LETTER

License Plate Detection and Character Segmentation Using Adaptive Binarization Based on Superpixels under Illumination Change

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SUMMARY In this paper, an algorithm is proposed for license plate recognition (LPR) in video traffic surveillance applications. In an LPR system, the primary steps are license plate detection and character segmentation. However, in practice, false alarms often occur due to images of vehicle parts that are similar in appearance to a license plate or detection rate degradation due to local illumination changes. To alleviate these difficulties, the proposed license plate segmentation employs an adaptive binarization using a superpixel-based local contrast measurement. From the binarization, we apply a set of rules to a sequence of characters in a sub-image region to determine whether it is part of a license plate. This process is effective in reducing false alarms and improving detection rates. Our experimental results demonstrate a significant improvement over conventional methods.

key words: *license plate detection, license plate character segmentation, binarization, superpixel algorithm*

1. Introduction

For any modern city with large population, the number of vehicles in use often exceeds the city's capacity to handle the traffic. Consequently, in order to prevent traffic jams, accidents, or parking problems, intelligent traffic systems are becoming essential on city streets and highways. LPR is one of the most important computer vision techniques in video-based traffic surveillance systems [1], [2]. In particular, LPR provides crucial information about the involved vehicles.

An LPR system generally consists of three stages: license plate detection, character segmentation, and character recognition. Recently, detector algorithms have advanced quickly due to the recent developments in machine learning. Accordingly, license plate (LP) detector and character recognition have become effective under normal illumination conditions. Du et al. [1] introduces an extensive study on LP detection. LP detection methods may be categorized based on the following features: edge, texture [3], or characters [4]. These methods are very effective under uniform illumination. However, outdoor light conditions are always changing, making this method impractical in real situations. Therefore, the use of suitable features in license plate recognition would result in better performance.

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Character images found from vehicle body parts need to be segmented from non-character images in order to be used as potential information for a possible LP after initial detection. For this reason, binarization becomes necessary as preprocessing so that it can prepare for the subsequent character recognition step. This task, however, is challenging because of the diversity of plate formats and complex outdoor environments. Therefore, most methods work only in certain restricted environments. For example, the improved Otsu (IO) method [5] chooses the threshold value automatically. Since this method reflects the distribution of total input, it experiences shortcomings when the intensity or color of the input image is changed locally. In order for binarization to remain effective in partial light changes, the Bradley [6] and Wolf [7] algorithms have been introduced. However, local mean by moving average, which these methods use, is vulnerable to sudden changes. Bernsen [8] proposed a method for handling uneven illumination, particularly for shadow removal; the improved Bernsen (IB) algorithm [9] is a method of calculating two threshold values so as to be more effective with noise. A character segmentation using superpixels was introduced by Zhou [10]. However, this method needs to train text feature and cannot distinguish the characters of LP from those of ordinary characters.

To mitigate the limitations encountered by the previously suggested methods, a novel LP character segmentation algorithm is proposed so that LPR becomes robust under sudden illumination changes. This paper improves the performance from our previous work [11] by suggesting the following methods: 1) merging rule of character component which is appropriate for Korean LPs, and 2) robust segmentation that reduces false alarm of the LP detections (LPDs). Improved performance of the proposed method is verified by the LPD and character detection of Korean LPs. This paper is organized in the following order. Section 2 describes what is adopted and what is proposed. A rule of character in LP is developed and represented in terms of a mathematical model. In Sect. 3, using training and test DB, experimental results of the proposed method and its comparison with conventional methods are presented for performance validation. Finally, conclusions are drawn in Sect. 4.

2. Proposed Method

2.1 The LPD and Character Segmentation Method

We used the AdaBoost classifier and a local structure feature with cross-shaped kernel [3] for finding LP candidate positions. An image pyramid is applied to deal with different sizes of LPs in the detection procedure. Lowering the detection threshold value can alleviate illumination sensitivity; however, a low threshold value may then result in an increased number of false alarms when applied to background images that contain structural patterns similar to an LP. We adopt binarization to ensure the proposed LPD is more robust to illumination changes while minimizing false alarms.

When binarizing an image, the threshold value plays the key role in the algorithm's overall performance. When choosing the threshold value, histograms are commonly employed to analyze the distribution of pixel brightness on an input image. A variety of factors affect captured images of LPs, including surface dust/mud, specular reflection, and/or optical shadow. Hence, the contrast between background and characters may not always be clear. Locally set thresholds may alleviate this difficulty. Among the various local binarizations, one that is frequently used with good results is an IB algorithm [9] which computes the threshold as follows:

$$T_1(x,y) = \frac{1}{2}\{\max_{-\omega\le k,l\le\omega} f(x+l,y+k) + \min_{-\omega\le k,l\le\omega} f(x+l,y+k)\} \tag{1}$$

$$T_2(x,y) = \frac{1}{2}\{\max_{-\omega\le k,l\le\omega} g(x+l,y+k) + \min_{-\omega\le k,l\le\omega} g(x+l,y+k)\} \tag{2}$$

where $f(.)$ is the original image, while $g(.)$ is the Gaussian blurred image. To obtain the binary image, the IB algorithm performs a simple threshold test in accordance with (3).

$$b(x,y) = \begin{cases} 0, & \textit{if } f(x,y) < \beta((1-\alpha)T_1(x,y) + \alpha T_2(x,y)) \\ 255, & \textit{otherwise} \end{cases} \tag{3}$$

where $\alpha \in [0,1]$ is the balance parameter between T_1 and T_2, $\beta \in [0,1]$ is a sensitivity parameter, ω is the window size, and σ is the standard deviation of the Gaussian filter generating the blurred image. Figure 1 (b) shows a result of IB binarization.

However, if a locally saturated LP case occurs, IB may misdetect a background under fixed IB parameters set at $\Phi = \{\alpha, \beta, \sigma, \omega\}$. To mitigate this problem, we propose a superpixel-based adaptive parameter estimation method. Superpixel algorithms group pixels into perceptually meaningful atomic regions. Simple linear iterative clustering (SLIC) [12], which is a type of superpixel algorithm, is used for superpixels.

Because of local illumination changes, a sub-area of

Fig. 1 An example of the IB binarization results on a locally saturated image.

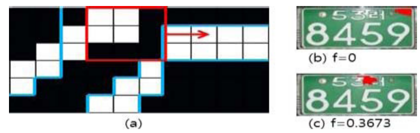

Fig. 2 (a): A way to detect the region of local illumination change. Blue line: a boundary of the superpixels. White box: a real boundary of characters. Red box: sliding window for finding illumination change. (b), (c): Local contrast measurement defined by Eq. (4). (b) Superpixel in background. (c) Superpixel with local saturation

an LP may be saturated and thereby subsequent errors with superpixel-based clustering may occur. Figure 1 (c) represents a case which includes a character region in the background cluster. In the case of a local illumination change like the red box in Fig. 1 (c), an error with the superpixels and binarization can occur. If a sub-region is saturated, or its colour is significantly affected by local illumination, the superpixel may contain areas with some gradients. This phenomenon is exploited for detecting regions of local illumination change in superpixels [11]. Figure 2 (a) represents how a region of local illumination change is detected. As Fig. 2 (a) shows, such a phenomenon occurs where the boundary of the superpixel differs from character edges. If an edge pixel possesses some values, this information can be used for a local contrast measurement and for detecting the saturation pixel. The local contrast measurement is defined by Eq. (4).

$$\mathrm{f(x,y)} = \frac{\sum_{\Delta x,\Delta y=-1}^{1} G(x,y)M((l(x,y), l(x+\Delta x, y+\Delta y))}{\sum_{\Delta x,\Delta y=-1}^{1} M((l(x,y), l(x+\Delta x, y+\Delta y))} \tag{4}$$

$$\text{where } \mathrm{G(x,y)} = \begin{cases} 1, & \textit{if } I(x,y) \textit{ is edge pixel} \\ 0, & \textit{otherwise} \end{cases}$$

$$\mathrm{M}(l_i, l_j) = \begin{cases} 1, & \textit{if } l_i = l_j \\ 0, & \textit{otherwise} \end{cases}$$

where I is the input image, G is the output of the Sobel edge detector, and l is the label index of a superpixel. M is the function that makes decisions for the label index. Figure 2 (b) and 2 (c) are examples of local contrast measurements. The red area is one of the superpixels. If there is no edge component in the superpixel, the proposed measurement is zero. In Fig. 2 (c), the light is scattered in the superpixel, so the superpixel includes characters and background. However, it has a small amount of edge components, although the pixel color is saturated. Therefore, the proposed measurement is activated with 0.3673. As shown by Eq. (4), the proposed factor is arrived at through the ratio between the number of edge components and the

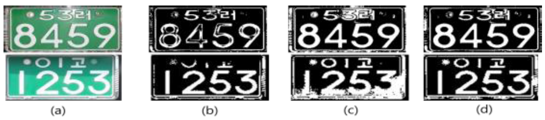

Fig. 3 The result of the effective proposed local binarization method: (a) input image, (b) binary image with parameter set 1, (c) binary image with parameter set 2, and (d) binary image with the proposed method.

Fig. 4 The merging and LP-NNC processing of Korean LP detection.

total number of pixels in the superpixel. The two parameter sets ($\Phi = \{\alpha, \beta, \sigma, \omega\}$) of IB-based algorithms are adopted for making the proposed system robust under illumination changes. Finally, to obtain the binary image, one of the parameter sets is selected according to local contrast measurements as follows:

$$bw(x, y) = b(I(x, y), \boldsymbol{\Phi}) \tag{5}$$

$$\text{where,} \quad \boldsymbol{\Phi} = \begin{cases} \boldsymbol{\Phi_1} = \{\alpha_1, \beta_1, \sigma_1, \omega_1\}, & \textit{if } f(x, y) > T \\ \boldsymbol{\Phi_2} = \{\alpha_2, \beta_2, \sigma_2, \omega_2\}, & \textit{otherwise} \end{cases}$$

where *bw(.)* is the output binary image and function *b(.)* is the binarization function with parameter set Φ. Adjusting the variable set of the IB algorithm based on whether the area is saturated or not separates the characters more precisely. Figure 3 shows the robust effect of the proposed binarization algorithm under a local illumination change.

2.2 Character Segmentation and LP-NNC

A labelling algorithm based on connected component analysis (CCA) is naively employed to classify the LP detection boxes into individual clusters. Korean characters typically form clusters by syllables, meaning that each cluster of characters is formed by a combination of consonants and vowels. In written form, these clusters are formed as shown by the third letter "모" in Fig. 4 where "ㅁ" is a consonant and "ㅗ" is a vowel. Once a CCA is completed, these consonants and vowels should be merged into clusters of syllables. A merging rule, therefore, is needed with the following criteria:

$$w_{c_i} \approx w_{c_j} \quad : \quad \frac{3\pi}{8} < \tan^{-1}\left[\left|\frac{y_{c_i} - y_{c_j}}{x_{c_i} - x_{c_j}}\right|\right] < \frac{5\pi}{8} \tag{6}$$

$$h_{c_i} \approx h_{c_j} \quad : \quad -\frac{\pi}{8} < \tan^{-1}\left[\left|\frac{y_{c_i} - y_{c_j}}{x_{c_i} - x_{c_j}}\right|\right] < \frac{\pi}{8} \tag{7}$$

where w_{c_i} and h_{c_i} are the width and height of an i^{th} component and x_{c_i} and y_{c_i} are the centroid of the i^{th} component. Equations (6) and (7) are, respectively, the criteria for the horizontal and vertical merging rule. If both criteria are satisfactory, the i^{th} component and j^{th} component are merged as a member of a cluster. Figures 4 (a) and 4 (b) are examples of a Korean LP detection box that uses the LP nearest neighbor chain (NNC) algorithm [13], showing all the labelling, including false detections on non-characters.

The blobs contain the characters on the LP and other noise, including the boundaries or the screws of the LP. Hence, we employ a rule of sequence in the LP to eliminate those blobs resulting from noise and other non-character objects. Such false labelling can be removed by recognizing that the size of bounding boxes capturing these clusters are similar and that they are typically in proximate locations.

$$\mathrm{d_c}(c_i, c_j) < k \cdot \min(h_{c_i}, h_{c_j}) \tag{8}$$

$$h_{c_i} \approx h_{c_j} \tag{9}$$

$$x_{c_i} < x_{c_j} \tag{10}$$

The above Eqs. (8)–(10) are represented in the following ways: the distance ($\mathrm{d_c}$) between the components, the similarity between the height of the components and the relative positions of and between the components. If the component pair is satisfied by the above criteria, the component pair is called "nearest neighbor (NN)". After all NN pairs have been produced, the pairs are concatenated into an NNC if one connected component (CC) of an NN pair is the same as one CC of another NN pair.

Figure 4 (c) shows a result that has eliminated the labels except for the characters which include combinations such as "모" through the Korean alphabet combining process. Afterwards, the classified elements are finally decided to constitute an LP image that satisfies the criteria regarding location relationships between the characters and features of the characters, such as the number of letters. The DB in this experiment contains three types of Korean LPs depending on aspect ratio (2 : 1 or 5 : 1) or character and background colors (Black/White or White/Green). In the case of a 5 : 1 LP, the information used is that the distance between the 3^{rd} and 4^{th} characters is longer than the others used.

3. Experimental Results

To evaluate the performance of the proposed method, datasets were acquired in underground garages, pedestrian overpasses or roads in daylight and nighttime conditions. Images in the dataset were taken in low illumination, locally shaded, or over-saturated environments. The test set is composed with characters of heights from 24 to 120 pixels. The detection rate (DR) and false alarms (FA) were used as performance indicators for detecting an LP or characters. If the detected region and the ground truth have a mutually overlaid region covering more than 50% of the ground truth and the detection box contains all of the characters, the detection box is classified a success. For the measurement of performance in detecting characters, only the correctly detected LP regions were considered as the detection domain.

For verification of the proposed method, the following commonly used binarization algorithms were compared: the IO, Bradley, Wolf and IB methods. The number of test DB was 500 per type of LP. Table 1 shows that the FA of the AdaBoost detector with a low threshold is very high. Suitable binarization algorithms can reduce the FA; among the

Table 1 Comparisons of LPD performance

Method	2:1 W/G		2:1 B/W		5:1 B/W	
	DR(%)	FA(%)	DR(%)	FA(%)	DR(%)	FA(%)
Only Detection	97.8	70.2	97.6	45.1	91.2	17.1
Det + IO [5]	82.6	17.2	97.8	12.5	91.8	7.6
Det + Bradley [6]	63.6	18.3	98.6	18.3	91.8	8.7
Det + Wolf [7]	48.4	30.7	77.2	16.6	90.4	7.6
Det + IB [9]	89.4	11.8	96.8	15.1	91.0	7.9
Det + Proposed	**90.8**	**11.1**	**94.2**	**2.5**	**91.0**	**5.9**

Table 2 Comparisons of character detection performance

Method	2:1 W/G		2:1 B/W		5:1 B/W	
	DR(%)	FA(%)	DR(%)	FA(%)	DR(%)	FA(%)
IO [5]	88.9	8.0	88.1	0.7	90.8	1.6
IB [9]	76.1	5.3	90.6	2.0	90.4	2.2
Proposed	**96.9**	**8.5**	**94.7**	**1.6**	**93.6**	**2.2**

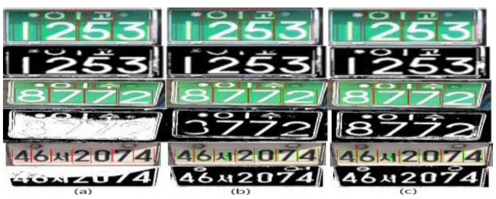

Fig. 5 Examples of character detection and binarization results: (a) Otsu's method, (b) improved Bernsen, and (c) proposed method.

binarization methods, the proposed method has exhibited some of the best detection performances while maintaining the lowest FA. The DR is slightly lower than that of the IB in the case of 2 : 1 Black/White LPs; however, the proposed method demonstrated far more robustness against FA. It has been observed that the performance of these methods suffers in general when tested against White/Green LPs. One of the key reasons for the poor performance can be attributed to a lower contrast between the background and the characters compared to the ones from Black/White LPs. Moreover, it is hard to set up an effective merging rule for LP-NNC, since this type of LP has two rows with different sizes of and gaps between the characters. In order to compare their performance, an additional experiment was performed to verify the accuracy of character detection. The proposed method is compared with the IO and IB methods. Table 2 shows the performance of character detection. Through these experiments, it is clearly shown that the performance of the proposed method is better than that of the others. The proposed method is robust to local illumination changes, as is described and shown in Fig. 5. All of these processes were done in real-time.

4. Conclusions

In this paper, a robust binarization method was developed to increase the performance of LP detection. The detector with a low threshold was adopted for a high DR, yet with a high FA. A local contrast measurement approach was proposed in terms of a local contrast measurement based on a superpixel algorithm for better selection of thresholds in the binarization. The proposed method achieved improved performance under substantial local illumination changes. The method was tested on a representative set of LP images and was compared with conventional binarization methods. The algorithm was shown to be efficacious in improving LPD performance in terms of significantly lowering FA compared to the other binarization methods. In addition, segmentation performance of the proposed method under various lighting conditions has shown improvements over the well-known conventional method. In addition, all the performance measurements were conducted in real-time, confirming it is accurate and robust in real-time LPD and LPR applications.

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