

License Plate Recognition from Low-Quality Videos

Chih-Chiang Chen and Jun-Wei Hsieh *

Department of Electrical Engineering,
Yuan Ze University, Taiwan

*shieh@saturn.yzu.edu.tw

Abstract

This paper presents a novel hybrid method for extracting license plates and recognizing characters from low-quality videos using morphological operations and Adaboost algorithm. First of all, the hybrid method uses the Adaboost algorithm for training a detector to detect license plates. This algorithm works well to detect license plates having lower intensities but fails to detect license plates if they are skewed. Thus, we use a morphology-based scheme to detect inclined license plates. The morphology-based scheme extracts important contrast features for searching 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. Then, a new segmentation method is proposed for character segmentation and recognition. Even though lower-quality video frames are handed, our method still performs very well to recognize desired license plates. The proposed technique can locate and recognize multiple plates in real time even if they have different orientations or lower intensities. Experimental results show that the proposed method improves the state-of-the-art work in terms of effectiveness and robustness for license plate recognition in low resolution and low quality source.

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], [2]. 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. In the literature, there have been a number of techniques [2]-[7] proposed for license plate detection. The major features used for license plate detection include colors [3], corners [4], vertical edges [5], symmetry [6], projections of vertical and horizontal edges [6], and so on. For example, K. K. Kim *et al.* [3] 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 *et al.* [7] used the projections of edges with different orientations for determining peaks of the histograms as possible locations of license plates. Moreover, M. Yu and Y. D. Kim [5] proposed an edge-matching algorithm for grouping all possible positions of license plates. When the scene is complex, many unrelated edges will disturb the

determination of the correct positions of license plate for the above approaches. After license plate detection, the following is to segment each character from the extracted license plate for character recognition. Past works [1]-[7] on character segmentation assume that there is no occlusion between any two adjacent characters. Then, different characters can be well segmented using a vertical projection technique. However, when low-quality video frames are handled, two characters tend to be occluded together due to the processes of quantization and compression. Thus, the above projection technique will fail to extract and recognize characters embedded in low-quality video frames. The above problems will be well tackled in this paper.

This paper presents a novel approach for detecting and recognizing license plates in low-quality videos. First of all, we use the Adaboost 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. 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 a license plate if its orientation is new. In order to tackle the skewed problem, we use morphological operations to extract important contrast features for detecting desired license plates. The contrast feature is invariant to several geometrical transformations like car color, camera translation, rotations, and scaling. After labeling, each high contrast area is a license plate candidate. Then, according to its orientation, it can be further verified whether it is a real license plate using the Adaboost algorithm. Thus, even though license plates have different orientations, we still can detect them very stable and accurately. The hybrid method can avoid the significant growth of training samples for training the detector to detect license plates having a new orientation. Especially, the proposed detector is very useful for detecting license plates at night time. After extracting a license plate, a novel segmentation algorithm is then proposed to segment it into different characters. The algorithm uses a "recognition before segmentation" scheme to effectively extract desired characters even though they are highly occluded to other characters. Thus, even though low-quality videos are handled, different license plates still can be well extracted. 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

The paper presents a technique for automatically detecting

and recognizing license plates from still images and video sequences. Figure 1 shows the flowchart of the whole system. The proposed system uses two complementary methods to detect various license plates from video 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 inclined license plates. After that, a novel character segmentation method is proposed for extracting text characters from the license plates even though they are embedded in a low-quality video. Then, each character can be well recognized using a distance transformation.

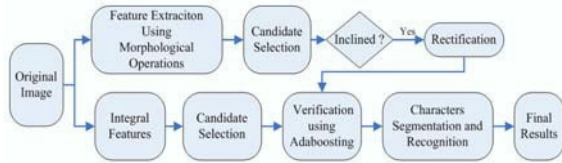


Figure 1. Flowchart of the proposed recognition system.

3. License Plate Detection Using Adaboost Algorithm

The learning method we use is the Adaboost algorithm which combines a set of ‘important’ weak classifier to form a strong classifier for object detection. A weak classifier uses a simple feature to determine positive samples from negative samples and is required to be only slightly better than a chance. In this paper, we use the integral image [10] to generate a bank of rectangle features for license plate detection. Figure 2 shows three kinds of rectangle features generated here for license plate detection. (a), (b), and (c) correspond to edge, line, 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 a license plate detector. After feature extraction, we use the ‘‘Adaboost’’ learning algorithm to iteratively learn a strong classifier from a set of weak classifiers. At each iteration, a ‘‘good’’ weak classifier is selected and added in turn to form a strong classifier. Details of the Adaboost algorithm can be found from [9]. Then, with the cascaded structure introduced by Viola and Jones [10], the detector can extremely fast detect all desired license plates.

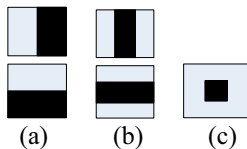


Figure 2. Different kinds of rectangle features. (a) Edge features. (b) Line features. (c) Center-surround feature.

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 a license plate. Figure 3 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. Figure 4 shows the license-plate-analogue segmentation using the suggested morphological operations.

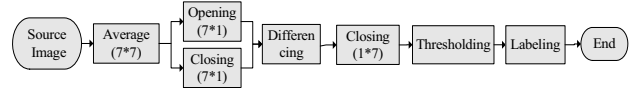


Figure 3. Details of the proposed method to extract useful features for license plate detection.

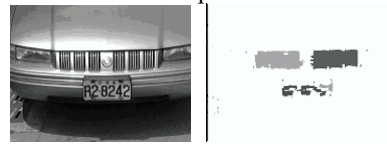


Figure 4. Results after applying the suggested morphological operations to different images.

Due to the settings of camera, it is often to detect an inclined license plate. 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 Adaboost algorithm.

5. License Plate Recognition

After detecting a license plate, the following task is to recognize all of its embedded characters. Figure 5 shows the flowchart of our novel character recognition engine. First of all, an image enhancement technique is used to enhance the quality of each plate region. Then, a two-pass character segmentation scheme is proposed to extract each embedded character from the extracted license plate. After that, a recognition engine is then proposed for recognizing each character.

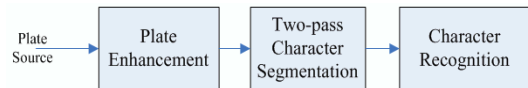


Figure 5. Flowchart of license plate character recognition.

An extension technique is first used to extract a complete license plate from its pieces of segments. In addition, since the size of video frame is too small, before recognition, we use a bi-interpolation scheme to rescale the size of the extracted license plate to a fix recognition size. Then, an equalization algorithm [8] is used to adjust pixel intensities so that each embedded character has a uniform intensity.



Figure 6. License plate for character recognition.

Figure 6 shows a license plate extracted from a low-quality video. Since the frame quality is low, two adjacent characters often occlude together and lead to the failure of character recognition. To tackle this problem, we

propose a novel two-pass segmentation algorithm to extract various text characters from a license plate. The first stage uses a vertical projection to roughly extract various characters from a license plate. Then, a “segmentation after recognition” scheme is proposed for finding all correct characters.

To obtain the result of vertical projection, traditional methods use a thresholding scheme to convert a license plate into a binary map and then accumulate each column horizontally. However, when the lighting effect on the license plate is not uniformly distributed, binarizing the plate will become difficult. Therefore, instead of using a binary map, we directly accumulate pixel intensities for obtaining the result of vertical projection. Assume that R is the processed license plate. We define its vertical projection as follows:

$$H(x) = \sum_{y=0}^{y=h_R-1} R(x, y),$$

where $R(x, y)$ is the intensity of a pixel (x, y) in R and h_R is the height of R . Figure 7(a) shows the result of vertical projection of Figure 6. Then, the peaks of $H(x)$ can provide useful information for separating the license plate into different character parts. In case that the background pixels are darker than the foreground character pixels, the valleys of $H(x)$ will be sought for character segmentation.

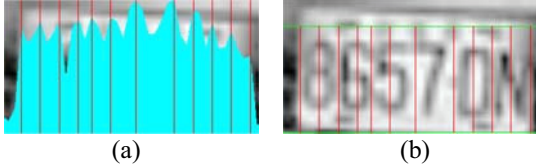


Figure 7. Character segmentation using a vertical projection. (a) Result of vertical projection. (b) Over-segmentation of characters.

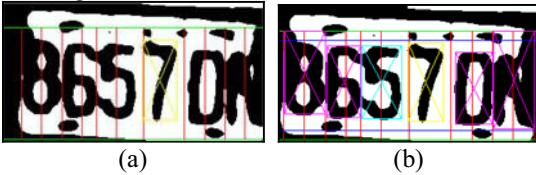


Figure 8. Results of binarization and segmentation of a license plate. (a) Rough segmentation (b) Fine segmentation.

After seeking the peaks of $H(x)$, we can use them to divide R into different segments. However, these segments do not exactly correspond to the character components. Like Figure 7(b), some characters will tend to be over-segmented into two different parts. So, any two adjacent regions will possibly form a new character candidate. Assume that R is divided into n regions using the peaks of its vertical projection. There are $(n-1)$ possible combinations for merging any two adjacent regions and each combination also forms a character candidate. Then, we can generate $(2n-1)$ candidates for character recognition. Based on the rough segmentation, we want to present a novel scheme to refine the above segment result. The idea of the refinement is to recognize all the $(2n-1)$ candidates in advance. The candidate with the lowest

matching error is considered a reference character. With the reference character, we will use a divided-and-conquer algorithm to determine the final segmentation.

To recognize each character candidate, the first stage is to binarize the processed license plate R . In the previous section, we use the vertical projection to segment R into n regions. For any two adjacent regions, we use the k -means algorithm [8] to cluster them into two classes. The initial centers of the foreground and background classes are set to 0 and 255, respectively. Figure 8 shows the result of binarization of Figure 7. After binarization, we can recognize all the $(2n-1)$ candidates using their distance map. Assume that r_c is the candidate with the lowest matching error and w_c is its width. r_c and w_c will be used to estimate other characters' widths and positions. Like Figure 8(a), '7' is the candidate r_c for finding other possible characters.

Assume that P_j is one partition to separate the license plate R into different characters r_i . Then, the width w_i of r_i should be similar to w_c . In addition, the matching error $dis(r_i)$ of the character r_i to all characters in the database should be smaller. Then, we want to seek an optimal partition \bar{P} which satisfies the following equation:

$$\bar{P} = \arg \min_{P_j} \sum_{r_i \in P_j} dis(r_i) + \left(\frac{w_i - w_c}{w_c} \right)^2,$$

where $dis(r_i)$ is defined in Eq.(1).

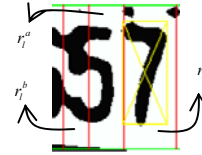


Figure 9. Reference region selection for character recognition.

If a license plate contains m characters, there would be C_m^{2n-1} partitions for separating R into different components. Like Figure 8, n and m are 12 and 6, respectively so that the number of possible partitions will be very huge. We will propose a divide-and-conquer to find the optimal partition \bar{P} . First of all, we use r_c as a reference and then partition R into two sub-regions R_l and R_r . From the left sub-region R_l , we search another reference r_c' , which is closest to r_c for dividing R_l into a smaller region R_r' . Assume that r_l^a and r_l^b are two character segments which are closest to r_c and located in R_l , and r_l^c is the union of r_l^a and r_l^b . Like Figure 9, r_c is the character '7' and r_l^a and r_l^b are the two segments located in the character '5'. Then, r_c' can be selected by satisfying the following equation:

$$r_c' = \arg \min_{r \in \{r_l^a, r_l^b, r_l^c\}} dis(r) + \left(\frac{w_r - w_c}{w_c} \right)^2.$$

Then, replace r_c and R_l with r_c' and R_r' , respectively. The searching process is recursively performed until the left boundary of R is touched. Similarly, we apply the same searching process to R_r for obtaining the characters 'D' and 'N' accordingly.

When recognizing the characters "P" and "I", since their widths are smaller than other characters, some additional

decision rules should be added. Usually, if a real character ‘I’ or ‘l’ appears, we can check whether its both sides have two higher peaks in its vertical projection histogram.

After segmentation, the following task is to recognize each extracted character. To verify a character C , this paper uses a distance transform to convert C to a distance map. Then, based on this map, different characters can be well verified. Assume that B_C is the set of foreground pixels extracted from C . Then, the distance transform of a pixel p in C is defined as

$$DT_C(p) = \min_{q \in B_C} d(p, q)$$

where $d(p, q)$ is the Euclidian distance between p and q . In order to enhance the strength of distance changes, the above equation is further modified as follows:

$$\overline{DT}_C(p) = \min_{q \in B_C} d(p, q) \times \exp(\kappa d(p, q))$$

where $\kappa = 0.1$. Thus, a set F_C of character features can be extracted from C . In practice, due to different environment changes (like lighting), a character C will have different visual appearance changes. To tackle the visual changes, we collect a set of training samples for representing the shape characteristics of C more accurately. Assume that C has N templates which are collected in the set Q . Then, given an unknown character r_i , the distance between r_i and Q is measured using the equation:

$$d(r_i, Q) = \min_{V \in Q} \left[\frac{1}{|H|} \sum_{s \in V} \overline{F}_H(s) + \frac{1}{|V|} \sum_{p \in r_i} \overline{F}_V(p) \right], \quad (1)$$

where $|r_i|$ and $|V|$ denote the numbers of foreground pixels in r_i and V , respectively. According to $d(r_i, Q)$, the unknown character r_i can be well recognized.

6. Experiment Results



Figure 10. Result of license plate detection.

In order to analyze the performance of the proposed approach, different video sequences were used for testing. Figure 10(a) shows the detection result of license plate when a low-quality video frame was handled. Figure 10(b) shows another result of license plate detection when a darker video frame was handled. It is noticed that three license plates appear in Figure 10(b). Even though the lighting condition was very low, our method still successfully detected them. Figure 11 shows the recognition result when a video sequence was handled. The sizes of the license plate appearing in the video sequence changed significantly. No matter what size a license plate had, it still can well detected using our proposed methods. The average frame rate of plate detection is 15 *fps*. Figure 12 shows another result of license plate detection when a video

sequence was captured from a slanted view of the camera. All of them were corrected detected and recognized. The average accuracy of detection is 98.9% and the recognition correct rate is 95%. The superiority of the proposed method can be verified through these experimental results.



Figure 11. Result of license plate detection and recognition under low quality video.



Figure 12. Result of detection and recognition.

References

- [1]. R. Zunino and S. Rovetta, “Vector quantization for license-plate location and image coding,” *IEEE Transactions on Industrial Electronics*, vol. 47, pp.159–167, Feb. 2000.
- [2]. M. Shridhar, Miller, G. Houle, and L. Bijnagte, “Recognition of license plate images: issues and perspectives,” *Proc. of the Fifth International Conference on Document Analysis and Recognition*, p.17–20, 1999.
- [3]. K. K. Kim, *et al.*, “Learning-based approach for license plate recognition,” *Proc. of IEEE Workshop on Neural Networks for Signal Processing*, vol. 2, pp.614–623, 2000.
- [4]. H.A. Hegt, R.J. Haye, and N.A. Khan, “A high performance license plate recognition system,” *Proc. of IEEE Intern. Conf. on SMC.*, pp. 4357–4362, 1999.
- [5]. Y. Mei and D.Y. Yong, “An approach to Korean license plate recognition based on vertical edge matching,” *Proc. of IEEE International Conference on SMC.*, pp.2975–2980, 2000.
- [6]. D. S. Kim and S.I. Chien, “Automatic car license plate extraction using modified generalized symmetry transform and image warping,” *IEEE International Symposium on Industrial Electronics*, vol. 3, pp. 2022–2027, 2001.
- [7]. Y. Dai, *et al.*, “A high performance license plate recognition system based on the web technique,” *Proc. of IEEE Proceedings ITS.*, pp.325–329, 2001.
- [8]. M. Sonka, V. Hlavac, and R. Boyle, *Image Processing, Analysis and Machine vision*, Brooks/Cole Publishing Company, 1999.
- [9]. Y. Freund, and R. E. Schapire, “A decision-theoretic generalization of on-line learning and an application to boosting,” *In Proc. Second European Conference on Computational Learning Theory*, pp. 23–37. 1995.
- [10]. P. Viola and M. J. Jones, “Robust real-time face detection,” *IJCV*, vol. 57, no. 2, pp.137–154, May 2004.