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License plate recognition based on SIFT feature

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ABSTRACT

Although license plate recognition (LPR) system is widely applied in practice, its some key techniques that cannot meet application requirements in natural scenes still need more attention, such as Chinese character recognition, candidate filtration, tilt correction, and character segmentation. In this paper, a novel method based on SIFT feature is devised to solve the four problems simultaneously. Promising experimental results demonstrate that the proposed is robust to various adverse factors, such as complex background, scaling variation, rather large tilting angle, contamination, illumination variation, partial occlusion, and defective character. The success rates of Chinese character recognition and candidate filtration reaches to 96%; the tilt correction accuracies reach to 0.177° and 0.238° in horizontal and vertical directions respectively; and the success rate of character segmentation approaches 100%. Remarkably, the average execution time for these four processes is lower than 268 ms, which may favor real-time processing.

1. Introduction

License plate recognition (LPR) plays an important role in various applications, such as automatic toll collection, traffic analysis, traffic law enforcement, security control of restricted areas, and parking solutions or inventory management. Recently, some key techniques for LPR have been in stage of high application level, such as license plate location, letter recognition, and number recognition, etc. However, some other ones that cannot meet application requirements in natural scenes still need more attention, such as Chinese character recognition, candidate filtration, tilt correction, and character segmentation.

1.1. Chinese character recognition

Countries and areas where LPR system is paid much attention to mainly include three characters: number, letter, and Chinese character. So far, the developments of number and letter recognition are of a very high level, particularly for those based on ANN (artificial neural network) and SVM (support vector machine). Chinese character recognition, however, cannot satisfy application requirements in natural senses effectively because of various challenges, such as more complex structure, defective character, tilt, noise, scaling, illumination variation, contamination, etc. Although some Chinese character recognition methods based on ANN [1,2] and SVM [3,4] are proposed recently, they are not robust to these adverse factors simultaneously.

1.2. Candidate filtration

Once attaining some license plate candidates, we need to find out the real one before character segmentation. This is the main task for candidate filtration. Generally, candidate filtration methods are nearly based on some prior knowledge, such as color, geometrical information, character number, gray jumps, license plate position, and character symmetrical edge, etc. [5–7]. However, these methods generate some false positive cases unavoidably and noise candidates will influence character segmentation and recognition processes seriously. Moreover, because many license plate location methods can merely process single-layer license plates, we expect candidate filtration helps to relocate two-layer one according to the single-layer output.

1.3. Tilt correction

Tilt correction is usually needed after candidate filtration, due to viewpoint variation in image collection. Ordinarily, tilt correction

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methods can be divided into five categories: Hough line detection [8], random line detection [9], main orientation analysis [10], corner detection [11], and maximum or minimum projection [12]. However, some disadvantages restrict their application in practice. Firstly, they are all sensitive to completeness of license plate and background noise. Secondly, the first three can merely realize tilt correction in horizontal direction. Thirdly, although the later two perform both in horizontal and vertical directions, their correction accuracies are lower.

1.4. Character segmentation

Comparing to gray image, binary image divides target and background into two individual parts, which has obvious advantages in feature extraction and pattern recognition fields. Hence, binarization is a key part of character segmentation commonly. However, even some robust binarization methods, e.g. the adaptive one [13], cannot perform effectively in complex natural scenes. Binarization effect is always a main restraining factor for character segmentation. On the other hand, segmentation process can perform by three categories of specific methods: projection [14], connected region analysis [12], and prior knowledge [15]. Yet, the first two are sensitive to illumination variation, noise, and contamination; and rely on the effects of tilt correction, binarization, and noise reduction. Furthermore, although the prior knowledge one is robust to these adverse conditions, including character stroke fracture and conglutination, its performance is completely determined by accurate selection of criterion position. So far, the selection approach proposed can only perform well under many restraint conditions.

To solve the previous problems simultaneously, we need to find a tool that may provide representative information to the four processes. SIFT descriptor, a highly distinctive invariant, is proposed by David G. Lowe [16], which is proved to be effective and robust in varieties of pattern recognition applications, including letter and number detection in license plates [17,18]. In this paper, we will introduce SIFT feature to Chinese character recognition for LPR application in China. Moreover, a specific Chinese character can be seen the most representative feature for a license plate so that this recognition process also implements the task of candidate filtration. The last but not the least is that SIFT feature point includes orientation and position information, which is probably to favor tilt correction and character segmentation substantially.

The rest of the paper is organized as follows. Section 2 introduces the SIFT fundamental. Section 3 details the proposed method, including Chinese character recognition, candidate filtration, tilt correction, and character segmentation based on SIFT feature. And then, experimental results are given in Section 4. Finally, Section 5 provides the conclusions.

2. SIFT fundamental

SIFT consists of four major stages: scale-space extrema detection, feature point localization, orientation assignment, and feature point descriptor.

In the first stage, potential feature points are detected by searching over all scales and image locations. It is implemented efficiently by using a difference-of-Gaussian (DoG) function pyramid to identify potential interest points that are invariant to scale. The DoG is a close approximation to the scale-normalized Laplacian-of-Gaussian $\sigma^2\nabla^2 G$ which is required for true scale invariance. Mikolajczyk [19] found that the extrema (maxima and minima) of $\sigma^2\nabla^2 G$ produce the most stable image features. Hence, the locations of the extrema in the DoG correspond to the most stable features with respect to scale variances, and are identified as candidate feature points.

In the second stage, for each candidate feature point, a detailed model is fit to the nearby data for location, scale, and ratio of principal curvatures. This information allows candidate feature points to be rejected that have low contrast (and are therefore sensitive to noise) or are poorly localized along an edge. Sub-sample accurate position and scale is computed for each candidate feature point by fitting a quadratic polynomial to the scale space DoG function and finding the extremum, giving

$$\hat{X} = -\frac{\partial^2 D^{-1}}{\partial X^2}\frac{\partial D}{\partial X}, \tag{1}$$

where $\hat{X} = (x, y, \delta)^T$ is the extremum position providing accurate position and scale. Feature points are selected based on measures of their stability and eliminated if found to be unstable.

In the third stage, the dominant orientation is assigned to each feature point based on local image gradient directions. Dominant orientation is determined by building a histogram of gradient orientations from the feature point's neighborhood, weighed by a Gaussian and the gradient magnitude. Every peak in the histogram with a height of 80% of the maximum produces a feature point with the corresponding orientation. A parabola is fit to the peak(s) to improve accuracy. The assigned orientation, scale and location enables SIFT to construct a canonical view for the feature point that is invariant to image transforms.

In the final stage, for each feature point, the feature descriptor is created by sampling the magnitudes and orientations of the image gradients in the 16×16 neighboring region around the point. The region has been previously centered about the feature point's location, rotated on the basis of its dominant orientation and scaled to the appropriate size, and partitioned into 16 sub-regions of 4×4 pixels each. For each pixel within a sub-region, SIFT accumulates the pixel's gradient to orientation histograms with eight bins by weighting the contribution of each gradient according to its magnitude and a Gaussian function with σ equal to one half the width of the descriptor window. A 4×4 array of histograms, each with eight orientation bins, captures the rough spatial structure of the neighboring region. This 128-element vector, i.e. the feature descriptor for the point, is then normalized to unit length.

3. The proposed method

3.1. Chinese character recognition and candidate filtration

There are two categories of license plate in China: the single-layer license plate and the two-layer one. The first character for each single-layer license plate and upper layer of each two-layer one is definitely a Chinese character. Since SIFT feature is robust to changes in scaling and rotation, complex background, illumination variation, affine distortion, and etc., we can recognize a Chinese character directly by SIFT feature matching between a smaller region in a license plate candidate and each prepared template. On the other hand, similar Chinese characters may hardly appear in vehicle body and road background. Hence, this recognition process can realize candidate filtration and two-layer license plate redetection else, as shown in Fig. 1. Firstly, we extract and store SIFT feature of each Chinese character template respectively. And then, SIFT feature of potential target region in each license plate candidate is extract to perform feature matching. If the region excludes a Chinese character, two-layer license plate redetection will be implemented. Similar recognition process for potential upper layer for this candidate is conducted. Once a Chinese character is discovered, we can get complete two-layer license plate from an original image. Yet, mismatch denotes that this candidate is a noise area.

Due to relative stationary location of Chinese character, we extract a potential target region instead of adopting the complete

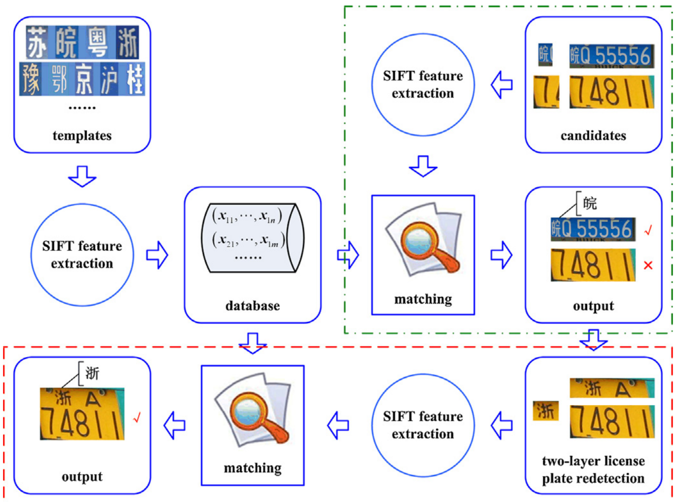

Fig. 1. The flow of Chinese character recognition and candidate filtration.

license plate candidate. This will improve efficiency of SIFT feature extraction and matching. Firstly, vertical edge image for a candidate is achieved. An edge density for a rectangle scanning window is defined as

$$\mathrm{den} = \frac{r \times s}{w \times h}, \tag{2}$$

where r and s are edge pixel area and connected edge number; w and h are width and height of the window. Once $\mathrm{den} > T$ ($T = 0.8$), this window is selected as the potential target region.

If a target region and a template have m and n feature points respectively, 128-D descriptor for two kinds of points are denoted as $X_i = (x_{i1}, \ldots, x_{i128})$, $i = 1, \ldots, m$ and $Y_j = (y_{j1}, \ldots, y_{j128})$, $j = 1, \ldots, m$. Then, distance between the two feature points is defined as

$$D_{i,j} = \left|X_i - Y_j\right| = \sqrt{\sum_{l=1}^{128} (x_{il} - y_{jl})^2}. \tag{3}$$

Given that $D_{i,\min1}$ and $D_{i,\min2}$ are the first-nearest and second-nearest distance respectively, this two feature points can be seen as a pair of stable matching ones if $D^2_{i,\min1} < \sigma D^2_{i,\min2}$, $0 < \sigma < 1$. Then, we define ratio of stable matching points as

$$R = \begin{cases} \dfrac{p}{12} & m < 4 \\ \dfrac{P}{\min(m, n)} & \text{else} \end{cases}, \tag{4}$$

where, p is the number of stable matching points. When $R \geq T_p$ ($T_p = 0.25$), the certain template can be denoted as a recognition output. A sample of Chinese character recognition is shown in Fig. 2, including SIFT feature points of each template and target region, and feature matching progress.

3.2. Tilt correction and character segmentation

Tilt correction can be seen as an affine transformation from tilting license plate to normal one. The affine transformation model is presented as

$$\begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = A \begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{12} & a_{22} & a_{23} \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x' \\ y' \\ 1 \end{pmatrix}. \tag{5}$$

where, A is affine transformation matrix and (a_{11}, a_{12}, a_{13}, a_{21}, a_{22}, a_{23}) is its transformation factors; (x', y') and (x, y) denote coordinates of a same point before and after transformation respectively. Expecting to get affine transformation matrix A, we need coordinates of three points before and after transformation. Remarkably, SIFT feature matching points between each Chinese character and its template are able to meet the needs, since location information is a fundamental factor for each SIFT feature point. Hence, tilt correction algorithm is given as follows:

(1) Acquire SIFT feature matching points of the Chinese character and select the four closest to the character rim.

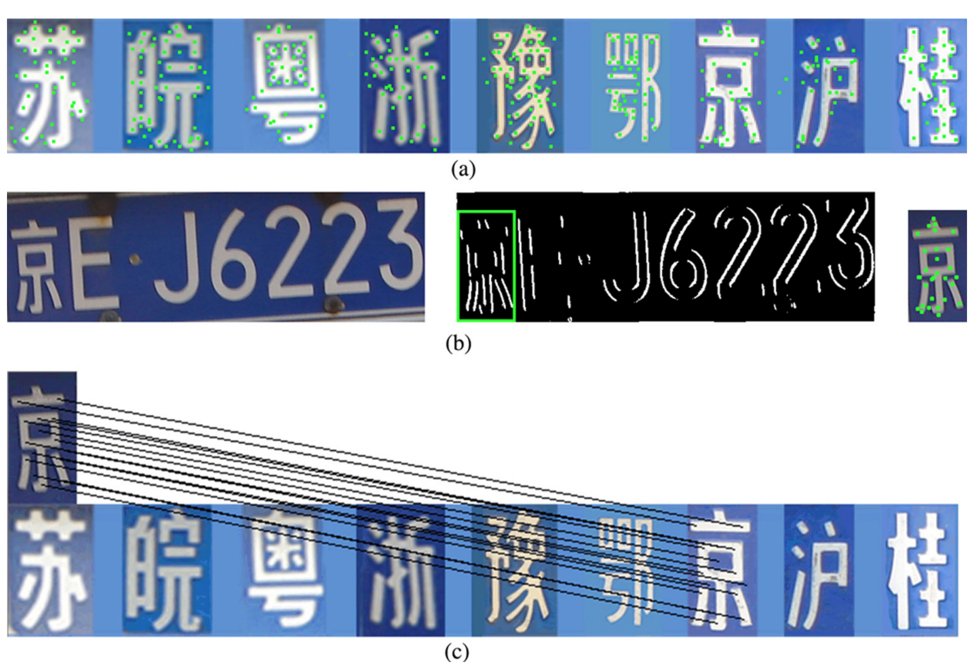

Fig. 2. A sample of Chinese character recognition: (a) SIFT feature points of each template, (b) SIFT feature points of potential target region and (c) feature matching.

Fig. 3. Target points selection in tilt correction.

Fig. 4. The tilt correction sample corresponding to Fig. 2(b).

(2) Random three points from them can form four triangles; select those three points as the target ones whose triangle has the maximum area, as shown in Fig. 3.
(3) Solve affine transformation matrix A by coordinates of the target points and the matching ones in corresponding template.
(4) Implement tilt correction for the license plate by affine transformation matrix A and output result.

Fig. 4 illustrates the tilt correction sample corresponding to Fig. 2(b). Actually, this process also normalizes license plate characters according to dimension of the template, which may favor the character segmentation method based on prior knowledge [15]. Furthermore, the SIFT matching points provide accurate criterion position without binarization operation. Here, relative location of each matching point in a Chinese character or in a template is stationary. Given a matching point (x, y) as shown in Fig. 5, we can get

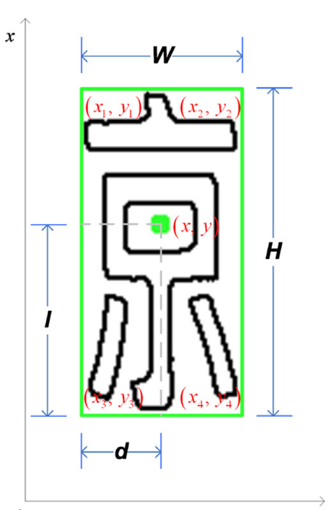

Fig. 5. Relative location of a matching point in a Chinese character.

Fig. 6. The segmentation sample corresponding to Fig. 4.

coordinates of four vertices in segmentation rectangle, (x_1, y_1), (x_2, y_2), (x_3, y_3), and (x_4, y_4) as

$$\begin{cases} x_1 = x_3 = x - W \times R_1 \\ x_2 = x_4 = x + W \times (1 - R_1) \\ y_1 = y_2 = y + H \times (1 - R_2) \\ y_3 = y_4 = y - H \times R_2 \end{cases} . \tag{6}$$

where, the constants $R_1 = d/W$ and $R_2 = l/H$ are relative location ratios of the matching point in a Chinese character. Since normal license plate characters have regular geometrical and arrangement characteristics, we can segment other characters by the segmentation rectangle of Chinese one and prior knowledge. Segmentation algorithm is detailed as follows:

(1) Select the matching point that is closest to Chinese character center as the target point.
(2) Acquire segmentation rectangle of the Chinese character through relative location of the target point in corresponding template, as presented in Eq. (6).
(3) If the license plate is a single-layer one, segment other characters by segmentation rectangle of the Chinese one and prior knowledge, and turn to (7); or, turn to (4).
(4) Segment anther character in the upper layer by segmentation rectangle of the Chinese one and prior knowledge.
(5) Calculate a new segmentation rectangle suitable for character dimension in the lower layer by the primary rectangle size and prior knowledge.
(6) Segment characters in the lower layer by the new segmentation rectangle similarly.
(7) Output result.

Fig. 6 shows the segmentation sample corresponding to Fig. 4. In practice, we can perform proper adjustment by character edge, so as to acquire more accurate segmentation result.

4. Experimental results

4.1. Chinese character recognition and candidate filtration

To evaluate the proposed method, a dataset is built, containing 800 license plate candidate images. These candidates include 700 real license plates and 100 noise areas. Chinese character region extracted range from 20×39 to 112×200 and each template is fixed to 55×100. Most of the license plates are involved in tilting, noisy, and illumination variation cases of different extent. Moreover, some of which refer to more complex conditions, such as contamination, partial occlusion, and defective character, etc.

Experimental results in Table 1 show that the recognition success rate for Chinese character is 95.4%; the one for noise region is 100%; and the one in total or candidate filtration is 96.0%. Some adverse factors, e.g. serious contamination, blurring, and low resolution, cause false negative of 32 Chinese characters. However, false positive rate of 0 demonstrates the effectiveness of the proposed, especially for candidate filtration. Furthermore, with average execution time of 258 ms (PC: Pentium IV at 2.4 GHz and 1 GB RAM; Tool: VC++6.0), it may favor real-time processing.

Table 1
Experimental results of Chinese character recognition and candidate filtration.

	Chinese character recognition	Noise region recognition	Recognition in total or candidate filtration
Success rate	95.4%	100%	96.0%
Average executive time	260 ms	244 ms	258 ms

Due to characteristics of SIFT feature, the proposed is robust to various adverse conditions in dataset, as some samples illustrated in Fig. 7. There is different noise in each character image and some even include noise character, fixed bolt and frame, and etc., as illustrated in Fig. 7(a). In some cases as shown in Fig. 7(a), scaling variation reaches to three or four times. Similarly, tilting case occurs ordinarily and some serious one reaches to 45°, as shown in Fig. 7(c). Illumination variation distorts colors in a character image and contamination will worsen this situation further, as shown in Fig. 7(d). However, the proposed are capable of processing these cases smoothly. Moreover, as a local feature descriptor, SIFT operator can generate many stable matching feature points. Hence, the proposed also do well in processing the cases of partial occlusion and defect character, as shown in Fig. 7(d and e).

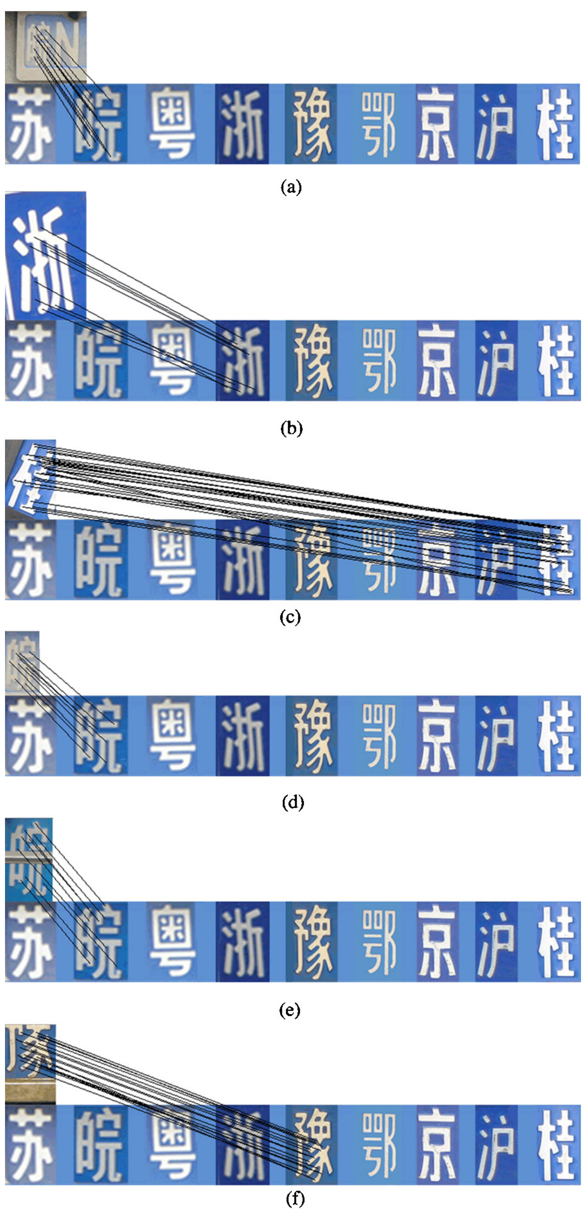

Fig. 7. Recognition samples under various adverse conditions: (a) complex background, (b) scaling variation, (c) rather large tilting angle, (d) contamination and illumination variation, (e) partial occlusion, and (f) defective character.

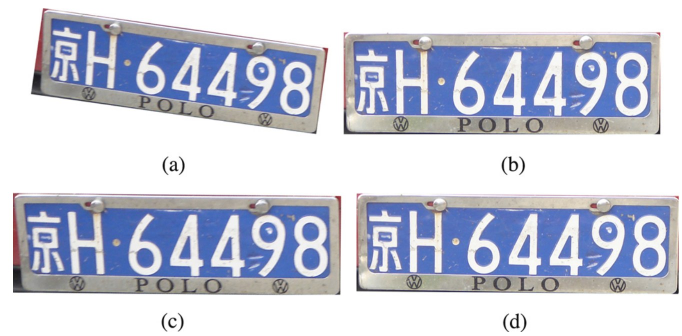

Fig. 8. Tilt correction in horizontal and vertical orientations: (a) a license plate tilting in horizontal and vertical orientations, (b) maximum or minimum projection, (c) main orientation analysis, and (d) the proposed.

4.2. Tilt correction and character segmentation

After Chinese character recognition process, 60 license plate candidate images with little tilt are selected and divided into three groups. Some preprocessing for them are conducted: the first group and the second one are rotated by a same angle in vertical and horizontal directions respectively; and the third one are rotated by the same angle both in these two directions. Then, these three groups of images are applied to comparing tests for correction methods of main orientation analysis [10], maximum or minimum projection [12], and the proposed. Finally, other 60 candidate images under the conditions of contamination, fading, partial occlusion are selected to test our tilt correction and character segmentation method simultaneously (PC: Pentium IV at 2.4 GHz and 1 GB RAM; Tool: Matlab7.8.0).

Comparing experiment results of tilt correction are shown in Table 2. The proposed performs better than the other two do in correction accuracy, real-time characteristic, and robustness. Its horizontal and vertical correction accuracies reach to 0.177° and 0.238° respectively; and average execution time is merely 5 ms. Although the correction accuracy of maximum or minimum projection is the lowest, main orientation analysis cannot perform vertical correction (Fig. 8), because of its basis on horizontal character arrangement. Furthermore, since the proposed applies information of SIFT matching points in Chinese character recognition directly, less computation is needed. Yet, unavoidable high computation in tilting angle detection makes efficiencies of other two rather lower than that of the former. In aspect of robustness, the proposed is not sensitive to license plate completeness and dependence, and robust to complex background noise, as illustrated in Fig. 9(d). The other two, however, are sensitive to noise, which lower the correction accuracies rapidly, as illustrated in Fig. 9(b and c). Moreover, Fig. 10 demonstrates that they are not able to solve the cases of fading, partial occlusion, and defective character as smoothly as the proposed does.

On the other hand, the joint test of tilt correction and character segmentation denotes that the proposed can correct and normalize those samples of fading, contamination, partial occlusion, and etc., effectively; and that this process attains Chinese character location and size accurately, which provides criterion position with high confidence to the segmentation method based on prior knowledge. Therefore, segmentation success rate approaches 100%. Fig. 10 shows some samples under these adverse conditions. In which,

Table 2
Comparing experiment results of tilt correction.

	Horizontal correction accuracy	Vertical correction accuracy	Average execution time (ms)	Robustness
Main orientation analysis [10]	0.784°	0.814°	86	Worst
Maximum or minimum projection [12]	0.556°	–	9	Weak
The proposed	0.177°	0.238°	5	Robust

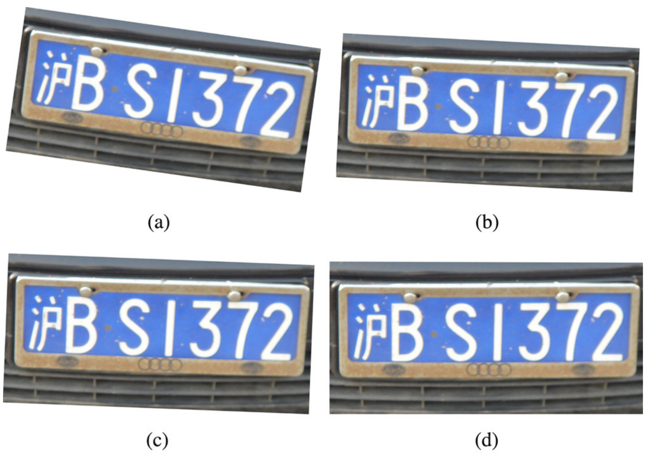

Fig. 9. Tilt correction under the condition of complex background noise: (a) a tilting license plate with complex background noise, (b) maximum or minimum projection, (c) main orientation analysis, and (d) the proposed.

Fig. 10. Tilt correction and character segmentation under some adverse conditions: (a) color breaking off, (b) contamination and fading, (c) partial occlusion, and (d) a two-layer license plate with contamination and fading.

Fig. 10(d) illustrates a sample of a two-layer license plate with contamination and fading. After accurate correction, the letter in the upper layer is segmented by the size of Chinese character. Then, the calculated sizes for lower layer character also meet practical needs; and fading and contamination have little influence on segmentation process. Remarkably, the average execution time for tilt correction and character segmentation is lower than 10 ms, which may favor real-time processing else.

5. Conclusions

Four LPR key techniques, Chinese character recognition, candidate filtration, tilt correction, and character segmentation, are discussed in this paper. The distinct characteristic of the proposed method is to merge these four problems into a one that can be solved smoothly by SIFT feature matching. Based on Chinese character recognition, this method first realizes candidate filtration through the uniqueness of Chinese character in a license plate. In this case, the success rate of Chinese character is the one of candidate filtration so that false positive instance hardly occurs. Secondly, SIFT feature matching points can helps to acquire affine transformation matrix from a tilting license plate to a normal one. This matrix can realize tilt correction both in horizontal and vertical correction and character normalization simultaneously. On the other hand, these matching points include accurate relative location information, which provide criterion position with high confidence to character segmentation method based on prior knowledge. Therefore, character segmentation implements smoothly and efficiently. Notably, the four processes give attention to single-layer and two-layer license plates, including two-layer one redetection in candidate filtration, which further meet application requirements in practice. Moreover, since computation of the proposed nearly focuses on Chinese character recognition, the average execution time for these four processes is lower than 268 ms, which may favor real-time processing.

Due to characteristics of SIFT feature, the proposed is robust to various adverse factors, such as complex background, scaling variation, rather large tilting angle, contamination, illumination variation, partial occlusion, and defective character. However, some contamination, blurring, and low resolution cases cannot be processed successfully, because stable SIFT feature points cannot be extracted effectively. For the first two cases, we will try to solve them by improving robustness of our method. And for the low resolution cases, we may consider to recur to ANN or SVM else.

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