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Morphology-based License Plate Detection from Complex Scenes

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1. Introduction

With the rapid development of public transportation system, automatic identification of vehicles has played an important role in many applications during the past two decades [2]-[3], [5]. For examples, the identification system can be utilized for managing park facilities, monitoring unauthorized vehicles entering private areas, detecting stolen vehicles, controlling traffic volume, ticketing speeding vehicles, and so on. One of the most effective and useful identification methods is the license-plate recognition (LPR) through visual image processing.

A LPR system is mainly composed of three processing modules; that is, license plate detection, character segmentation, and character recognition. Among them, the task “license plate detection” is considered as the most crucial stage in the whole LPR system. In the past, a number of techniques [1]-[6] have been proposed for locating the plate through visual image processing. The major features used for license plate detection include colors [4], vertical edges [1], symmetry [6], corners, and so on. For examples, K. K. Kim et al. [4] used color information and neural networks to extract license plates from images. However, color is not stable when lighting conditions change. The major problem in these approaches is the used features depend strongly on the intensity differences between the extracted license plate and car colors, which are not stable at different changes of lighting conditions and view orientations.

This paper tackles the problem of detecting license plates from visual images, and presents a novel approach for identifying the plates based on morphological operations. The proposed system consists of three main stages. In the first stage, a morphology-based technique is devised to locate possible positions of license plates. Since a license plate is a pattern with high variations, the features used to locate the plates should be robust to the changes of lighting conditions and view orientations. The morphological operations are used to extract the contrast features within a license plate as the important cues to extract license plates. The contrast feature is invariant to several geometrical transformations like car color, camera translation, rotations, and scaling. Therefore, the proposed method works stable under different image alterations. In the second stage, due to noises, a license plate cannot avoid being segmented into several fragments. Therefore, a recovery procedure should be applied for recovering the whole plate for recognition. The recovery algorithm is cluster-based and thus invariant to different geometrical changes. The last stage of the proposed system is to perform plate verification. In this step, each plate candidate is verified according to the number of characters appearing in the candidate, which can be extracted from the character analysis algorithm. Once the set of registration characters has been extracted, a standard optical character recognition system can be applied soon for vehicle identification.

The proposed license plate detection technique can locate multiple plates with different orientations. In addition, the morphology-based segmentation process is able to significantly speed up the subsequent plate recognition since less than five candidates are extracted for further verification. In the experiments, 130 cluttered images including different lighting and orientation variations are used to test the effectiveness of the proposed system. 128 plates are successfully located and thus the accuracy rate of detection is approximately 98%. In average, the proposed approach requires less than 0.5-second to finish the detection task. Experiments show that the proposed method is a great improvement in terms of effectiveness and robustness for license plate detection.

2. Overview of the Proposed System

Fig. 1: Flowchart of the proposed system.

The paper presents a technique for automatically detecting license plates in complex scenes. Fig. 1 is the flowchart of the whole system. The proposed system is composed of three major parts: feature extraction, selection of license plate candidates, and license plate verification. Each part is described in the following sections.

3. Feature Extraction Using Morphological Operations

It is known that a license plate is a pattern composed of several characters, which have high contrast intensities to their background. In this paper, we use several mor-
phological operations to find the high contrast area as important features to detect license plates. Before introducing the proposed method, some morphological operations should be introduced first.

Let $S_{m,n}$ denote a structuring element with size $m \times n$ where $m$ and $n$ are odd and all entries in $S_{m,n}$ are one. Let $I(x,y)$ denote a gray-level input image. Besides, let $\oplus$ denote a dilation operation, and $\ominus$ denote an erosion operation. According to $S_{m,n}$, we define several useful morphological operations as follows:

- **Closing Operation**: $I \ast S_{m,n} = (I \ominus S_{m,n}) \oplus S_{m,n}$
- **Opening Operation**: $I \circ S_{m,n} = (I \oplus S_{m,n}) \ominus S_{m,n}$
- **Smoothing Operation $E$**: $E_{mn}(I(x,y)) = \frac{1}{mn} \sum_{j=-m/2}^{m/2} \sum_{i=-n/2}^{n/2} I(x+i,y+j)S_{mn}(i,j)$

Then whole procedure of morphology-based feature extraction is shown in Fig. 2.

Fig. 2: Details of the proposed method to extract useful features for license plate detection.

Firstly, in order to eliminate noises, a smoothing operation with a structure element $S_{1,7}$ is applied first. Then, the closing and opening operations with a structure element $S_{1,7}$ are performed into the smoothed image such that the images $I_s$ and $I_o$ can be obtained, respectively. In order to detect vertical edges, a differencing operation is further applied into the images $I_s$ and $I_o$. All possible vertical edges can be extracted with a thresholding operation. It is known the vertical edges in a license plate are close and adjacent to each other. These adjacent edges can be connected together through a closing operation and then form a connected segment. Therefore, before thresholding, a closing operation is applied first to let all adjacent vertical edges form a connected region. Then a labeling process is executed to extract the license-plate-analogue segments. Then, a set of potential license plates can be obtained from a cluttered environment.

4. License Plate Segmentation

After labeling, a set of potential license plates can be extracted from the images. However many incorrect license plates may be extracted from the cluttered environment. For instances, frames of windows, trees, edges among a set of books, etc. are frequently segmented as license-plate-analogue pixels. Therefore, some geometries and texture information are used first at this stage to remove these unwanted regions.

4.1. Candidate Extraction

Three criteria are defined here for eliminating impossible license plates. Let $R$ denote the extracted region with the size $w \times h$. The first criterion is the density of the region $R$: $den = A/(h \times w)$, where $A$ is the area of $R$. The second criterion is the ratio $r$ between the width and height of $R$, i.e., $r = w/h$. The third criterion is the size of a license plate should be larger than a fixed size, for example, $60 \times 25$. If the size of a license plate is not larger enough, the characters in the license plate will be too small for recognition. These criteria will significantly reduce the number of potential license-plate-analogue segments into few candidates.

4.2. License Plate Recovery

Due to noises or different lighting conditions, the extracted license plate region may not be a whole plate without fragments. For examples, in Fig. 3, the extracted region in (a) is a fragment of (b). Therefore, before verification, the incomplete license plate should be recovered first. A straightforward method to tackle this problem is to use a vertical intensity projection to calculate the average width and height of characters appearing in the fragment. Then, with the information, the whole plate is recovered from the fragments. However, this method is not stable under different skewing, scaling, and rotation of the extracted plate. In this paper, a cluster-based method is proposed for calculating the common geometrical properties of characters and then using the information to recover the whole plate. The method is robust to different skewing, scaling, and rotations of the extracted plate.

Fig. 3: Result after license plate recovery.

Let $R$ denote the extracted region with the size $w \times h$. For each character in $R$, a set $S_i$ of character candidates can be selected though binarization and labelling. Then based on $S_i$, a clustering method is presented for calculating the common geometrical properties of characters to guide the verification. Let $d_i$ denote the summation of distances of characters in $S_i$ to the $i$th cluster and $s_i$ denote a counter to record the number of characters be-
longing to the $i$th cluster. Initially, each character in $S_i$ forms a cluster. Then, the algorithm to calculate the common properties of characters in $S_i$ can be illustrated as follows:

**Character Analysis (CA) Algorithm:**

Step 1: Set $d_i$ and $s_i$ to be zero for all clusters.

Step 2: Let $c_i$ be an element in $S_i$ with size $h_i \times w_i$.

For each pair $(c_i, c_j)$, do the following steps:

Step 2.1: Calculate the distance between $c_i$ and $c_j$ as follows:

$$d_{ij} = \sqrt{(h_i - h_j)^2 + (w_i - w_j)^2}.$$

Step 2.2: If $d_{ij} \leq T_d$, calculate $d_i$ and $s_i$ by:

$$s_i = s_i + 1 \quad \text{and} \quad d_i = d_i + d_{ij},$$

where $T_d$ is a threshold to determine whether $c_i$ and $c_j$ are similar.

Step 3: Choose the index $k$ such that:

$$k = \arg \max_{1 \leq c \leq N} (s_c + 0.5/(1 + d_{ik})).$$

This attempts to find an index $k$ such that $s_k$ is maximized with a smaller $d_{ik}$.

Step 4: Let $w_k$ and $h_k$ denote the sum of widths and heights of each character in $S_k$ which is close to the $k$th cluster, respectively. Then, for each element $c_j$ in $S_k$, if $d_{ij} \leq T_d$, calculate $w_k$ and $h_k$ as follows:

$$w_k = w_k + w_i \quad \text{and} \quad h_k = h_k + h_i.$$

Step 5: The averages $\bar{w}_k$ and $\bar{h}_k$ of $w_k$ and $h_k$ can be calculated, respectively, by:

$$\bar{w}_k = w_k / s_k \quad \text{and} \quad \bar{h}_k = h_k / s_k.$$

Step 6: For each element in $S_k$, if its width and height are close to $\bar{w}_k$ and $\bar{h}_k$, respectively, the character can be recognized as a correct character. Then, we can obtain the correct set $\tilde{S}_k$ of characters from $S_k$ and the number $N_c$ of elements in $\tilde{S}_k$.

After analyzing the common properties of characters in $R$, a method is then presented to recover the complete whole license plate from its fragments. Let $t_R$ and $r_R$, $t_x$, and $b_x$ denote the most left, right, top, and bottom coordinates of $R$ in the $x$ and $y$ directions, respectively. In addition, assume the number of characters appearing in a standard license plate is a fixed number $N_p$. Then, the details of the license-plate recovery algorithm can be illustrated as follows.

**License-Plate Recovery Algorithm:**

Step 1: According to the CA algorithm, obtain the average weight $\bar{w}$, the average height $\bar{h}$, and the number $N_c$ of correct characters in $R$.

Step 2: If $N_c$ is less than $N_p$, enlarge $R$ with the following equations:

$$l^e_R = l_R - (N_p - N_c) * \bar{w}$$

$$r^e_R = r_R + (N_p - N_c) * \bar{w};$$

Step 2.1: if any pixel in $S_i$ touches to the top of $R$,

update $t_R$ by $t^e_R = t_R - \bar{h}/5$;

Step 2.2: if any pixel in $S_i$ touches to the bottom of $R$, update $b_R$ by: $b^e_R = b_R + \bar{h}/5$.

Step 3: Binarize the new region $R^e$. Then, after labelling, a new set $S^e$ of possible characters is obtained from the region $R^e$.

Step 4: Apply the CA algorithm into $S^e$ and get the desired correct character set $\hat{S}^e$ and the new number $N^e$ of characters.

Step 5: Let $x_{left}$, $x_{right}$, $y_{top}$, and $y_{bottom}$ denote the boundary coordinates of $\hat{S}^e$ in the $x$ and $y$ directions, respectively. If $|N_c^e / N_p - 1| < 0.2$, $R^e$ is recognized as a license plate with the boundaries $x_{left}$, $x_{right}$, $y_{top}$, and $y_{bottom}$.

### 4.3. Inclined Plate Rectification

Due to different camera orientations, it is difficult to guarantee an inclined license plate will not appear in the captured image. In order to recognize characters correctly, a plate rectification procedure is needed for compensating the inclined effect. Let $R_p$ denote the inclined license plate. Like Fig. 4, let $(x_p, y_p)$ denote the center of $R_p$ and $w_p$ its width. In addition, let $D_R$ denote as the height difference between the centers of the first and the last characters in $R_p$. Assume $R_p$ is the plate of $R_p$ after rectification. For each pixel $(x, y)$ in $R_p$, its intensity is compensated as follows:

$$R_p(x, y) = R_p(x, y - (x - x_p)D_R / W_p)$$ \hspace{1cm} (1)

Fig. 4: The geometry of an inclined plate.
5. Experimental Results

In order to analyze the performance of the proposed approach, 130 images are used for testing. For increasing the complexity of the test database, the images are acquired at different lighting conditions including the time at a sunny or cloudy day, day time, night time, and so on.

Fig. 5 shows the detection results of cars when the colors between the license plates and their backgrounds are similar. In such case, edges between the plates and background are not clear. That will lead to the failure of plate detection for methods that considers the boundary of a license plate as an important cue for detection. However, our morphology-based method still works well.

Fig. 6 shows the results when the license plates are inclined. Fig. 7 shows the cases when the input image with a smaller license. In this case, many small edge and textures appear in these images. However, the desired license plates are also successfully located by the proposed method.

For comparisons, the method proposed by M. Yu and Y. D. Kim [1] was implemented. This approach uses vertical boundaries of a license plate as important features to do license plate detection. Fig. 9 shows the comparison result. Since many vertical edges exist in this image, there are more than one hundred of candidates generated for verification and leading to the failure of detection. For our method, the wanted license plate is successfully extracted since only three candidates are generated in (c).

The average accuracy of license plate detection is 98%. In other words, under the experimental database; only two examples got from 130 images are failed. The superiority of the proposed method can be verified through the preceding experimental results.

Fig. 5: Results of license plate detection when the colors between the license plate and background are similar.

Fig. 6: Results of license plate detection when these plates are inclined.

Fig. 7: Results of license plate detection when smaller plates appear into the input images.

Fig. 8: The detection results when the lighting on the license plate is too light or dark.

Fig. 9: Comparisons between the proposed method and the method proposed by M. Yu and Y. D. Kim.

References