Detecting License Plates from Videos Using Morphological Operations and Adaboosting Algorithm

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Abstract

This paper presents a novel hybrid detection method for extracting license plates from cluttered images using morphological operations and Adaboosting algorithm. First, the hybrid method uses the Adaboosting algorithm for training a detector to detect license plates whose embedded characters are horizontally aligned. Then, the method uses a morphology-based scheme to detect inclined license plates. The morphology-based scheme extracts important contrast features to search possible license plate candidates. The contrast feature is robust to lighting changes and invariant to different transformations. The hybrid method can avoid the significant growth of training samples for training the detector to detect any oriented license plates. The proposed detection technique can locate multiple plates with different orientations and even with very low intensities. Experimental results show that the proposed method improves the state-of-the-art work in terms of effectiveness and robustness for license plate detection.

1. Introduction

With the rapid development of public transportation system, automatic license-plate recognition (LPR) has played an important role in many applications during the past two decades [1], [3]. Due to the widespread application fields, LPR has been an important key function in an intelligent transportation system.

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. Once the license plate has been well located, the result can be fed into the character recognition module for identifying the actual vehicle, which has been explored broadly in optical character recognition applications [2]. In the past, a number of techniques [3]-[8] have been proposed for locating the desired plate through visual image processing. The major features used for license plate detection include colors [4], corners [5], vertical edges [6], symmetry [7], projections of vertical and horizontal edges [7], 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 have changes. On the other hand, Dai Yan *et al.*[8] used the projections of edges with different orientations for determining peaks of the histograms as possible locations of license plates. When the scene is complex, many unrelated edges will disturb the determination of the correct plate locations. Moreover, M. Yu and Y. D. Kim [6] proposed a vertical edge-matching algorithm for grouping all possible positions of license plates through edge matching. In this approach, they assumed the vertical boundaries between a license plate and its backgrounds are strong. However, when the colors of the license plates are similar to their backgrounds, the assumption will no longer exist. Other methods using features like corners [5] and symmetries [7] also made the same assumption. 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 when the lighting condition, camera orientation, or car color changes.

This paper presents a novel approach for detecting license plates from visual images using the Adaboosting algorithm and morphological operations. First of all, we use the Adaboosting algorithm to learn the visual characteristics of license plate. Then, based on the learned integral features, a cascaded structure is then used to quickly locate desired license plate candidates. The learning method has good abilities to robustly detect license plates if they are horizontally aligned. However, when skewed license plates are handled, the method will fail to work. The major drawback of the training method is the need of a new set of training samples to train the detector for detecting license plates if they have a new orientation. In order to tackle the skewed problem, we use morphological operations to extract the contrast features within a license plate as an important cue to extract license plates. The contrast feature is invariant to several geometrical transformations like car color, camera translation, rotations, and scaling. Even through lighting changes, the high intensity difference between the characters and the backgrounds is still maintained. After labeling, each high contrast area can be extracted and served as a license plate candidate. Then, according to its orientation, it can be further rectified using a rectification process such that all its embedded characters embedded are horizontally aligned. Then, the Adaboosting method can be applied for verifying whether the candidate is a correct one. Thus, even though license plates have different orientations, the proposed method still can work very stable under different captured conditions. Once a license plate is successfully extracted, a standard optical character recognition system can be applied directly for vehicle identification. The morphology-based method can significantly reduce the number of extracted candidates and thus speeds up the subsequent plate recognition. The hybrid method can avoid the significant growth of training samples for training the detector to detect license plates having different orientations. In addition, the proposed detection technique can locate multiple plates with different orientations in one image. Especially, the proposed detector can detect license plates with very low intensities. The property is very useful for detecting license plates at night time. Since a cascade structure is used to train the classifier, all license plates can be detected in real time. Experiment results show that the proposed method is a great improvement in terms of effectiveness and robustness of license plate detection.

2. Overview of the Proposed System

Fig. 1 shows the flowchart of the whole system. Input of this system is a sequence of video captured by a general camera. Then, the proposed system uses two complementary methods to detect various license plates from images (or frames), i.e., the boosting-based and morphology-based ones. The boosting algorithm is used for detecting 'normal" license plates and the morphology-based one is used for detecting inclined license plates. Here, a license plate is called as "normal" if its embedded characters are horizontally aligned. For the boosting algorithm, a strong classifier is trained from a set of training samples using their integral features. However, when an inclined plate is handled, the boosting method will fail to detect it. For tackling this problem, the paper then proposes a morphology-based method to extract all regions which have high contrast as candidates for license plate detection. Basically, the characters embedded in a license plate are specially designed to have distinctive intensities to their backgrounds. Therefore, this paper designs a series of morphological operations for detecting all the high contrast areas as possible license plate candidates. Thus, even though an inclined license plate is handled, it still can be well detected using the proposed morphology-based method. After that, each extracted candidate will be rectified to a normal direction and then verified using the previous boosting algorithm. In what follows, details of the two methods are discussed.

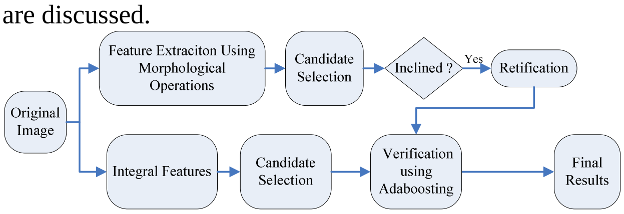


Fig.1: The proposed license plate detection system.

3. License Plate Detection Using Adaboosting Algorithm

This section presents a learning method to learn a strong classifier from a set of training images for license plate detection. The learning method we use is the Adaboosting algorithm which combines a set of 'important' weak classifier to form a strong classifier for object detection. Each weak classifier uses a specific feature for quickly filtering out impossible candidates.

It is well known that image intensities are very sensitive to different lighting variations. The same object with different illuminations may own considerably different colors or gray intensities. Then, the Adaboosting algorithm is used further for license plate detection.

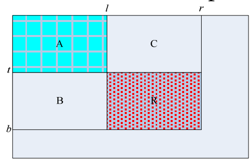


Fig. 2: Calculation of integral image.

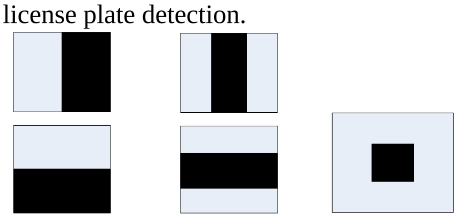
For the task of license plate detection, it is better to use region feature rather than pixel-level feature since region feature has more robustness than pixels. Here, we use the integral image to generate a bank of rectangle features for representing a license plate. Given an image I, its integral image $S(x, y)$ contains the sum of intensity values of pixels in I accumulated from the original (0, 0) to the pixel (x, y), i.e.,

$$S(x,y)=\sum_{i=0}^{x}\sum_{j=0}^{y}I(i,j). \quad (1)$$

Given a rectangle R bounded by (l, t, r, b), its sum of pixel intensity value can be very efficiently achieved by taking advantages of the integral image S. Like Fig. 2, the sum $F(R)$ of pixel intensity in R can be easily calculated with the form

$$F(R)=(A+B+C+R)+A-(A+B)-(A+C)$$
$$=S(r,b)+S(l,t)-S(l,b)-S(r,t).$$

Fig. 3 shows three kinds of rectangle features generated for license plate detection. (a), (b), and (c) correspond to edge feature, line feature, and center-surround feature, respectively. The size of the base region used in this paper is 40×20. From the base region, there are totally 312660 features generated for training license plate detector. Then, in what follows, the adaboosting algorithm is applied to learning a strong classifier for robust license plate detection.



(a) (b) (c)

Fig. 3: Different kinds of rectangle features. (a) Edge features. (b) Line feature. (c) Center-surround features.

"Adaboosting" is a learning algorithm to iteratively learn a strong classifier from a set of weak classifiers. A weak classifier uses a simple feature to determine positive samples from negative samples and is required to be only slightly better than chance. At each iteration, a "good" weak classifier is selected and added in turn to form a strong classifier. The AdaBoost [10] is described below.

Step1: Given training samples $(x_1,y_1),...,(x_n,y_n)$ where $y_i\in\{-1,1\}$ for positive and negative examples respectively.

Step2: Initialize weights $w_{1,i}=\frac{1}{2m},\frac{1}{2l}$ for $y_i=[0,1]$ respectively, where m and l are the number of negatives and positives respectively.

Step 3: For $t=1,...,T$:

1. Normalize the weights, $w_{t,i} = w_{t,i}(\sum_{j=1}^{n} w_{t,j})^{-1}$, where w_t is a probability distribution.
2. For each feature, calculate the error for the classifier h_j, and its weight w_j by evaluating:

$$\varepsilon_j = (\sum_{i=1}^{T}\beta_i)^{-1}\sum_{i=1}^{T}\beta_i\left|y_i - h_j(x_i)\right| \text{ and } w_j = \log\left(\frac{1-\varepsilon_j}{\varepsilon_j}\right).$$

3. Choose the classifier with the lowest error ε_t
4. Update the weights:

$$\beta_{i,j+1} = \beta_{i,j}\exp\left(w_j\left|y_i - h_j(x_i)\right|\right), \quad i = 1,\dots,n.$$

Then, the final classifier is the weighting vote of the components classifier: $fin(x) = \text{sign}\left(\sum_{j=1}^{T} w_j h_j(x)\right)$.

The Adaboosting algorithm improves the classification performance by iteratively adding features to the strong classifier. When more features are added, the adding technique will directly increase lots of computation time to detect objects. If a cascaded structure is used, the efficiency of the strong classifier will be significantly improved. The cascaded structure is introduced by Viola and Jones [11] and shown in Fig. 4. With the cascade, the detector can extremely fast detect all desired objects.

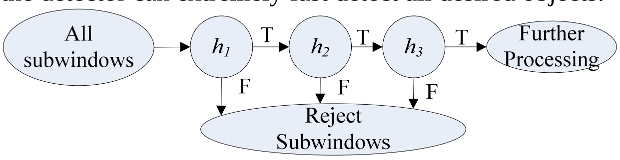


Fig. 4 Cascaded structure of the designed classifier.

4. License Plate Detection Using Morphological Operations

A license plate is a pattern composed of several characters that have high distinctive intensities to their background. The high contrast area can be used as a key feature to detect the desired license plates. In the following, we describe a morphology-based method to find the high contrast area to detect license plates. Fig. 5 shows the whole procedure of morphology-based feature extraction. In order to eliminate noises, a smoothing operation is applied first. Then, the closing and opening operations are performed into the smoothed image such that the images I_c and I_o can be obtained, respectively. In order to detect vertical edges, a differencing operation is further applied into the images I_c 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. Therefore, before thresholding, a closing operation is applied to let all adjacent vertical edges form a connected region. Then, a connected component analysis [9] is applied to labeling the license-plate-analogue segments. After that, a set of potential license plates can be obtained for further verification. Fig. 6 shows the license-plate-analogue segmentation using the suggested morphological operations.

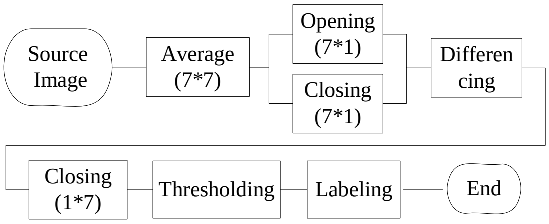


Fig. 5: Details of the proposed method to extract useful features for license plate detection.

Fig. 6: Results after applying the suggested morphological operations to different images.

As described before, due to the settings of camera, it is often to detect an inclined license plate from the captured image. Thus, we use the above morphological operations to detect high-contrast area as possible license plate candidates. Then, we estimate its orientation for plate rectification. After rectification, each candidate can be then verified by the Adaboosting algorithm. In what follows, a moment-based orientation estimation method is first described for compensating the inclined effects.

Given a two-dimensional binary region $R(x, y)$, the central moments of R can be defined as

$$(\mu_{p,q})_R = \sum_{(x,y)\in R}(x-\bar{x})^p(y-\bar{y})^q \qquad (2)$$

where $(\bar{x},\bar{y}) = |R|^{-1}(\sum_{(x,y)\in R} x, \sum_{(x,y)\in R} y)$ and $|R|$ is the area of R. Here, if a pixel (x, y) belongs to R, the value of $R(x, y)$ is one; otherwise, its value is zero. Then, the orientation θ_R of R can be obtained as

$$\theta_R = \frac{1}{2}\tan^{-1}\left[\frac{2\mu_{1,1}}{\mu_{2,0} - \mu_{0,2}}\right]. \qquad (3)$$

After orientation estimation, we use a affine transform to rectify and recover the license plates.

5. Experimental Results

In order to analyze the performance of the proposed approach, different still images and video sequences were used for testing. The sizes of all processed images vary significantly from 320×240 to 1280×960. Fig. 7 shows the detection results of cars when the plate has similar color to its background or two plates appear in the same image. In such case, edges between license plates and background are not clear. It will lead to the failure of license plate detection for methods that considers the boundary of a license plate as an important cue for detection. Furthermore, the size of license plates also will affect the detection accuracy. However, our proposed method still works very well to detect all desired license plates.

Fig. 7: Result of license plate detection when the plate has similar color to its background or two plates appear.

Fig. 8: Results of license plate detection when the scene contains complicated background or is lowly lighted.

Fig. 9: Result of license plate detection when a video sequence was handled. The sizes of license plate in each frame change significantly.

Fig. 10: Result of license plate detection when a video sequence was handled.

Fig. 8 shows the cases of license plate detection when the scene contains complicated background or was captured under a lowly lighted condition. In the first cases, many small edge and textures appear in these images and will disturb the accuracy of license plate detection. In the second case, when the scene was poor lighted, most approaches in the literatures would fail to deal all desired license plates. However, our propose method works very well to detect different license plates when they are lowly lighted.

Fig. 9 shows the result when a video sequence was handle. The sizes of the license plate appearing in the video sequence changed significantly. No matter what sizes the license plate had, all the desired license plates can be well detected by the proposed methods. The average frame rate of plate detection is 15 *fps*. Fig. 10 shows another result of license plate detection when a video sequence was captured from side of view of a camera. The average accuracy of detection is 98.9%. The superiority of the proposed method can be verified through the preceding experimental results.

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