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Learning Based Character Segmentation Method for Various License Plates

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Abstract

This paper proposes a novel method for license plate character segmentation using a classifier. Conventionally, a three-step method of detection, segmentation, and recognition is commonly used for license plate character recognition systems. Although a machine-learning based method is widely used in the detection and recognition steps, only a heuristic method based on a projection or connected component analysis is used in the segmentation step. The method proposed in this paper, however, uses a machine-learning based method for segmentation, unlike previous researches. The proposed method consists of several steps. First, locating the common region in the license plate, extracting the area containing all license plate types from this region, classifying it to determine the license plate type and estimating the location of the remaining characters based on the structural information of the determined license plate type. Experimental results show that the performance rate of the proposed method is 98.2% for over 10,000 license plate images.

1 Introduction

With an increase in the number of vehicles and the development of image processing technology, researches on the automatic acquisition of traffic information in the field of intelligent transportation systems (ITS) have been continuously carried out. In particular, license plate recognition (LPR) technology for extracting the license plate information from vehicle images is widely used in vehicle traffic measurements, speed control, tolling, access control, parking violation crackdowns, and so on. Conventional LPR technology consists of three parts: license plate detection, character segmentation, and character recognition. License plate detection is used to find the region that has a plate in the input image roughly. Character segmentation is applied to segment and locate each character position on the license plate image. Because there are many license plate types, it is necessary for the LPR system to be able to recognize the type of the a plate and this is usually processed in this stage. The classification of the license plate type is also carried out during the segmentation step. Optical character recognition (OCR) is applied to recognize characters in the license plate image using the information acquired during the segmentation step. Fig. 1 shows a conventional LPR system and an example.

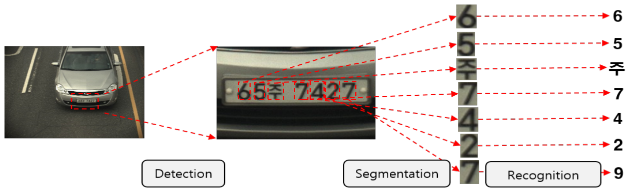


Figure 1. Example of a conventional LPR system.

Recently, there have been various studies on the end-to-end recognition of images having a limited number of classes, such as house numbers, using a single recognizer, along with the development of machine-learning technologies such as deep neural networks [1]. However, because there are many license plate types and the numbers of characters are more than those of house addresses, it is difficult to process them using a single recognizer. It is therefore preferable to constitute the three steps according to the conventional method.

In this paper, we propose a quasi-automated method of character segmentation of a license plate image by applying a classification technique based on machine learning, which is different from a conventional approach. The proposed method consists of three steps. The result of the license plate detection is binarized to extract common character locations based on a connected component analysis. From this, we extract images that can include all license plate types, and determine the license plate types using a classifier based on a machine-learning method. We estimate the locations of the remaining non-common characters by using the prior information of the determined plate type, and determine the final location through a fine adjustment. Fig. 2 shows an overview of the proposed approach along with a sample.

The rest of this paper is organized as follows. Previous related studies are described in Section 2. A novel character segmentation method is proposed in Section 3. The experiment results are detailed in Section 4. Finally, some concluding remarks are given in Section 5.

2 Related Works

Previous research on license plate segmentation can be classified into the use of projection, prior knowledge, connected components, and character recognition [2]. In [3], the number of character rows is determined by comparing the numbers of pixels between the foreground and background in a binarized image. If a double row of characters exists, the upper and lower rows are divided using horizontal projection. A connected component analysis is implemented in each row area, and candidate blobs are selected based on a distance analysis between the blobs. This method can deal with a multi-row plate type, but it requires an accurate detection region. In [4], after image preprocessing such as size normalization is applied, the image is partitioned into blobs through a vertical projection. In each partitioned blob, a blob subsection line is extracted using a horizontal projection.

The segmentation methods using rough detection result are widely used because it is difficult to acquire an accurate plate region in detection step. In [5], to obtain a better binary image, a vertical projection is used after mean filtering is applied. In [6], the authors also use a vertical projection, and apply various morphological methods to restore broken and concatenated character images. In [7], the authors also use a vertical projection. To improve the projection quality, they apply various types of image preprocessing including size normalization, uneven illumination correction, contrast enhancement, incline correction, and edge enhancement. In addition, various types of post processing are also applied. In [8], instead of a linear sum of the intensity, the intensity variance of the projection directions is used to achieve robustness to illumination. In [9], after binarizing through several different methods, binary elements are analyzed and the blobs are extracted. Each blob is recognized if it is a number by the character recognizer. Then, only number blobs are considered as blob candidates. Considering the blob distance, width, and height, the appropriate blob connection is determined as a plate blob. According to our study, it often occurs that the edge of the license plate is mistaken for the number 1. Therefore, significant care should be taken for a method utilizing a character recognizer. In [10], the authors extract the connected components by binarizing using different thresholds, and extract four digits by applying an energy model to the components. The height similarity, vertical distance to the center point, and the threshold value are considered in the energy model. This study is similar with our work in that it utilize four digits. But they do not apply machine learning method after that. In [5], a plate image is divided and binarized through local vector quantization. After binarization, blobs are extracted from the connected component analysis. The broken and attached components are restored using an expert system. In [11], preprocessing, Otsu binarization, and a connected component analysis are used to extract blobs with a specified width, height, and area for Iranian license plates.

In short, methods using a connected component analysis work well for tilted license plates, but are dependent on the binarization performance and are sensitive to noise. They may fail to separate the characters if the connected components of the characters are separated or attached. In addition, when the size of a character is small or its complexity is such that it does not form a single connected component, it is difficult to distinguish between noise and the character.

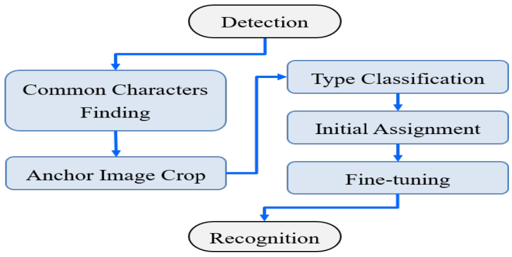


Figure 2. Overview of the proposed approach.

Type	Character Brightness	Background	ETC	Example
1	Dark	White	Wide	
2			Narrow	
3		Yellow	1 row	
4			2 rows	
5	Bright	Green	3+4 characters	
6			3+5 characters	
7			4+5 characters	
8			2+7 characters	
9		Orange	2+7 characters	

Figure 3. Korean license plate types. Types are classified according to the character brightness, background color, and the number of rows.

3 Proposed Method

We propose to use machine learning method in character segmentation. License plate segmentation is regarded as a regression problem because it is used to find the continuous value of a location. However, we think that it can be regarded as a type of classification because the character locations depend on the type of license plate, and the number of license plate types is limited. Our key idea is that the approximate locations of all characters can be estimated if the type and a few character positions are known. Thus license plate seg-

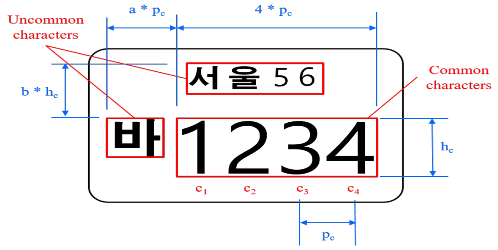


Figure 4. Representation of license plate size using pitch and height of the common characters.

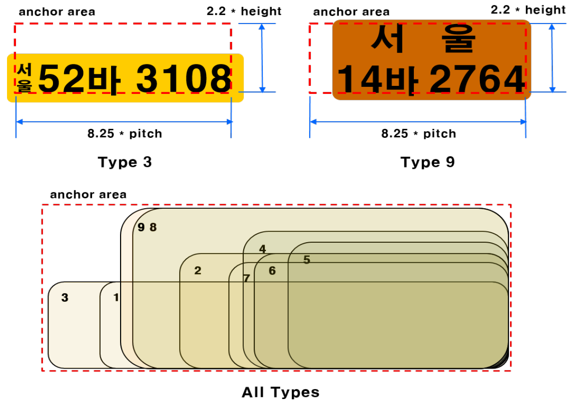


Figure 5. Anchor areas based on license plate type. Type 3 is the longest type in the horizontal direction and type 9 is the highest type in the vertical direction.

mentation can be regarded not as a regression problem but as a classification problem with finite plate types.

In this paper, we extract only the location of specific characters, unlike the existing methods of finding the location of entire characters. It is very good characteristic for license plates with small characters, because small characters are difficult to segment by the previous methods. The proposed method needs only the locations of common characters, which are usually large. Although we use a connected component analysis to locate the specific locations, other methods can also be used. The type of the license plate is then determined using a classification method, and the approximate locations of the remaining characters are estimated using the structural information on the license plate type. The estimated location is finally fine-tuned.

3.1 Common Characters Detection

Korean license plates can be classified into two kinds, that is, dark or bright plates based on the contrast between characters and background, and are additionally classified into nine types according to the background color, the constituent elements of the characters, and the number of rows. As shown in Fig. 3, the shapes of Korean plates vary, but all have large four-digit numbers in the bottom-right, which are defined as c_1, c_2, c_3, and c_4 from left to right as shown in Fig. 4. The proposed method finds the common character locations in a plate image. It is easier to find the common characters because they are the large and simple numeric characters.

We extract four successive component units as common region in the binary image. It should be noted that multiple candidates can be extracted unlike previous studies, because a highly credible type classifier can find the right one and reject others later. Type classifiers in the next process have more than 99.9% of performance, so most of the wrong images can be filtered out. This is a great advantage of the proposed method in comparison with the previous studies.

3.2 Type Classification

Based on the locations of the common characters in a license plate, the region corresponding to the union containing all nine license plate areas is extracted. The extracted region is called the anchor area. To obtain the same results regardless of the actual size of the image, the average pitch of the four common characters is set as the reference metric in the horizontal direction, and the average height of the common characters is set as the reference metric in the vertical direction. The size of the anchor area is represented by not actual pixel values but based on the average pitch and average height of the common characters. The equations for which are as follows:

$$p_c = \frac{1}{n-1} \sum_{i}^{n-1} |c_{i,x_c} - c_{i+1,x_c}| \qquad (1)$$

$$h_c = \frac{1}{n} \sum_{i}^{n} c_{i,h} \qquad (2)$$

where n is the number of common characters, c_i is a i-th common character, c_{i,x_c} is the center position of c_i in the horizontal direction, and $c_{i,h}$ is the height of c_i.

The size of the plate image, which is expressed based on the ratio of the pitch to height, and not on the actual plate size, is the longest in the horizontal direction for type 3 and the highest in the vertical direction for type 9 in Fig. 3. Therefore a region containing type 3 in the horizontal direction and type 9 in the vertical direction based on the average pitch and the average height is extracted from the original image, and used as an input to the type classifier. In the case of the Korean license plates, the area with 8.25 times the average pitch and 2.2 times average height can contains

Figure 6. Original images used in the experiment.

(a) Positive images (b) Negative images

Figure 7. Training images for a type classifier

all characters in all plate types. Fig. 4 shows the pitch and the height in the license plate structure. Fig. 5 shows the anchor area, which can cover the area of all license plate types. Note that the anchor area is aligned with the lower right part in the common characters and also includes non-plate area. It makes easy to classify the plate type because there are little position variance in anchor images. Also note that just two common character locations are sufficient to extraction an anchor image unlike the previous studies using projection which needs most character locations. Even if some characters are damaged, the anchor image can be extracted.

Fig. 7a shows examples of actual anchor images. The actual sizes of the extracted images depend on the type of license plates, and the aspect ratios are also different between images. However, a size based on its own pitch and average height has the same value. The type classifier classifies the anchor image. The classifier should be able to distinguish between the nine types of plates and the background, which is not an anchor image.

3.3 Fine-tuning

Because the location of non-common characters can be known as prior information, it can be estimated when the type of the plate is determined. The estimated location is near the actual location of the character. However, the estimated location and actual location are often different from each other because the locations and sizes of the characters may vary depending on the license plate maker and the time of production. In most cases, the estimated location and the actual location are close to each other, and thus a precise location can be obtained through a slight fine-tuning.

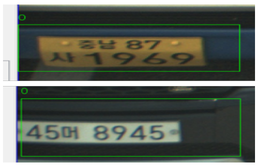
4 Experimental Results

This paper aims to solve the problem of recognition of various types of license plates. Korean license plates are suitable for testing the proposed method because they have nine types including multiple rows. About 50,000 license plate images were collected and used as the training data, and the results were tested on 10,881 separate independent images. All images of 1624*1224 resolution were collected in the real environments of expressways and national highways, and license plates that were impossible to distinguish by human eyes were excluded from the test. However, plates that were difficult to read owing to blurring, diffuse reflections, aging, contamination, tortuosity, or occlusions were included in the test data when visual readability was possible. Fig. 6 shows the original images used for the training and testing. The ratio of type 1 is about 45%, and that of type 2, 3, 4, 5, 7 are about 10%. Others are less than 10%.

The collected data were vehicle images that include a license plate. Because this paper deals with only character segmentation in an LPR system, it was necessary to extract plate images from the original image. The license plate detection was processed using the MCT-Adaboost method [12]. For the training, the anchor images were generated using the ground truth of the character location in the extracted license plate image. Negative images were also extracted considering the cases that often occur under real circumstances. Because the locational misidentification mainly occurs in character units, negative images were extracted through a shifting of one character unit to the left or right. In addition, background images without a license plate were used for the training images. Fig. 7 shows the images used for training. Only the anchor images were considered as positive data, and the others were viewed as negative data even if they contained a partial or full license plate image.

We used HOG-SVM [13] as a type classifier. Table 1 shows the results of the type classification. The output column indicates the type of classes to be classified. All(9) indicates the nine classes from type 1 to type 9 in Fig. 3, Dark(4) indicates four classes from type 1 to type 4, and Bright(5) indicates five classes from type 5 to type 9. Table 1 shows that the accuracy is more than 99.8% even for the test data. We believe this high performance comes from the regulated position of the anchor image. In addition, normalization of the size of the anchor image based on the pitch and

Figure 8. Successfully recognized images



(a) Anchor image

(b) Common characters

(c) Type classifier

(d) Fine-tuning

Figure 9. Unrecognized images and the causes

height will make the classifier achieve better results. Although the All type classifier showed a good level of performance, we adopted Dark and Bright as the type classifiers because they showed a better performance.

In general, the detection performance is represented by the intersection over the union value, but it is not proper to measure the segmentation performance. Therefore the segmentation performance was measured based on the value that affects the final recognition rate. The equation is as follows:

$$E_{seg} = E_{total} - E_{det} - E_{rec} \tag{3}$$

where E_{total} is the final error number, E_{det} is the number that fails to contain a full plate region during the detection, and E_{rec} is the number of failed attempts to recognize the characters in a plate when the exact character location is provided from ground truth. Table 2 shows the step-by-step results for the test data. According to (3), the final error rate was 1.80%, and the detection error rate was 0.24%. Because the recognition error rate was 0.84% when measured separately given the exact character location, the segmentation error rate was estimated to be 0.72%. In other words, the proposed method decreased the final LPR accuracy by 0.72%. Fig. 8 shows the successfully recognized images in our systems.

Table 1. Type Classifier Results

Output(number)	Input Size	Accuracy
All(9)	96×42	99.88%
Dark(4)	96×48	99.95%
Bright(5)	96×48	99.94%

Table 2. Performance in each steps

	Det.	Seg.	Rec.	Total
Number	10,855	10,777	10,707	10,881
Rate	99.76%	99.04%	98.20%	100%

Table 3. Error and cause in the segmentation

Cause	Anchor Image	Common Character	Type Classifier	Fine Tuning
Error	14	33	2	29
Rate	0.13%	0.30%	0.02%	0.27%

Table 4. Comparison with other methods

Method	Accuracy
Otsu-CCA	78.8%
Difference of Gaussian-CCA	94.6%
Multi Binarization-CCA	96.8%
Proposed(without fine-tuning)	94.2%
Proposed(with fine-tuning)	**98.2%**

Table 3 lists the errors caused by the character segmentation. For an anchor image, the license plate was located on the left side of the image, so the anchor image could not be extracted because of a lack of space. The type classifier column in Table 3 indicates the failed image number to classify the plate type, which is only two. This good result complies with the results of Table 1. The HOG-SVM classifier is sufficient for the proposed system because of the well-positioned anchor image. Common character column indicates the case that the four common characters were not detected because of dirt, illumination, and plate aging. Fine-tuning column indicates that the exact locations were not detected because of the close plate edge. Most errors occurred while finding the four common digits, and during fine-tuning, which are difficulties in a conventional method. Fig. 9 shows the unrecognized images along with the cause.

Table 4 shows the results for the various methods. Because of the various shapes in Korean license plates, the methods like as using plate color and projection cannot be applied directly. We made some segmentation modules using binarization and CCA[9], tested for the same, and got the results in table 4, which shows that the proposed method with fine-tuning in BD image is better than the previous methods.

5 Conclusion

In this paper, we propose a novel method using a classifier based on machine learning, unlike a conventional method, for locating the character positions on a license plate. Although it has been tested only for Korean License Plates, we believe that it can handle any other country's plates if the anchor image can be extracted with the common characters. For example the last two characters in Japan's and the last three characters in USA's can be the common characters.

There are some contribution in this paper. First, we normalize plate images using average pitch and the average height of the common characters as a basic unit, allowing them to be processed regardless of the image size and type. Second, we use an anchor image for character segmentation unlike previous studies using 1-dimensional data from projection. The previous methods need that all character positions should be acquired, but the proposed method needs just common character positions for an anchor image, which are normally larger and simpler than non-common characters. This makes our method robust to the damaged plate images. Third, we introduce a classification learning method based on machine learning in the license plate character segmentation process, and automate the processing. As a result, the performance of the character segmentation module can be improved by simply training a large amount of data without developing a complicated algorithm. Moreover the performance of the classifier is over 99.8% due to the well positioned anchor image and carefully selected negative samples.

The proposed method is not only fast and accurate, but also does not need GPU. It can be processed by multi-thread and its throughput increases as CPU core number. Despite these good features, the proposed method has certain disadvantages. If the license plate image is located too far to the left, it cannot extract the anchor image because it cannot secure a sufficient area. In addition, if it fails to find the common characters, then the proposed method cannot be applied. In the future, additional research will be conducted to resolve these shortcomings.

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