

License Plate Character Recognition Using Block-Binary-Pixel-Sum Features^{*}

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Abstract - Since license plate character recognition plays a very important role in vehicle control, such as electronic toll collection (ETC) for highways and management for parking lots, the cost of management can be reduced and the implementing efficiency can be promoted by automatizing license plate character recognition. As the technology of image processing, classifiers, and computational speed on computer advances, we adopt Sobel operators to detect the boundaries of objects in order to extract license plate regions. After extracting license plate regions, we segment corresponding characters and then standardize these characters in order to find out the features of characters, and finally use the classifiers of support vector machine (SVM) and K-nearest neighbor (KNN) to train and then recognize characters. Experimental results show that classifiers and features are closely linked, and KNN is more appropriate for block-binary-pixel-sum features than SVM, and its recognition rate is up to 98.51 % on average.

Index Terms – License plate localization, license plate region extraction, license plate character segmentation, license plate character recognition, block-binary-pixel-sum feature.

1. Introduction

As the economy improves and the per capita income rises, the number of possessing cars and/or motorcycles gradually increases, thereby leading to more and more traffic problems and vehicle management issues. Our aim is to utilize image processing techniques, such as contrast enhancement, noise reduction, edge detection, feature extraction [1-2], to provide an effective and efficient way of recognizing license plate characters. In order to achieve the goal, three main procedures are implemented: license plate region extraction or license plate localization, license plate character segmentation, and license plate character recognition. It can be expected that the overall recognition rate will be raised as each procedure is improved.

There have been many papers studying the license plate recognition. Du et al. [3] gave a comprehensive review of automatic license plate recognition (ALPR). They categorized techniques for ALPR according to the used features and compared the pros and cons, recognition rate, and processing

speed of each method. Angeline et al. [4] proposed an algorithm for license plate character recognition based on signature analysis and feature extraction. They combined the characteristics obtained by signature analysis and feature extraction to form a feature vector with a length of 56 for each character, and then used a feedforward back-propagation neural network to classify characters. Signature analysis [5] combined with connected component analysis was used to locate the dynamic vehicle license plate. Zhou et al. [6] proposed a scheme to automatically locate license plates by discovering principal visual words (PVWs) and matching local features. The method can be extended to detect logos and trademarks.

Chen et al. [7] presented a method to recognize license plates. The method first used salient features to locate the license plates, then segmented each character of a license plate, and finally used a feature-salience classifier to recognize characters. Guo and Liu [8] dedicated to license plate localization and character segmentation. First, histogram equalization was employed to solve low-contrast and dynamic-range problems, and then they used texture features to locate the license plate. On the other hand, they used a hybrid binarization technique to segment characters of the license plate.

The rest of the paper is organized as follows. Section 2 introduces the methods of locating license plates, segmenting characters, and recognizing characters. Section 3 discusses the experimental results. Section 4 gives some important conclusions.

2. Methods

In the following, we first introduce how to locate license plates and extract their corresponding regions, then segment these characters on located license plate, and finally use support vector machine (SVM) and K-nearest neighbor (KNN) classifiers to recognize these segmented characters.

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A. License Plate Region Extraction

In order to effectively locate license plates and extract their corresponding regions, we first implemented the preprocessing of an image using the following procedure:

1. Input an image with a license plate (640x480).
2. Transform the RGB image into a grayscale image using the transformation formula proposed by Hasan and Karam [9]:

$$Y = 0.299R + 0.587G + 0.114B. \quad (1)$$

3. Reduce the image by cutting 150 pixels along the top and bottom side, respectively, and 195 pixels along the left and right side, respectively, in order to effectively search for the license plate region.
4. Use a median filter to lower the effect of salt and pepper noise.
5. Binarize the filtered image.

After preprocessing an image, we utilized the obvious changes of edges to locate the license plate regions as summarized in the following procedure:

1. Detect vertical edges of images and then horizontally project these vertical edges.
2. Find out all possible boundaries of the top and bottom of license plate regions.
3. Vertically project these possible license plate regions and further find out all possible boundaries of the left and right side of license plate regions.
4. Implement image morphology.
5. Find out the unique license plate region.

In the case of detecting vertical edges, we used the Sobel mask in the x -direction. In order to reduce possible noise and raise the success rate of searching license plate regions, we set a limit (in this paper, we set it as 10) to remove potential noise and other possible edges in the second step. If the number of accumulated pixels from projection is smaller than the limit, then the number will be reset as 0. Then find out the regions of the accumulated pixel numbers being larger than 0. In the third step, we vertically projected the regions obtained by the previous step, reset the accumulated pixel numbers smaller than the limit as 0, and then remained regions are possible license plate ones. In order to accurately segment license plate regions, we applied the closing operator of image morphology to possible license plate regions in the fourth step, making the boundaries of license plate regions connective. In the fifth step, we redid a vertical projection, found out the regions with accumulated pixel numbers being larger than 0, and finally found out the unique license plate region with the ratio of length to width being closest to 3.5 (for Taiwan).

B. License Plate Character Segmentation

After extracting license plate regions, segmenting license plate characters are summarized as followed:

1. Locally binarize license plate regions.
2. Negatively transform the binarized image.

3. Label the connected components or objects, calculate the number of pixels for each connected component, and then sort them in a descending order.
4. Correct the order of characters of the original license plate.
5. Standardize the size of each segmented character into an image of size 40x20.

In the first step, we applied an adaptive document image binarization, proposed by Sauvola and Pietikäinen [10], to the license plate regions. The textual binarization formula is of the form

$$T(x, y) = m(x, y) \left[1 + k \left(\frac{s(x, y)}{R} - 1 \right) \right], \quad (2)$$

where $m(x, y)$ is the local mean, $s(x, y)$ the local standard deviation, R the dynamic range of standard deviation, and k a positive parameter. In order to be suitable for labels for the connected components, we give a negative transform of the binarized image in the second step.

In the third step, each object is 8-connected. We then calculated the number of pixels for each connected component, sorted them in a descending order, and finally selected the first six objects as license plate characters. If a particular need, such as for other types of cars, we can select other numbers as a threshold, and therefore the idea is very flexible. Since the order had been changed after sorting, a correction must be made into the original character order. We used the label values of objects to reestablish the original order in the fourth. In order to make feature extraction convenient and consistent, we modified every segmented character into a fixed matrix of size 40x20. The fifth step is called standardization.

C. License Plate Character Recognition

After segmenting license plate characters, we used classifiers to recognize the characters as summarized in the following procedure:

1. Divide each segmented character into different sizes of blocks.
2. Choose the sum of pixels being 1 of each block as a member of features.
3. Use classifiers to recognize characters.

In this procedure, a very important step is to choose the most suitable ones among feasible features. Since the shape of every character is different from one another, more or less, we first divided each segmented character into different sizes of blocks: 5x5, 5x10, 10x5, and 10x10. Second, we calculated the number of pixels being 1 of each block for different sizes of blocks and chose it as a member of features. Finally, we used two classifiers, support vector machine (SVM) and k-nearest neighbor (KNN) [11], to recognize which character the features of each input character belong to.

In this paper, the feature is referred to as block-binary-pixel-sum, which was applied in the paper of Aghdasi and Ndungo [12]. They provided an automatic license plate

recognition system to recognize plate characters. In the recognition phase of the system, characters first were taken from an image and each character was placed into an image of size 24x12 in a binarized form. Second, each character was divided into 24 blocks of size 4x3 and the sum of foreground pixels of each block was calculated. These 24 numbers were used to be a feature vector. Finally, a correlation or template matching approach and a feed forward neural network with three layers were used to find the most appropriate character.

TABLE I Recognition rate of license plate characters using SVM

Block Type	Arg.=20	Arg.=25	Arg.=30	Arg.=35	Arg.=40	Mean
5x5	96.29	97.14	97.14	97.14	97.14	96.97
5x10	95.71	95.71	96.00	96.00	96.00	95.89
10x5	96.00	96.29	96.57	96.86	96.57	96.46
10x10	93.43	94.00	94.57	94.29	94.57	94.17
Mean	95.36	95.79	96.07	96.07	96.07	95.87

In the following section, we will show that a different combination of three main procedures gives an improvement to the recognition rate.

3. Experimental Results and Discussion

In this paper, we used SVM and KNN algorithms to classify the features of each input character into one of 35 characters for Taiwan, 10 Arabic numerals and 25 English characters except for the character O. For training and testing, we randomly chose 20 segmented images of size 40x20 for each character; in total, 700 images of size 40x20 were used, where 10 images of each character were used as a training set and the other 10 images of each character as a testing set. Experimental results are listed in Tables 1 and 2.

It is obvious from these two tables that the recognition rate on average is about 95.87 % for the SVM classifier and about 98.51 % for the KNN classifier. The highest recognition rate for all arguments and block types for SVM are 97.14 %, occurring at argument being 25, 30, 35, and 40, together with block 5x5; the highest recognition rate for all k s and block types for KNN are 100 %, occurring at k being 3 and 5, together with block 5x5. The highest recognition rate for block type is block 5x5, and the second is 10x5, no matter which classifier. Their recognition rates are 96.97 % (SVM) and 99.77 % (KNN), respectively. The most appropriate arguments for SVM are 30, 35, and 40; their mean recognition rates are all 96.07 %. The most suitable k for KNN is 1; its mean recognition rate is 99.07 %.

TABLE II Recognition rate of license plate characters using KNN

Block Type	$k = 1$	$k = 3$	$k = 5$	$k = 7$	$k = 9$	Mean
5x5	99.71	100	100	99.71	99.43	99.77
5x10	99.14	98.29	97.14	97.43	97.71	97.94
10x5	99.71	99.71	99.71	99.43	99.43	99.60
10x10	97.71	97.14	97.71	96.29	94.86	96.74
Mean	99.07	98.79	98.64	98.21	97.86	98.51

4. Conclusions

The aim of the paper is to raise the recognition rate of license plate characters through a combination of three main procedures. All trained and tested characters came from the following two main procedures: extracting license plate, segmenting characters. As a rule, the effectiveness of character processing will affect the effect of selected features, and then further affects the efficacy of chosen classifiers. As expected, experimental results show that our proposed combination of three main procedures does give a very high recognition rate, which can be up to 100 % for KNN.

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