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# Chinese license plate character segmentation using multiscale template matching

**Jiangmin Tian, Guoyou Wang,* Jianguo Liu, and Yuanchun Xia**
Huazhong University of Science and Technology, School of Automation, State Key Laboratory for Multispectral Information Processing Technology, 1037 Luoyu Road, Wuhan 430074, China

**Abstract.** Character segmentation (CS) plays an important role in automatic license plate recognition and has been studied for decades. A method using multiscale template matching is proposed to settle the problem of CS for Chinese license plates. It is carried out on a binary image integrated from maximally stable extremal region detection and Otsu thresholding. Afterward, a uniform harrow-shaped template with variable length is designed, by virtue of which a three-dimensional matching space is constructed for searching of candidate segmentations. These segmentations are detected at matches with local minimum responses. Finally, the vertical boundaries of each single character are located for subsequent recognition. Experiments on a data set including 2349 license plate images of different quality levels show that the proposed method can achieve a higher accuracy at comparable time cost and is robust to images in poor conditions. *© 2016 SPIE and IS&T* [DOI: 10.1117/1.JEI.25.5.053005]

Keywords: license plate character segmentation; multiscale template matching; maximally stable extremal region detection; Otsu thresholding; normalized correlation coefficient.

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## 1 Introduction

As one of the core techniques of intelligent transportation system, automatic license plate recognition (ALPR) has been applied to many aspects of vehicle management,[1,2] such as electronic toll collection, traffic law enforcement, access control of constrained area, and theft pursuit. As the primary task of character recognition, segmenting characters from a license plate image also plays an important role in ALPR. For constant improvement in accuracy, many methods have been developed.[3] However, they are time consuming or lack robustness in dealing with license plates in poor conditions, such as plates having location error, frame adhesion, quality degradation, and distortion in character alignment.

According to the image type for segmentation, research in the literature can be classified into two categories: grayscale image processing and binary image processing. The former uses the intensity contrast between license plate character and background directly. In Ref. 4, the normalized correlation coefficient (NCC) is adopted to segment the characters on gradient images vertically and horizontally with variable-length templates. As an excellent blob detection algorithm, maximally stable extremal region (MSER)[5] has recently begun to be applied to license plate character segmentation (CS).[1,6,7] After a set of MSERs is obtained, constraints on geometrical properties and the conditional random field are utilized, respectively, to identify the MSERs of the characters. Taking advantage of the scale-invariant feature transform (SIFT) in local feature detection and description, Wang et al.[8] put forward a solution of segmenting the first Chinese character by SIFT, based on which the positions of other characters are inferred by prior knowledge.

In the second category, since methods are based on binary images, their performance is codetermined by the result of binarization and the technique of segmentation. Different methods often focus on different parts. In Refs. 9 and 10, image processing techniques, such as Gaussian filtering and Laplacian sharpening, are utilized to reduce the influence of nonuniform illumination and plate frame on Otsu binarization. To obtain a more satisfying result, adaptive thresholding is provided as well.[11,12] Next, with different techniques being used on the binary image, different performances are achieved as follows.

The first kind of technique is connected component analysis (CCA). Giannoukos et al.[13] present a two-round CCA method to separate characters from background. To deal with license plates in complex conditions, Yoon et al.[14] applies CCA to several binary images to ensure all characters are extracted. Then the noise components are removed by support vector machine (SVM). In Ref. 15, the likeliest character regions are found by operating CCA on an edge image, based on which the remaining characters are searched using an energy evaluation function.

Vertical projection (VP) is another popular technique used for CS. It takes advantage of the gap between characters. In Refs. 16 and 17, the projection vector of the binary image is computed by counting foreground pixels along columns and then columns with projections at valleys are considered as segmenting points. Utilizing the wider gap that separates a license plate number into two parts, Liu et al.[18] locate other gaps by prior knowledge and Nomura et al.[19] apply an adaptive morphological approach for degraded character images. To overcome the influence of uneven illumination, multiple binary images are obtained for projecting.[20] In Ref. 21, VP is combined with CCA to distinguish character blocks from noise. To avoid the problem of undersegmentation and

*Address all correspondence to: Guoyou Wang, E-mail: gywang1110@gmail.com

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oversegmentation, Abtahi et al.[22] combine deep reinforcement learning with VP to find the segmentation paths between characters.

In addition, template matching (TM) is also employed as a common solution, with template and matching criteria differing from method to method. Reference 23 uses a template that has the same character and space distribution as a standard license plate. By sliding the template under different scales, the position containing a maximum of character pixels is selected as the correct segmentation. A variation of TM is proposed in Ref. 24, which identifies the detected blocks through a comparison between their midpoints and that of the template. In our past work,[25] a harrow-shaped template with minimum response was designed to improve the robustness of matching. But due to the use of adaptive thresholding, the time cost for image preprocessing is high and the fixed spatial relationship between character blocks and space blocks limits the performance.

To sum up, the existing methods have the following advantages and disadvantages. First, the grayscale-based methods avoid information loss during binarization and make full use of the character feature. However, the techniques adopted for segmentation have their own defects. For example, NCC often results in oversegmentation, MSER fails in detection of merged characters, and SIFT is time consuming. Next, for methods working on binary images, we have the following conclusions: (1) CCA is easy to operate but depends too much on the result of binarization; (2) VP is fast and effective for license plates of high quality. But in complex conditions, the analysis will become complicated and error prone; (3) TM-based methods are robust to merged and broken characters and have strong ability to distinguish characters from noise. Nevertheless, they are insufficient in the design of template and matching criteria.

In this paper, a CS method using multiscale TM is proposed. It works on a binary image containing adequate contextual information. To segment the characters accurately, a uniform harrow-shaped template with variable length is designed and a three-dimensional (3-D) matching space is built to facilitate the search of candidate segmentations. Last but not least, the vertical boundaries of each character are also located for subsequent recognition. To summarize, the main contributions of our work are listed as follows.

1. MSER detector is adopted for binarization and combined with Otsu thresholding in case of missing of merged characters.
2. A uniform harrow-shaped template with variable length is designed for multiscale matching.
3. A 3-D matching space is constructed to facilitate the search of candidate segmentations.
4. A method for the location of each character's vertical boundaries is introduced.

This paper is organized as follows. In Sec. 2, the detail of the proposed method is presented. Experiments are conducted in Sec. 3 to show the performance of our method. Finally, the conclusions are drawn in Sec. 4.

## 2 Proposed Method

In this section, details on how to segment a license plate into separated characters are introduced. As depicted by the flowchart given in Fig. 1, the proposed method is composed of three stages. In the first stage, binarization is accomplished by integration of two binary images. Then the characters are segmented horizontally with a bank of templates. Finally, for each single character, its vertical boundaries are located on an edge image. Moreover, it is worthy to note that the input of CS is an isolated license plate image, which may have horizontal and vertical skewness. Since the proposed method can hardly handle the segmentation of an image with a large skew angle, a correction step is required before segmentation. For skewness in the horizontal direction, the method presented in Ref. 26 using KL expansion is adopted. The vertical skewness is handled by the approach introduced in our past work.[25]

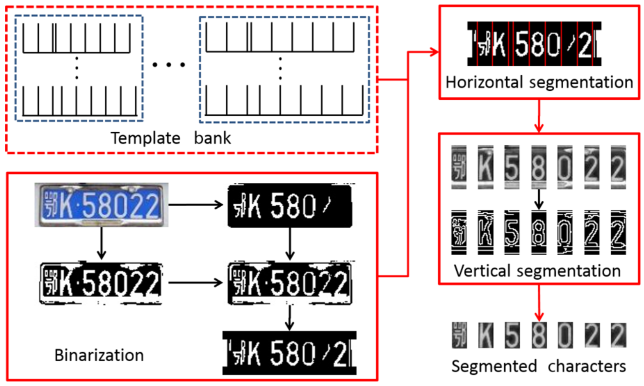


**Fig. 1** Flowchart of the proposed method for license plate CS.

### 2.1 *Image Binarization*

For CS based on a binary image, it is important to convert the grayscale image appropriately. In this work, we hope to include all the alphabetic and numeric characters of a license plate in the foreground of the binary image. To this end, a hybrid method combining MSER detector and Otsu thresholding is presented. It is implemented by five steps, as follows.

Step 1: Estimate the upper boundary $t$ and the lower boundary (LB) $b$ of the character region and set $h = b - t + 1$. For this purpose, the horizontal gradient image is computed to obtain a projection array $\mathrm{p}_h$ containing the average gradient value of each row. With $\mathrm{p}_h$, the vertical gradient center $i_c$ of the image is given by

$$i_c = \frac{\sum_{i=1}^{H} i \cdot \mathrm{p}_h(i)}{\sum_{i=1}^{H} \mathrm{p}_h(i)}, \tag{1}$$

where $H$ is height of the image. Then based on $i_c$ and its projection value $\mathrm{p}_h(i_c)$, the vertical boundaries are found by starting at $i_c$ and searching upward and downward, respectively, until the rows whose projection values $<p_h(i_c)/2$ are met.

Step 2: Obtain a binary image $I_1$ by keeping MSERs with expected properties, such as the height is $>h/3$ and the aspect ratio is [1.5,2.5].

Step 3: Obtain a binary image $I_2$ with the global threshold computed on a region bounded by $[t, b]$ vertically and by $[l, r]$ horizontally using Otsu's method, where $l$ and $r$ are the left and right boundaries of the character region.



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They are calculated by $l = j_c - h$ and $r = j_c + h$ on the basis of the horizontal gradient center $j_c$

$$j_c = \frac{\sum_{j=1}^{W} j \cdot \mathrm{p}_v(j)}{\sum_{j=1}^{W} \mathrm{p}_v(j)}, \tag{2}$$

where $\mathrm{p}_v$ is a projection array containing the average vertical gradient value of each column and $W$ is the width of the image. Note that the calculation of $l$ and $r$ are conservative to ensure that only license plate pixels are involved in the computation of the threshold.

Step 4: For each pixel $p$, compute its value in the binary image $I$ by

$$I(p) = \begin{cases} I_2(p), & \text{if } \sum\limits_{q \in p_{n\times n}} I_1(q) = 0, \\ I_1(p), & \text{otherwise}, \end{cases} \tag{3}$$

where $p_{n\times n}$ is the $n \times n$ neighborhood of $p$. Since the MSER detector performs very well in most situations and the Otsu thresholding is introduced to work for license plates with merged characters, $n$ should be approximately equal to the character width. Experimentally, $h$ is greater than the real character height and $n = h/3$ is set to avoid missing characters.

Step 5: Remove foreground pixels outside the vertical boundaries and blobs with heights that are smaller than $h/3$.

After the above steps, a desirable binary image is acquired. For two samples shown in Fig. 2(a), the results of each step are given in Figs. 2(b)–2(f).

### 2.2 *Horizontal Segmentation via Multiscale Template Matching*

In methods based on TM, the design of the template and the matching criteria have direct influence on the segmentation. In this paper, a uniform harrow-shaped template is designed, as shown in Fig. 3(a). It consists of three parts: seven character blocks with equal width $w$, one space block with width $d$, and nine segmentation lines $j_k$, $(k = 1,2,\ldots,9)$. According to the Ministry of Public Security standards for license plates,[27] the physical sizes of $w$ and $d$ are 57 and 22 mm, respectively. Since it is difficult to estimate the value of $w$ accurately, $w$ is allowed to range within $[0.3h, 1.5h]$ to cover the real character block width. Then based on the space-to-character ratio $r_{\mathrm{sc}} = d/w = 22/57 \approx 0.39$, a fixed value can be calculated for $d$. But considering the cases shown in Fig. 3(b), $d$ is designed to be variable and varies within $[0.2w, 0.5w]$. Hence, the proposed template has the following equation:

$$T(j; d, w) = \begin{cases} 1, & \text{if } j \in \{j_k\}, \\ 0, & \text{otherwise}, \end{cases} \qquad 0 \le j \le w_T - 1, \tag{4}$$

where $w_T = 7w + d$ is the length of the template. By using different combinations of $w$ and $d$, a template bank is built, with which multiscale matching is feasible. For better understanding, templates in the bank are organized into groups, with each group taking a different character width and each template within a group taking a different space width, as shown in Fig. 1.

Next, the response between a template and a license plate is defined to prepare for the introduction of the matching criteria. Denote the VP of the license plate's binary image by $p(j)$, $(j = 0,1,\ldots,W-1)$. Then the response at match $(x, d, w)$ is given by

$$\begin{aligned} r(x, d, w) &= \sum_{j=0}^{w_T - 1} [p(j + x) \cdot T(j; d, w)] \\ &= \sum_{k=1}^{9} p(j_k + x), \end{aligned} \tag{5}$$

where $x (0 \le x \le W - w_T)$ is the offset at which the template starts to overlap with the license plate. It can be seen that the response actually equals the number of foreground pixels lying on the segmentation lines. When appropriate values are assigned to $d$ and $w$, it is observed that the response curve over different offsets has a peak–valley–peak distribution

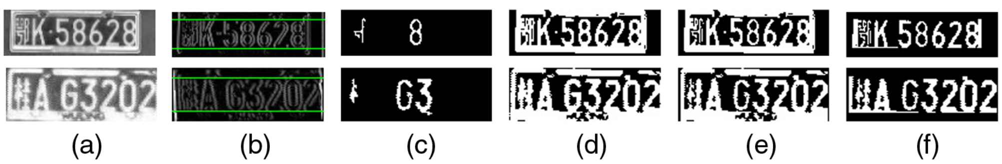


**Fig. 2** The binarization process: (a) gray images, (b) estimated vertical boundaries, (c) MSER images, (d) Otsu's results, (e) integrated binary images, and (f) binary images after denoising.

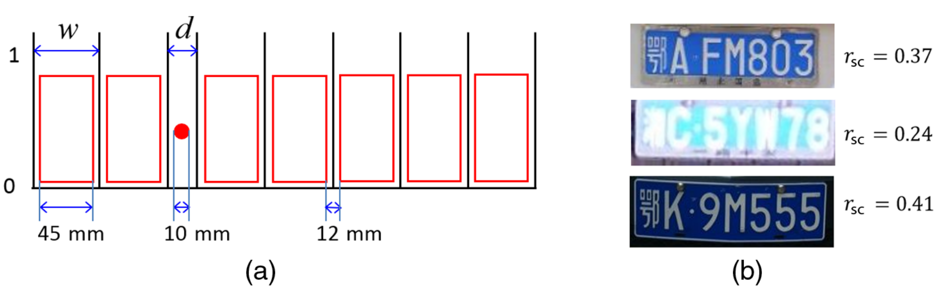


**Fig. 3** (a) The uniform harrow-shaped template. (b) Three cases with different space-to-character ratios.



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and the match corresponding to a certain valley tends to give a correct segmentation. Based on this, matches with local minimum responses are considered as candidate segmentations. However, there will be too many candidates if the local minimums are searched in the one-dimensional response curve for every given $d$ and $w$.

Fortunately, it is found that the above observation is also applicable to the response curve over different space widths for fixed $x$ and $w$, and over different character widths for fixed $x$ and $d$. Thus, the idea of detecting local minimums in a 3-D matching space is proposed. The $X$-axis, $Y$-axis, and $Z$-axis of the space represent the offset, the space width, and the character width, respectively, as shown in Fig. 4(a). For a match, its response $r(x, d, w)$ is thought to be a local minimum if the following conditions are met at the same time:

1. $r(x,d,w) \le r(x-1,d,w)$ and $r(x,d,w) < r(x+1,d,w)$.
2. $r(x,d,w) \le r(x,d-1,w)$ and $r(x,d,w) < r(x,d+1,w)$.
3. $r(x,d,w) \le r(x,d,w-1)$ and $r(x,d,w) < r(x,d,w+1)$.

It can be seen that the comparison is performed between $r(x, d, w)$ and its six neighbors, as marked by red and yellow in Fig. 4(a). By searching in the 3-D space, the number of matches with local minimums is greatly reduced. To show the effect of the proposed matching criteria, several candidate segmentations of a sample are given in Fig. 4(b). Below each segmentation, the corresponding response at the detected match is displayed as well. For clarity, these segmentations are aligned into groups according to the position of the space block, as introduced in the following.

It has been known that there is usually more than one candidate segmentation produced. To identify the best one, an effective two-step approach is presented. First, the segmentations are divided into groups and within each group, only the match with the minimum response is kept. The rule for dividing is that segmentations with overlapped space blocks are grouped together. For license plates with no interference on the left and right sides, there is only one segmentation reserved after this step. To deal with the situation of multiple groups of segmentation, the second step uses the NCC for distinction. Following the method presented in Ref. 4, the expression of the template is modified into

$$T(j; d, w) = \begin{cases} 1, & \text{if } j \in \{j_k\} \cup (j_3, j_4), \\ 0, & \text{otherwise}, \end{cases} \qquad 0 \le j \le w_T - 1 \tag{6}$$

and the NCC for each segmentation $(x, d, w)$ is computed by the following equation:

$$\mathrm{NCC}(x,d,w) = \frac{\sum_{j=0}^{w_T-1}\{[p_v(j+x)-m_1(x)]\cdot[T(j;d,w)-m_2]\}}{\sqrt{\sum_{j=0}^{w_T-1}[p_v(j+x)-m_1(x)]^2}\sqrt{\sum_{j=0}^{w_T-1}[T(j;d,w)-m_2]^2}}, \tag{7}$$

where $m_1(x) = (1/w_T)\sum_{j=0}^{w_T-1} p_v(j+x)$, $m_2 = (1/w_T)\sum_{j=0}^{w_T-1} T(j;d,x)$, and $p_v$ is the projection vector denoted in Step 3 of Sec. 2.1. Accordingly, the segmentation with the maximal NCC is chosen as the best.

### 2.3 *Vertical Segmentation*

Although the upper and LBs of the character region have been located in the binarization stage, more accurate boundaries are attempted to be found for each single character using an edge-based method. This method is composed of two parts: rough location and precise adjustment. In the first part, an edge image is acquired by Canny detector and the vertical boundaries are roughly found by starting at the middle row of the image and searching upward and downward, respectively, until blank rows are met. Here, a row is called blank if there are no edge pixels in it. A sample is shown in Fig. 5(a) with the boundaries marked by green lines.

In the second part, adjustments are made to some unreasonable boundaries from a global view. Taking the LBs, e.g., the adjustment is implemented by following the steps.

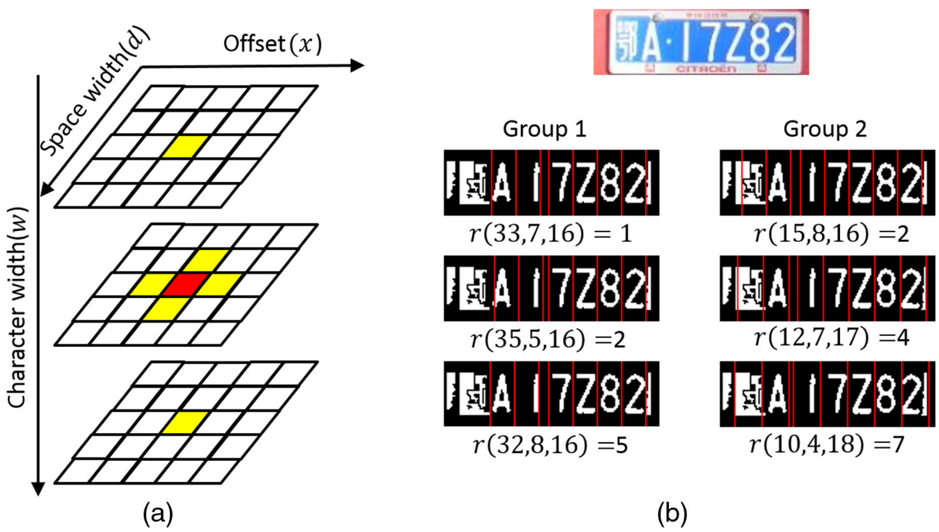


**Fig. 4** (a) Illustration of the 3-D matching space model and the searching strategy for local minimums. (b) Several candidate segmentations of a sample.



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(a) (b)

**Fig. 5** The location results of the upper and LBs of characters (a) rough and (b) adjusted.

1. Denote the LB set by $\{\mathrm{lb}_k\}$, $(k = 1,2,\dots,7)$ and for each $k$, compute the distance between $\mathrm{lb}_k$ and others by $D(k) = \sum_{i=1}^{7} |\mathrm{lb}_k - \mathrm{lb}_i|$. Find the boundary $\mathrm{lb}_{k^*}$ with $k^* = \arg\min_{k\in[1,7]} D(k)$.
2. Compute the smallest LB difference by $d_{\min} = \min|\mathrm{lb}_i - \mathrm{lb}_j|$, $(i,j = 1,2,\dots,7, i \neq j)$.
3. Start at $k^*$ and turn leftward and rightward, respectively. For the left, if $\mathrm{lb}_{k-1} - \mathrm{lb}_k > d_{\min}$, set $\mathrm{lb}_{k-1} = \mathrm{lb}_k + d_{\min}$; for the right, if $\mathrm{lb}_{k+1} - \mathrm{lb}_k > d_{\min}$, set $\mathrm{lb}_{k+1} = \mathrm{lb}_k + d_{\min}$.
4. Especially for the first Chinese character, if $\mathrm{lb}_1 < \mathrm{lb}_2$, set $\mathrm{lb}_1 = \mathrm{lb}_2$.

Using the same idea, the upper boundaries are adjusted and the results after adjustment are shown in Fig. 5(b).

## 3 Experiments

### 3.1 *Testing Data*

To evaluate the effectiveness of the proposed method, a data set containing 2349 Chinese license plate images is built. It is divided into three groups (high, middle, and low) according to the quality level of each plate, which is determined by the MSER detection result. Examples of each group and corresponding MSER images are shown in Fig. 6. It can be seen that: (1) in the "high" group, all the characters are detected separately; (2) in the "middle" group, characters are adhered to rivets or there is noise between characters; (3) the last group includes license plates in poor conditions and failed detections.

### 3.2 *Performance Evaluation*

#### 3.2.1 *Metrics*

In our experiments, the performance of a CS method is evaluated coarsely and accurately from two aspects. The first is the plate segmentation rate (PSR), which is computed by the number of license plate images segmented correctly divided by the total number of images. To give more details on the definition of correct segmentation, the following denotations are made. For a character, denote its labeled left and right boundaries by $l_g$ and $r_g$, its segmented boundaries by $l_s$ and $r_s$, then it is correctly segmented if the condition $[(|[l_s, r_s] \cap [l_g, r_g]|)/(|[l_g, r_g]|)] > 0.8$ is met, where $|\cdot|$ denotes the length of an interval. The segmentation of a license plate is correct only when all its characters are segmented correctly. Under this condition, the left term represents the overlapping ratio between a segmented interval and the corresponding labeled interval. The threshold for it is set to 0.8 to accept segmentations with slightly oversegmented characters, since they may be recognized correctly.

For further and more objective evaluation, the character recognition rate (CRR) is chosen as another aspect. It is computed by the number of characters recognized correctly divided by the number of characters presented, which equals $n$ times the number of license plates segmented correctly. In the experiments, the CRR of the first Chinese character and the other six characters are counted separately, and $n = 1$ and $n = 6$ are used for each count. Usually, a higher CRR means a better segmentation quality. A method is considered to offer good segmentation performance if it has both a high PSR and CRR. Since this metric is dependent on a character recognition method, the algorithm[28] combining the histogram of oriented gradient with SVM is applied.

#### 3.2.2 *Comparison methods*

For comparison, five state-of-the-art methods are chosen to show the effectiveness of our method. These methods are typical and denoted as "CRF,"[6] "VLTM,"[4] "AMA,"[19] "DTCP"[23], and "HSF,"[25] respectively. Among them, CRF and VLTM are free from binarization and apply the techniques of CCA and TM, respectively. The remaining methods are based on binary images. AMA combines VP with a morphological algorithm to segment fragmented, overlapped, or connected characters adaptively. The last two methods are both TM based, but they differ from each other in the template and the matching criteria.

#### 3.2.3 *Experimental results*

In Table 1, the PSR of our method and the comparison methods for each testing group are given. From this table, we can see that the proposed method outperforms others on all groups except the "high" one, on which it is slightly inferior to CRF that works perfectly for plates with separate and noise-free character blobs. On average, our method achieves a PSR of 98.7%, higher than CRF by 3.8%, VLTM by 7%, AMA by 14%, DTCP by 23.9%, and HSF by 2.6%. Moreover, with the level decline of each group, the performance of our method falls more slowly than others, indicating its robustness to plate quality variation. Especially, we obtain a PSR of 95.2% on the "low" group, which is even higher than the PSR of VLTM, AMA, and DTCP on the group of high-quality level.

Additionally, the time cost of each method is also presented in Table 1. It can be seen that the proposed method


**Fig. 6** Samples of license plate with different quality levels.



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**Table 1** PSR of the comparison methods on different groups of license plate.

| Methods | High (1268) (%) | Middle (770) (%) | Low (311) (%) | Average (2349) (%) | Average time (ms) |
|---|---|---|---|---|---|
| CRF | 100 | 97.5 | 71.1 | 94.9 | 44.35 |
| VLTM | 93.4 | 94.7 | 84.6 | 91.7 | 11.66 |
| AMA | 89.7 | 83.9 | 67.5 | 84.7 | 30.15 |
| DTCP | 75.6 | 75.6 | 67.2 | 74.8 | 23.80 |
| HSF | 97.3 | 95.2 | 91.6 | 96.1 | 31.04 |
| Proposed | 99.2 | 99.2 | 95.2 | 98.7 | 30.37 |

takes an average of 30.37 ms to segment a license plate, which is acceptable in comparison with other methods except VLTM. In Sec. 1, it is mentioned that HSF is time consuming in image preprocessing, which takes about 25.71 ms. By contrast, 13.30 ms, the average time for preprocessing in the proposed method is much faster. In this way, more time is allowed for the segmentation by multiscale matching. And this is the reason why a higher PSR is achieved at a comparable time cost. Note that all the methods are realized using Visual Studio 2008 and OpenCV, and the experiments are implemented on a Microsoft Windows XP operating system, Intel Core 3.07 GHz CPU and 1.92 GB RAM.

From the aspect of CRR, the performance of each method is shown in Table 2. Since the Chinese characters often have a lower recognition rate than the digits and the letters, the results of them are reported separately. For each group of data set, it is observed that the recognition rate counted on characters segmented by our method is higher than that of other methods, indicating the proposed segmentation method has more accuracy. On the groups of high- and middle-quality level, the recognition rate for the two types of characters is up to 95% and 98%, respectively. Due to the factor of low resolution, frame adhesion, and quality degradation, CRRs on the "low" group drop a lot, especially the CRR of the Chinese character. But it is still superior to other methods, higher than CRF by 6.7%, VLTM by 16%, AMA by 11.5%, DTCP by 19.3%, and HSF by 6.1%.

From Sec. 3.2.3, we draw the conclusion that at a time cost comparable to current best performing methods, the proposed method is more accurate and robust in segmenting license plates of different qualities. The effectiveness of our method is mainly due to three reasons. The first is the hybrid binarization method. Due to the excellent performance in blob extraction under changing illumination, MSER has begun to be used for license plate detection and CS. However, it results in failures when characters are connected to the plate frame, as reported in CRF. To make up the shortage of MSER, the Otsu's method is introduced in this paper as a backup. The second reason for our method achieving a better performance is the uniform harrow-shaped template with variable length. It is designed to improve the flexibility to license plate images with problems of narrow spaces caused by over exposure or adhesion and deformation caused by side viewpoint. Additionally, the two variables relate with the template facilitating the construction of a 3-D matching space, which is the last reason for our superiority. The space is of great help in reducing the number of

**Table 2** CRR of the comparison methods on different groups of license plate.

| Methods | High (1268) | | Middle (770) | | Low (311) | |
|---|---|---|---|---|---|---|
| | Chinese | Character | Chinese | Character | Chinese | Character |
| CRF | 94.2% | 98.6% | 95.1% | 97.5% | 81.5% | 92.7% |
| | (1194/1268) | (7504/7608) | (714/751) | (4393/4506) | (172/211) | (1173/1266) |
| VLTM | 85.6% | 91.3% | 84.9% | 92.3% | 72.2% | 86.1% |
| | (1014/1184) | (6485/7104) | (619/729) | (4036/4374) | (190/263) | (1358/1578) |
| AMA | 91.9% | 96.3% | 86.2% | 92.7% | 76.7% | 87.5% |
| | (1045/1137) | (6567/6822) | (557/646) | (3594/3876) | (161/210) | (1103/1260) |
| DTCP | 85.1% | 93.1% | 82.8% | 91.8% | 68.9% | 87.8% |
| | (815/958) | (5349/5748) | (482/582) | (3206/3492) | (144/209) | (1101/1254) |
| HSF | 93.7% | 96.7% | 95.3% | 96.4% | 82.1% | 88.0% |
| | (1156/1234) | (7158/7404) | (670/733) | (4239/4398) | (234/285) | (1558/1710) |
| Proposed | 95.8% | 98.7% | 95.3% | 98.8% | 88.2% | 96.1% |
| | (1205/1258) | (7449/7548) | (728/764) | (4530/4584) | (261/296) | (1707/1776) |



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**Fig. 7** Segmentation results of comparison methods on license plates in high-quality level: (a) CRF, (b) VLTM, (c) AMA, (d) DTCP, (e) HSF, and (f) proposed method.

candidate segmentations and improving the segmentation accuracy.

### 3.3 *Segmentation Samples*

To show the segmentation performance of each method intuitively, some samples are given in this section. First, samples for the "high" group are presented, as displayed in Fig. 7. We can see that background pixels on the left and right side are the only interference and every method except DTCP can segment the characters correctly. This suggests the shortage of DTCP that finds the best matching by maximum variance between clusters. In addition, it is noted that the result of VLTM is inaccurate due to the slight difference between the traditional template and the captured license plates.

In Fig. 8, segmentation results on the second group are given to show the robustness of our method to adhesion and noise. For methods based on VP or TM, they are often not affected by adhesion with plate rivets or frame because the upper and LBs of the character region are often located before segmentation. As for CRF, the change in size of character blobs also hardly has an effect on labeling. But the noise between characters can lead to false labeling and segmentation. Thanks to the noise removing step in binarization, a clean binary image is obtained by our method, making the subsequent segmentation easier.

From the above discussion, the performances of CRF and HSF are seen to be almost equal to that of the proposed method. To show their weakness in segmentation, Fig. 9 presents samples for the group of low-quality images. As can be seen, CRF provides wrong labels in the case of an insufficient amount of character blobs and HSF produces incorrect segmentation positions for its limitation in templates of fixed length. By contrast, the proposed method segments each character accurately based on a binary image containing adequate contextual information, a flexible template, and a strong matching strategy.

Lastly, to analyze the limitations of our method, samples of wrong segmentation are summarized in Fig. 10. The first failure is attributed to the wrong decision made by NCC, which works as a filter to select the best from several


**Fig. 8** Segmentation results of comparison methods on license plates in middle-quality level: (a) CRF, (b) VLTM, (c) AMA, (d) DTCP, (e) HSF, and (f) proposed method.



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**Fig. 9** Segmentation results of comparison methods on license plates in low-quality level: (a) CRF, (b) VLTM, (c) AMA, (d) DTCP, (e) HSF, and (f) proposed method.

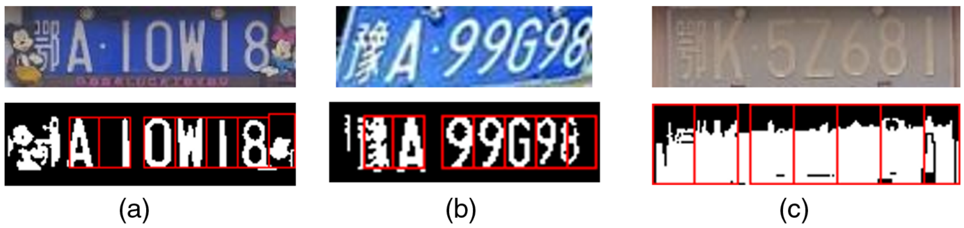

**Fig. 10** Failed segmentation samples on license plate with (a) background interference, (b) perspective distortion, and (c) dirt.

candidate segmentations. The other two instances occur on license plates with serious perspective distortion and dirty appearance.

## 4 Conclusion

In this paper, a CS method for Chinese license plates using multiscale TM is proposed. First, it presents a fast and effective algorithm of binarization, which combines MSER detector with Otsu thresholding. Next, a uniform harrow-shaped template with variable length is developed on the basis of our past work. It maximizes the adaptability of our method for license plates in different conditions and also minimizes its computational cost. Finally, searching matches with local minimums in the constructed 3-D space is of great help in including the correct match into the candidate segmentations and reducing the number of them. Experiments on three groups of data set show the promising performance of our method and its superiority to several representative methods.

Although the proposed method is focused on the segmentation of a Chinese license plate, it is believed to work well on other single-row license plates with different left–right structures by changing the position of the space block in the template, such as police vehicle plates and foreign plates with consistent background. This will be verified in our future work. In addition, against the limitations of our method, more efforts on strengthening the discrimination of NCC, correction of perspective distortion, and enhancement of dirty license plates will be made.

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**Jiangmin Tian** received her BS degree in software engineering from Huazhong University of Science and Technology (HUST) in 2010. Currently, she is working toward her PhD in pattern recognition and artificial intelligence at HUST. Her research interests include image processing, pattern recognition, and machine learning.

**Guoyou Wang** received his BS and MS degrees from HUST, Wuhan, China, in 1988 and 1992, respectively. Currently, he is a professor at HUST. His research interests include image processing, image compression, pattern recognition, and artificial intelligence.

**Jianguo Liu** received his BS degree from Wuhan University of Technology, Wuhan, China, in 1982, his MS degree from Huazhong University of Science and Technology (HUST) in 1984, and his PhD from Hong Kong University in 1996. Currently, he is a professor of HUST. His research interests include pattern recognition, fast discrete transforms, and neural networks.

**Yuanchun Xia** received his BS degree in communication engineering from HUST, Wuhan, China, in 2011. Currently, he is a PhD student in control science and engineering at HUST. His research interests include image processing, pattern recognition, and machine learning.



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