LICENSE PLATE LOCALIZATION BASED ON EDGE-GEOMETRICAL FEATURES USING
MORPHOLOGICAL APPROACH

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ABSTRACT

Malaysian car plates in general appear in different character styles, types (either single or double row), sizes, spacing and character counts. Such variations cause even detecting and localizing these plates a difficult problem. The problem of localization is aggravated further during night time due to poor illumination. In this paper, we introduce the idea of edge-geometrical features in detecting these plates. The edge part is obtained from the use of Difference of Gaussian operation followed by Sobel vertical edge mask. Prior to that, gamma correction is applied to increase the detection of edges. We then apply morphological operations to get the plate region candidates. Using these regions, together with the edge image, we calculate geometrical features of these regions and use rule-based classifier to correctly identify the true plate region. Finally, we test our method using our own data set which contains 250 images captured during day time and 100 images captured during night time. The result of the proposed method shows 96.9% success rate.

Index Terms— Gamma correction, Difference of Gaussian, Sobel vertical mask, Rule-based classifier

1. INTRODUCTION

Malaysian license plates are a bit unique compared to license plates of other countries in terms of the character sizes, ordering, types and fonts. Although the specifications are well defined for Malaysian license plate, there also exist other types of license plate with prefixes such as Putrajaya, SUKOM, BAMbee, PERODUA, Satria Perdana and WAJA. The possibility of vehicle owners to have personalized license plates as announced by Malaysian Transport Road Department (RTD) will create even more challenges in detecting and recognizing those plates [1].

In recent years, there have been many methods proposed to tackle problems of license plate localization. Edge statistic alone is not enough to locate the license plate region since there are many outliers in complex background sceneries. Some combinations have been proposed such as edge statistic with region growing [2] and edge statistic with mathematical morphology [3], [4] which yield very good results. In [2], candidate region was extracted at first using vertical edge density and then two-step region growing was added into the algorithm by defining upper and lower density threshold. In [3], closing operation was used to fill up holes followed by opening operation to eliminate noisy blob candidates. The exact location of the license plate region was found based on its dimension using vertical projection. Similar approach using erosion and closing operations can be found in [4]. Candidate region was found based on the number of the discontinuities found in the horizontal projections.

A purely morphological-based operation using opening and closing operations with different structuring elements was proposed in [5]. It resulted in an improvement in the detection rate with low computational complexity. In [6], a simple texture-based approach on edge information was proposed. Regions with high edge values were initially marked as potential candidates and were then finalized using rule-based classifier. In [7], license plate region was extracted using a set of conditions based on connected component labeling. In [8], simple geometrical features such as width, height and number of holes of an object were used to eliminate invalid candidates. Hough transform was then used to locate borders of the characters. Line segment and Haar-like features with Adaboost-cascade for locating license plate region were introduced in [9].

Despite all these methods, plate region detection still poses a challenge particularly in a situation where the illumination is low, plate numbers come with different styles, sizes, spacing and scales, and the image captured contains complex background [10]. In order to enhance the visibility of edges present in the image, we utilized DoG in the preprocessing stage. Prior to that, we performed contrast enhancement in order to increase dynamic range and thus improve the contrast. To produce several candidates in a form of rectangular region, we applied morphological operations on edges that were obtained using Sobel vertical mask only. Finally, we employed rule-based candidate filtering based on geometrical features to detect the exact location of the license plate.
2. PROPOSED METHOD

Figure 1 shows our proposed method in license plate localization. Generally speaking, it has similar components of a typical detection algorithm as described in [11]. The difference with our proposed system is the integration of edge and geometrical in forming reliable features. The rest of this section will describe our method in further detail.

![License plate localization steps](image)

**Fig. 1. License plate localization steps**

2.1. Contrast Enhancement

Our method is based on gray scale images. In order to improve the contrast of too bright and too dark images, we perform contrast enhancement procedure. This is critical in finding edges. Here, we use local contrast enhancement based on the local standard deviation \((\sigma_{i,j})\) as given in Eq. 1 [12]. It can be used to indicate the brightness within a region and the output \((I'_{i,j})\) is adjusted accordingly using Eq. 2 with slight modification as proposed in [11].

\[
\sigma_{i,j} = \sqrt{\frac{1}{(2n+1)(2m+1)} \sum_{k=i-n}^{i+n} \sum_{l=j-m}^{j+m} (x_{k,l} - \bar{x}_{i,j})^2}
\]

\[
I'_{i,j} = \begin{cases} 
  \text{maintainContrast} & \text{if } 0 < \sigma_{i,j} \leq 10, \\
  \text{increaseContrast} & \text{if } 10 < \sigma_{i,j} \leq 40, \\
  \text{slightlyReduceContrast} & \text{if } 40 < \sigma_{i,j} \leq 70, \\
  \text{reduceContrast} & \text{if } \sigma_{i,j} > 70.
\end{cases}
\]

(2)

2.2. Difference of Gaussian (DoG)

The next stage is to improve and enhance the visibility of edges. This is achieved by applying DoG. To get DoG image, we blurred the previously enhanced image by convolving with a Gaussian operator with two different Gaussian spread parameters \((\sigma_1, \sigma_2)\). Equation 3 shows the Gaussian operator.

\[
G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}
\]

The spread parameters essentially control the degree of blurriness of the image. Large \(\sigma\) will blur the character region in such a way that it would be difficult to detect vertical edges of characters in the subsequent process. On the other hand, a small \(\sigma\) will have no effect on the image. The proportion of \(\sigma\) has been set to 1:1.6 as the optimal selection [13].

As shown in Fig. 1, characters of the detected plate can be in either two cases: bright characters with dark background for normal plates or dark characters with bright background for taxi plates. In subsequent processes, we will extract edges and analyze geometrical features to detect valid license plate region.

2.3. Edge Detection and Morphological Operations

Ordinary license plate usually contains high variation of vertical and horizontal edges. However, in this work we only utilize the vertical edge which was obtained using Sobel vertical mask.

In order to connect broken edges as well as to eliminate noise pixels, we engaged a non-linear median filter and binary morphological operations. A standard 3x3 of all 1’s has been used for the structuring element. This is then followed by closing and dilation operations of 5x5 with a cross shape structuring element. This step is to connect edges together and form a region.

We followed the same approach given in [14] in which we removed top thirty percent and bottom ten percent of the image. The assumption is that these areas do not contain any valid license plate candidate. Figure 2 illustrates the vertical gradient image as well as the morphology image after applying the above mentioned steps.

![Vertical edge and morphology image results](image)

**Fig. 2. Vertical edge and morphology image results**

2.4. Geometrical Features Computation

In order to have a good recognition rate, the dimension of license plates should neither be too small nor too large [15]. In this paper, we set the resolution of the plate to be at least 15 to 80 pixels in height and at least 30 to 180 pixels in width. From our observation, single row plates have more rectangular shape compared to double row plates. The differentiation between Single Row Plate (SRP) and Double Row Plate (DRP) are done by simple ratio calculation of width over height. From here, every candidate is divided into two groups. For a candidate to be classified as SRP, the blob ratio must exceed the threshold value of 1.85. Otherwise, the candidate will be classified as DRP. This threshold value has been determined based on our empirical studies between SRP and DRP for Malaysian vehicles scenario. Once the type of plate is determined, we proceeded with the compactness measure which can be calculated as follows:
\[
\text{compactness} = \frac{A_b}{W_b \times H_b} \tag{4}
\]

where, \(A_b\) is the blob area, \(W_b\) and \(H_b\) are the blob width and height of the bounding box respectively [16]. From our empirical data, the potential candidate has to be more than forty percent compact or otherwise it is eliminated.

We then further refined each of the possible candidates by summing the non zero values at each column of every row as given in Eq. 5. If the total value at each row is less than forty percent of the blob width then this row will be set to zero.

\[
totalVal_i = totalVal_i + \sum_{col = j = 0}^{n} x_j \tag{5}
\]

\[
\text{minReq} = \frac{40}{100} \times W_b
\]

There are possibilities that some license plate regions may have a non rectangular region shape after the morphological operation. This could happen if the plate region is connected to a car logo or some other noisy blobs such as plate frame. Hence, by performing this row elimination such error can be minimized. Figure 3 shows an example before and after the row elimination process on the license plate candidate.

(a) Before (b) After

Fig. 3. Refining blobs candidate using row elimination process

A valid license plate region normally has many edges which come in the form of transitions of white and black pixels and vice versa in the edge-map image. Thus, we calculated the average transitions (\(Avg_t\)) at position \(H_b/3\), \(H_b/2\) and \(2H_b/3\). For a valid plate region, \(Avg_t\) should exceed the following threshold \(T_{Avg_t} = 19\) for SRP and \(T_{Avg_t} = 9\) for DRP.

To further differentiate between plate and non-plate regions, we computed the edge density of the region. Normally the plate region will have high edge density compared to non-plate region [17]. The edge density (\(E_d\)) is computed as follows:

\[
E_d = \frac{\sum_{i=0}^{y} \sum_{j=0}^{x} I_e}{W_b \times H_b} \tag{6}
\]

where, \(I_e\) is the edge image of candidate regions. We then continued with uniformity test (density variance) to remove all non-plate regions that have similar characteristics to the plate region such as the car logo, head lamps and grill. To achieve this, we first partitioned the candidate region into twelve equal size sub windows for SRP and three equal size sub windows for DRP candidates as shown in Fig. 4.

For a plate region, edges for each sub windows are relatively stable and evenly distributed [17]. In the case of SRP candidates, we calculated the density variance (\(D_v\)) and removed those regions which have values more than the pre-defined threshold (\(T_{D_v} = 0.55\)). The density variance is defined as:

\[
D_v = \frac{\sum_{i=1}^{N} |E_i - E_d|}{N \times E_d} \tag{7}
\]

where, \(E_i\) is the edge density at each \(N\) sub windows. Figure 4(a) and (b) show the distribution of edges in both plate and non-plate regions. From Eq. 7, \(D_v\) will remain low as long as each window exhibits a uniform distribution.

For DRP candidates, we checked the edge distribution at the middle sub windows (Fig. 4(c) and (d)). From our observation, plate regions should exhibit a certain edge density at the middle sub window compared to non-plate regions. A condition has been set based on experiments where \(E_d\) for the middle sub window should be greater than the following threshold value, \(T_{E_d} = 0.045\). By applying this condition, most invalid candidates such as car logo and head lamps were effectively eliminated.

(a) SRP candidate (b) SRP non candidate (c) DRP candidate (d) DRP non candidate

Fig. 4. Uniformity test

The final step is the verification stage. The candidate that satisfies the conditions in Eq. 8 is regarded as a valid license plate region. License plate usually has a specific shape and characters interval, thus we set the following criteria as the final verification for a valid plate region.

\[
\begin{align*}
30 < W_b < 180 & \quad \text{for SRP} \\
15 < H_b < 80 & \\
6 < Avg_{cc} < 16 & \quad \text{for DRP} \\
40 < W_b < 120 & \\
30 < H_b < 60 & \\
3 < Avg_{cc} < 8 &
\end{align*}
\]

where, \(Avg_{cc}\) is the average cross cut at \(H_b/3\) and \(2H_b/3\) of DoG binary image of the candidate. These values have been obtained from our experimentations.

3. EXPERIMENTAL RESULTS

We designed our algorithm using Microsoft Visual Studio 2008 with OpenCV 2.3.1 library. The database and details of
the proposed method are given in this section.

3.1. Database

Since this work focuses on Malaysian license plates, we have collected our own image samples. A total of 350 plate numbers have been captured with different background, angle, distance and illumination conditions. These images have been taken from a video camera and therefore, the resolution of the image has been set to 640x480. This is also to ensure that our method should be compatible with images taken with other CCTV cameras. From the total plate numbers, 250 images were taken during day time and the remaining were taken during night time.

3.2. Results

Table 1 shows the results on the localization methods proposed by previous researchers while Table 2 shows the results of our proposed method. Unlike previous methods, we provide detail of our achieved performance for day time and night time. From Table 2, a total of 339 license plate images have been located successfully and the localization accuracy during the day and night is up to 96.8% and 97.0% respectively. We found that 11 images failed to be located correctly. From our careful observation, this error was caused by the fact that those plate numbers were blurred during the sampling process. Besides, some failures occur during morphological operations where the plate is connected to a kangaroo bar at the front side of the vehicle. Here, the detection accuracy refers to the total number of correctly detected license plate with the whole character bounded by a bounding box. Even though the bounding box may slightly be larger than the exact location of the characters located, the precise location of the character can be solved during character segmentation process which is not the scope in this paper. Some samples of successful localization are presented in Fig. 5. Figure 5(a) shows the image of special plate at a near distance, Fig. 5(b) shows the image of DRP, Fig. 5(c) shows an image with the head lights on, Fig. 5(d) and (f) show images of vehicle bodies having the same color with the license plate and Fig. 5(e) shows a taxi plate having a plate number with opposite gray level intensity between the background and the foreground.

Table 1. Comparison on localization method

<table>
<thead>
<tr>
<th>Method</th>
<th>Localization Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Khalifa’s method [6]</td>
<td>92.1%</td>
</tr>
<tr>
<td>Saleh’s method [7]</td>
<td>97.4%</td>
</tr>
<tr>
<td>Velappa’s method [8]</td>
<td>95.0%</td>
</tr>
<tr>
<td>Setumin’s method [16]</td>
<td>95.0%</td>
</tr>
<tr>
<td>Mousavi’s method [18]</td>
<td>95.5%</td>
</tr>
</tbody>
</table>

Table 2. Proposed method

<table>
<thead>
<tr>
<th>Condition</th>
<th>Image Number</th>
<th>Localization Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day</td>
<td>250</td>
<td>96.8%</td>
</tr>
<tr>
<td>Night</td>
<td>100</td>
<td>97.0%</td>
</tr>
<tr>
<td>Sum</td>
<td>350</td>
<td>96.9%</td>
</tr>
</tbody>
</table>

Fig. 5. Successfully localize car plates

4. CONCLUSION

This paper has presented a localization method mainly for Malaysian license plates which are not conformable to any standard. In addition, change of illumination such as at night time will affect the accuracy of the plate localization. Two-step enhancement gamma correction and DoG were applied during the preprocessing stage. The goal of these operations is to increase the detection of vertical edges. We then applied the standard morphological operations such as median filter and labeling to coarsely find the license plate region. After that, we computed some geometrical features using both the edge image and the candidate regions. These features were then passed to the rule-based classifier for detecting the exact location of the license plate. Our results show the capability of the proposed system against real world environment by providing satisfactory results. Further work is in the progress to segment the characters for the purpose of plate number recognition.
5. REFERENCES