP) algorithm [20], and our SNSR method employing the PCA feature. The MLP-BP algorithm uses the same parameter configuration as the sample file letter_recog.cpp in OpenCV, where the strength of the weight gradient term [13] is 0.001. For the SNSR method, we divide the samples into two categories: 70% for training and 30% for testing. Table 1 shows the average results of training and testing. The experimental results show that the proposed method is superior to the others. In addition, it can be applied to low-definition fuzzy images that cannot be processed by existing algorithms. The results of the SNSR methods are not optimal because of the obstructed or inaccurate placement of the state name string. Additionally, precisely extracting the string from personalized license plates remains challenging.

3.2 Discussion

The proposed AULM method is based on template matching, requiring the collection of numerous logo templates. Therefore, the performance is not optimal. One way to improve performance is to utilize the geographic

Fig. 10: The matched results of Set 2. (a) the templates (b) the rectangles show the matched logos in the license plates.

Fig. 11: Samples in Set 2.

Table 1: Accuracy, N/A means Not Applicable

	Set 1 (%)	Set 2 (%)
SNSR (Contour, RBF-SVM in [1])	80.37	N/A
SNSR (PCA, MLP-BP)	83.38	N/A
SNSR (PCA, RBF-SVM)	87.33	N/A
The proposed method	95.17	94.55

location information to first match logos of nearby states. If no logo is found, then match the remaining logos. This strategy will significantly improve the performance of the system.

Table 2: Performance of the local low definition set, unit: ms

	Local Set
Without accelerating	71.90
With accelerating	14.88

Table 3: The applicable scope of different methods

Logo existence	Frame existence	Top/ Bottom name existence	AULM	SNSR	The proposed
Yes	Yes	Yes	**Yes**	Partial	**Yes**
Yes	No	Yes	**Yes**	**Yes**	**Yes**
No	No	Yes	N/A	**Yes**	**Yes**
No	Yes	Yes	N/A	Partial	Partial
Yes	Yes but fuzzy	Yes	**Yes**	N/A	**Yes**
No	Yes but fuzzy	Yes	N/A	N/A	N/A
Yes	Yes or No	No	**Yes**	No	**Yes**

For example, in Florida, the performance comparison on a local set (low definition, approximately 120 templates) is shown in Table 2. The test machine is a 2.79 GHz Core Duo CPU PC with 4 GB of memory, and the algorithm is implemented using VC 2010 and OpenCV 2.4.2.

The AULM method will not be affected by the license plate frame. Nevertheless, the AULM can only be used for license plates with logos and requires many templates. The SNSR method is suitable for all states but may be influenced by the license plate frames. A comparison of the applicable scope of the different methods is shown in Table 3.

In Table 3, "Partial" indicates that if the state name string is not obstructed by the license plate frame, the corresponding method is applicable."Top/Bottom name existence" means the state/province name is at the top or bottom of the license plate, and it is smaller than the main characters. For example, the license plates in the US, Canada, Maxico and Japan. However, some regions' license plates do not contain a smaller state/province region, which is embeded in the main character region, such as China. In such regions, the AULM method still can be applied if we think the state/province character as a logo.

4 Conclusions

An issuing state recognition method for license plates is proposed, using both logos and state name strings. The logo information can also be used for state/province or category (some logos represent a university, the navy, etc.) recognition. This method is suitable for both high- and low-definition images and videos. In some countries, there is only logo information that can be utilized, such as European Union (EU) countries, and the national abbreviation on a EU license plate can be regarded as a part of logo. Existing methods for the license plates including a state/province name only focus on state name strings and thus cannot be applied to noisy images captured by low-definition video cameras in some countries, especially the state/province name is smaller than the main characters. Moreover, the state name may be obstructed by the license plate frame. The SNSR method can also be applied to the results from the AULM method to reduce the number of classes. In most cases, we can recognize the issuing state using the logos, even if the state name string is blurred. The drawback of the AULM is that it is more time-consuming than other methods; however, we can utilize multi-processing and general purpose graphics processing units (GPGPUs) technologies to optimize the AULM strategy. The template matching and the multi-class SVM method are suitable for multi-core computation. Additionally, geographic information can be used to accelerate the algorithm. The experimental results show that the proposed method is superior to others and can be applied to the majority of license plates, including some low-definition plates without logos and those that are obstructed by frames.

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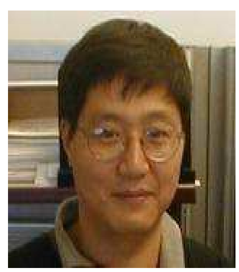

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