Segmenting the License Plate Region Using a Color Model

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1. Introduction

Humans can perform usual target recognition without too much effort. However, by computer the task of recognizing specific object in an image, one of the most difficult topics in the field of computer vision or digital image processing. Vehicle license plate detection (VLPD) task is quite challenging from vehicle images due to the multi-style plate formats, view point changes and the nonuniform outdoor illumination conditions during image acquisition (Anagnostopoulos et al., 2008) and (Jiao et al., 2009). In addition, VLPD system should operate fast enough (real time) to satisfy the needs of intelligent transportation systems (ITSs) and not to miss a single interest object from the vehicle image. VLPD is also very interesting in finding license plate area from vehicle image. The VLPD is widely used for detecting speeding cars, security control in restricted areas, in unattended parking zones, for traffic law enforcement and electronic toll collection, etc. With the rapid development of highway and the wide use of vehicles, people have started to pay more and more attention to the advanced, efficient, and accurate ITSs. Recently, the necessity of vehicle license plate recognition (VLPR) has increased significantly. The license plate detection is a crucial and indispensable component of VLPR system. One of the major problems in LP detection is determining LP systems. This system must guarantee robust detection under various weather and lighting conditions, independent of orientation and scale of the plate.

In the recent years developments dealing with simple images have been achieved with acceptable results. However, recent researches have been addressed to processing complex images with unconstrained conditions (Matas, 2005). The proposed license plate detection framework deals with such vehicle images.

In this proposed VLPD method, consists of two main stages. Initially, HSI color model is adopted for detecting candidate regions. According to different colored LP, these candidate regions may include LP regions; geometrical properties of LP are then used for classification. The proposed method is able to deal with candidate regions under independent orientation and scale of the plate. More than one license plate can be detected in the same image. Finally, the decomposition of candidate regions contain predetermined LP alphanumeric characters by using position in the histogram to verify and detect vehicle license plate region.

The focus of this chapter is on the consolidation of a new method to select automatically statistical threshold value in HSI color model for detecting candidate regions. Generally, as a common way of color-based VLPD system, threshold value is defined by predetermined coefficients or by user. It provides stable result, but in poor lighting condition it is too sensitive. Whereas in our experiments we calculate threshold value in a statistical way, 20% of sample data (only green, yellow and white LP areas) are randomly selected for training. After training from those sample data, the mean and standard deviation values of hue are computed for detection of green and yellow LP pixels. Detecting white license plate pixels, the mean and standard deviation values of saturation and intensity are computed to detect green, yellow and white LP from vehicle images.

In addition, the proposed method is able to deal with plates (candidate regions) under independent orientation and scale of the plate. More than one license plate can be detected in the same image. Furthermore, candidate regions may include LP regions; geometrical properties of LP are then used for classification. Finally, the decomposing of candidate region which contains predetermined LP alphanumeric character, by using position in the histogram to verify and detect vehicle license plate region is performed.

2. Relevant work

This section provides a descriptive summary of some methods that have been implemented and tested for VLPD. As far as detection of the plate region is concerned, researchers have found many methods of locating license plate. For example, survey paper (Anagnostopoulos et al., 2008), offers to researchers a link to a public image database to define a common reference point for VLPR algorithmic assessment. In addition, this survey paper discusses about current trends and anticipated research in VLPR system. In (Anagnostopoulos et al., 2006), a method based on image segmentation technique named as sliding windows (SW) has also been proposed for detecting candidate region (LP region). The main thought of image segmentation technique in LP can be viewed as irregularities in the texture of the image and therefore abrupt changes in the local characteristics of the image, manifest probably the presence of an LP. A conventional statistical classifier, based on the k nearest neighbor rule, is used to classify every pixel of a test image to obtain a pixel map where group of positive samples probably indicates the location of a license plate. In this system, time-consuming texture analysis is presented in (Cano & Perez-Cortes, 2003), where a combination of a “kd-tree” data structure and an “approximate nearest neighbor” was espoused. The computational resource demand of this segmentation technique is the main drawback, taking an average of 34 seconds to process of single image. In (Chacon & Zimmerman, 2003), the pulse-coupled neural network (PCNN) is proposed to generate candidate regions that may contain a license plate. If the license plate is not located in the set of candidate regions, the PCNN network parameters are adjusted to generate new regions for LP identification.

Fuzzy logic has been applied in detecting license plates. Authors made some intuitive rules to describe the license plates and gave some membership functions for fuzzy sets e.g. “bright,” “dark,” “bright and dark sequence,” “texture,” “yellowness” to get the horizontal and vertical plate positions (Chang et al., 2004). A technique based on extracts candidate regions by finding vertical and horizontal edges from vehicle region had also been proposed and this segmentation method is named as sliding concentric windows. Finally, vehicle license plate is verified and detected by using HSI color model and position histogram, respectively in (Deb et al., 2008a). Prior knowledge of LP and color collocation has been used to locate the license plate in the image (Gao et al., 2007) as part of the procedure of location and segmentation. In (Hongliang & Changping, 2004), a hybrid license plate localization algorithm based on the edge statistics and morphology for monitoring the highway ticketing system is proposed. This technique can be divided into four sections, which are, vertical edge detection, edge statistical analysis, hierarchical-based license plate location, and morphology-based license plate extraction. The average accuracy of locating license plate is an impressive rate of 99.6%. However, input images were acquired from a fixed distance and view point and therefore, candidate regions in a specific position are devote priority as already depicted. The license plate locations in images are identified by means of integrated horizontal and vertical projections that are scanned using a search window (Huang et al., 2009). Moreover, a character recovery method is exploited to enhance the success rate. A region-based license plate detection method has been presented in (Jia et al., 2007), which firstly applies a mean shift procedure in spatial-range domain to segment a color vehicle image in order to get candidate regions. According to the statistical analysis performed for comparison to other LP like objects; LPs adhere to a unique feature combination of rectangularity, aspect ratio, and edge density. These three features were then estimated to candidate regions to decide whether these regions interpret an LP or not. A usual failure of this method is the failure to detect license plates when vehicle bodies and their license plate have similar colors. In (Jiao et al., 2009), a method for multi-style LP recognition has been presented. This method has introduced the density-based region growing algorithm for LP location, the skew refinement algorithm, the multi-line LP separation algorithm, the optimized character segmentation algorithm and trainable character recognition method for character recognition. Hough Transform (HT) for line detection has been proposed on the assumption that the shape of license plate has been defined by lines in (Kamat & Gansen, 1995).

A modified color texture-based method for detecting license plate in images has been presented in (Kim et al., 2002). A support vector machine (SVM) has been used to analyze the color and texture properties of LPs and to locate their bounding boxes applied by a continuous adaptive mean shift algorithm (CAMShift). The combination of CAMShift and SVMs produces efficient LP detection as time-consuming color texture analysis for less relevant pixels is restricted, leaving only a small part of the input image to be analyzed. In addition, finding candidate areas by using gradient information, it has been verified whether it contains the plate area among the candidates and adjusting the boundary of the area by introducing a template of the LP in (Kim et al., 2002). Other approaches using mathematical morphology method to detect license plate area (Martin et al., 2002) and an approach for segmentation of vehicle plates such as edge image improvement to detect a number of car plates in (Ming et al., 1996) have also been proposed. The proposed method in (Nomura et al., 2005) is committed to the task of character segmentation, describing a morphology-based adaptive approach for degraded plate images.

Moreover, assuming that LP regions are detectable even in noisy low resolution presented, a robust superresolution algorithm for video sequences (Suresh et al., 2007) has been proposed to enhance the LP text of moving vehicles with promising results. In (Wang et al., 2007), a cascade framework, utilizing plate characteristics and developing fast one pass algorithms, has been used for a real-time plate recognition system.

Currently, some researchers prefer a hybrid detection algorithm, where license plate location method based on corner detection, edge detection, characteristics of license shape, character's connection, and projection has been presented in (Xu & Zhu, 2007), (Zhang et al., 2007) and (Yang et al., 2006) is another method which is based on the color collocation of the plate's background and characters combined with the plate's structure and texture to locate the VLP. In (Zhang et al., 2006), a cascade classifier for license plate detection algorithm using both global statistical features and local Haar-like features is proposed. Using Haar-like features makes classifier be invariant to the brightness, color, size and position of license plates. On the other hand, using global statistical features makes the final classifier simple and efficient. Image enhancement and sobel operator to extract out vertical edges and finally search plate region by a rectangular window has been presented in (Zheng et al., 2005).

3. Specific features of Korean VLP

In this section, the color arrangements of the plate and outline of the Korean VLPs that are considered in this study have been discussed.

3.1 Color arrangement of the plate

Korean license plates are well classified as shown in Fig. 1. Each style has a different plate color and/or character color. However, in all, only five distinct colors like white, black, green, yellow, and deep blue are used in these license plates. It is worth paying attention to three different plate colors while searching for LP in an input image. Other types of vehicles, such as diplomatic cars and military vehicles, are not addressed since they are rarely seen. Color arrangements for the Korean VLPs are shown in Table 1.

Fig. 1. Outline of the Korean license plate

3.2 Outline of the Korean VLP

Standard LP contains Korean alphabets and numbers which are shown in Fig. 1. Few LPs contain Korean alphabets and numbers in two rows; in future these kinds of LPs are to be converted into single-row types. Where plate color is white and character color is black, they contain seven alphanumeric characters written in a single line. In Fig. 1, where plate color is green and character color is white, they contain Korean LP in two rows. The upper row consists of two small Korean characters of region name followed by one or two numbers of class code or two numbers and one Korean character. The lower row is one Korean character and four big numbers or only four big numbers to indicate the usage and serial number, respectively. When plate color is yellow and character color is black, some LPs contain all alphanumeric characters written in a single line and another type of yellow LP is found that contain Korean LP in two rows. The upper row consists of two small Korean characters of region name followed by one or two numbers of class code. The lower row contains one Korean character and four big numbers to indicate the usage and serial number, respectively.

Vehicle type	Plate color	Character color
Private automobile	White	Black
	Green	White
Taxi, truck, and bus	Yellow	Deep blue
Government vehicle	Yellow	Black

Table 1. Styles of license plates

4. Proposed LP detection framework

In the author's previous work (Deb & Jo, 2008b), HSI color based vehicle license plate detection method was presented. We propose in this chapter an enhanced version of the framework for VLPD as shown in Fig. 2. Like the traditional LP detection method, automatic focus and white balancing of camera often cause the changing illumination. To overcome this problem, we propose an adaptive LP detection method for detecting white license plate pixels; we use it in the case of really high- or low-illumination condition as shown in Fig. 4. And also distinguish with the traditional LP detection method, as license plates can appear at many different angles to the camera's optical axis, each rectangular candidate region is rotated until they are all aligned in the same way before the candidate decomposition. The proposed framework can efficiently determine and adjust the rotated plate as shown in Fig. 8. Measurements such as center of area and the least second moment are employed to solve the rotation adjustment problem. The least second moment provides the principal axis as the orientation with the candidate object. General framework for detecting VLP region is shown in Fig. 2. In the proposed framework, detection is based on color properties of LP, shape-based verification and position histogram.

5. Vehicle license plate detecting module

The VLPD sequence is shown in Fig. 2, which is proposed in this paper, consists of four distinct parts. The first one deals with, by using HSI color model, the detection of the candidate region, i.e., the license plate. The second part allows procedures for refining candidate region by using labeling and filtering. According to different colored LP these candidate regions may include rectangular LP regions; geometrical properties of LP such as area, bounding box, and aspect ratio are then used for classification. The third part includes operations for determining the angle of the candidate – rotation adjustment. Measurements such as center of area and the least second moment are employed to solve the rotation adjustment. The fourth part includes performances for candidate's decomposition and finally, the decomposition of candidate region which contains predetermined LP alphanumeric character by using position in the histogram to verify and detect vehicle license plate (VLP) region.

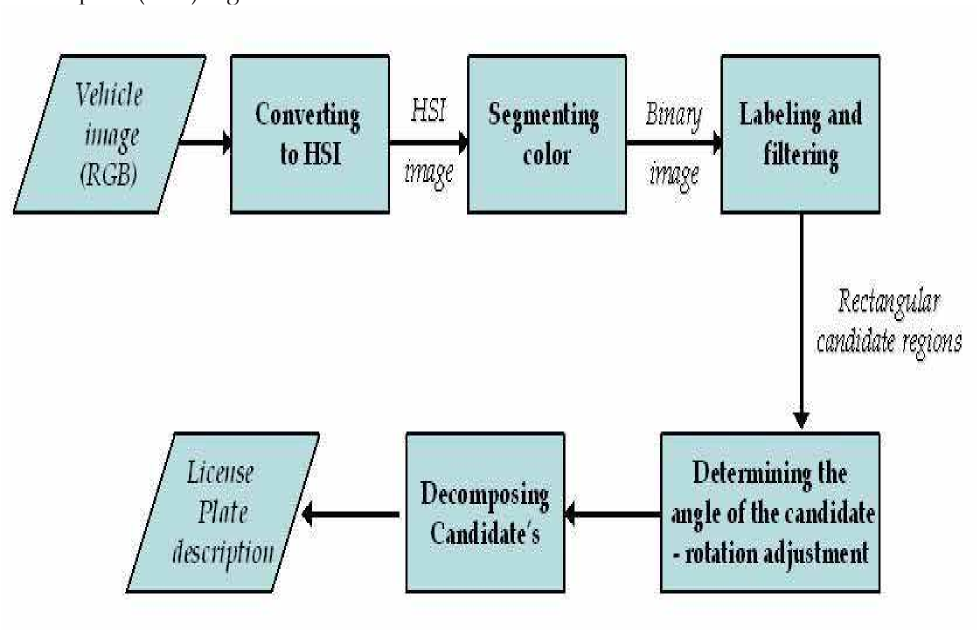

Fig. 2. Vehicle license plate detection framework

5.1 Segmenting color

In the proposed method, input vehicle images are converted into HSI color images. Then the candidate regions are found by using HSI color model on the basis of using hue, saturation and/or intensity. Many applications use the HSI color model. Machine vision uses HSI color space in identifying the color of different objects.

The RGB color model consists of the three additive primaries: red, green, and blue. Spectral components of these colors combine additively to produce a resultant color. Typically, HSI colors are not described on the basis of percentages of primary colors, but rather by their hue, saturation and intensity. The saturation is the "pureness" of the color, the hue is the color itself and intensity describes the brightness of the color. The HSI color model separates all the color information, described by hue and saturation, from the intensity component. The HSI color model is based on color descriptions that are more natural to humans and hence can provide an ideal tool for image processing algorithms. The HSI color space is represented by the diamond, as shown in Figure 3. The hue H is represented as angle 0, varying from 0° to 360°. Adjusting the hue will vary the color from red at 0°, through yellow at 60°, green at 120°, blue at 240° and back to red at 360°. Saturation S corresponds to the radius, varying from 0 to 1. When S =0, color is a gray value of intensity 1. When S =1, color is on the boundary of top cone base. Intensities I vary along Z axis with 0 being black and 1 being white.

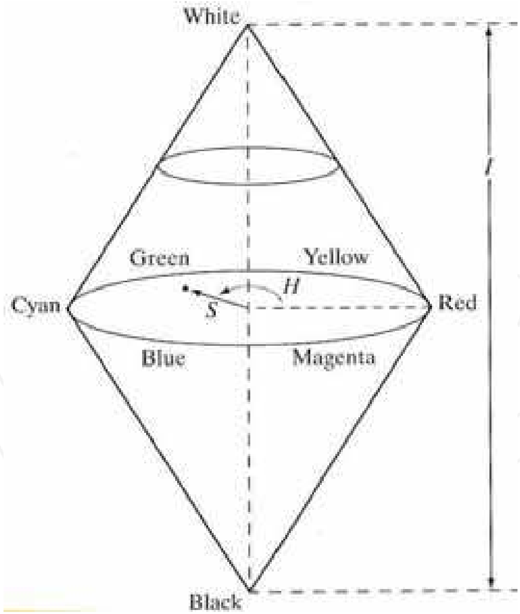

Fig. 3. The HSI color space

The transform from (R, G, B) to (H, S, I) in (Umbaugh, 1998) is

$$H = \cos^{-1} \frac{\frac{1}{2}\left[(R - G) + (R - B)\right]}{\left[(R - G)^2 + (R - B)(G - B)\right]^{\frac{1}{2}}}$$

$$S = 1 - \frac{3}{R + G + B} \min(R, G, B) \tag{1}$$

$$I = \frac{R + G + B}{3}$$

Plate color information is used to detect candidate regions in our experiments, and shape properties of LP allow reducing number of LP-like candidates. One of the common ways of color-based vehicle license plate detection can be formalized as follows:

$$R\ (x, y) > \alpha_R;\ G\ (x, y) > \alpha_G;\ B\ (x, y) > \alpha_B \tag{2}$$

$$R\ (x, y) - G\ (x, y) > \beta_{RG};\ R\ (x, y) - B\ (x, y) > \beta_{RB} \tag{3}$$

where *R, G* and *B* are red, green and blue components of x × y image. α and β are predefined coefficients. Equation (2) sets up limitations for the minimal values of pixel components. Equation (3) formalizes dependencies between pixel components for LP. Generally, common way of using color-based vehicle license plate detection is based on two types of restrictions: first, restriction is based on Eps. (2) and (3). It provides good results in good lighting conditions. However, it is not good for low-contrast images. Pixel belongs to green and yellow LP, respectively like following Eqs. (4) and (5)

$$b_{green} = \begin{cases} 1, \left[\{ R(x,y) \le 0.85 \cdot G(x,y) \} \ \& \ \{ B(x,y) \le 0.90 \cdot G(x,y) \} \right] \\ 0, \ otherwise \end{cases} \quad (4)$$

$$b_{yellow} = \begin{cases} 1, \left[\{ B(x,y) \le 0.90 \cdot R(x,y) \} \ \& \ \{ B(x,y) \le 0.80 \cdot G(x,y) \} \right] \\ 0, \ otherwise \end{cases} \quad (5)$$

where b_{green} and b_{yellow} are green and yellow candidate binary masks. The second restriction is based on Eqs. (4) and (5), and a threshold value is taken heuristically. It provides stable result whereas in bad lighting condition it is too sensitive.

In this proposed method, LP detection is based on its color properties, namely mean and standard deviation values of hue. For detection of green and yellow LP pixels, hue parameter of HSI color is used in our experiment. To detect white LP pixels hue value is meaningless, hence only saturation and intensity parameters are important for this case. To estimate these properties, we used 30 images of LP taken under different lighting and weather conditions. After training from those sample data, the mean and standard deviation values of hue are computed for detection of green and yellow LP pixels. Detecting white license plate pixels, the mean and standard deviation values of saturation and intensity are computed to detect green, yellow and white LP from vehicle images. For detection of green and yellow LP pixels, the binarization process can be formulated as follows:

$$b_{green} = \begin{cases} 1, \left[\{ \mu_H - \delta_H \le H(x,y) \le \mu_H + \delta_H \} \ \& \ \{ S(x,y) \ge 0.08 \} \right. \\ \left. \qquad \& \ \{ 0.05 \le I(x,y) \le 0.95 \} \right] \\ 0, \ otherwise \end{cases} \quad (6)$$

$$b_{yellow} = \begin{cases} 1, \left[\{ \mu_H - \delta_H \le H(x,y) \le \mu_H + \delta_H \} \ \& \ \{ S(x,y) \ge 0.12 \} \right. \\ \left. \qquad \& \ \{ 0.20 \le I(x,y) \le 0.80 \} \right] \\ 0, \ otherwise \end{cases} \quad (7)$$

where $H(x, y)$, $S(x, y)$, and $I(x, y)$ are hue, saturation and intensity components of xth, yth pixel, respectively. μ_H and δ_H are mean hue and hue standard deviation values for green and yellow LP of sample data, respectively.

However, the automatic focus and white balancing of camera often cause the changing illumination. Our proposed LP detection method can work well in normal illumination condition, but it seems not good enough to work in bad illumination conditions. To overcome this problem, we use an adaptive LP detection method; we use it in the case of really high- or low-illumination condition.

For normal, low- and high-illumination conditions of white license plate pixels, the binarization process can be formulated as follows, respectively:

$$b_{white(n)} = \begin{cases} 1, \left[\{ S(x,y) \le (\mu_S + \delta_S) \} \ \& \ \{ I(x,y) \ge \mu_I + 0.25 \cdot \delta_I \} \right] \\ 0, \ otherwise \end{cases} \quad (8)$$

$$b_{white(l)} = \begin{cases} 1, \left[\{ S(x,y) \le (\mu_S + \delta_S) \} \ \& \ \{ I(x,y) \ge \mu_I - 0.33 \cdot \delta_I \} \right] \\ 0, \ otherwise \end{cases} \quad (9)$$

$$b_{white(h)} = \begin{cases} 1, \left[\left\{ S\ (x, y) \le \left(\mu_S + \delta_S \right) \right\} \ \& \ \left\{ I\ (x, y) \ge \mu_I + 0.50 \cdot \delta_I \right\} \right] \\ 0, \ otherwise \end{cases} \tag{10}$$

where *S(x, y)* and *I(x, y)* are saturation and intensity components of *x*th, *y*th pixel respectively. μ_S and μ_I are mean values for saturation and intensity, δ_S, δ_I are standard deviation values for saturation, intensities of white LP of sample data, respectively. $b_{white(n)}$, $b_{white(l)}$ and $b_{white(h)}$ are white candidate binary masks. An LP image and its color segmentation results are depicted in Fig. 4(a) – (c) (green, yellow and white back ground LP), respectively.

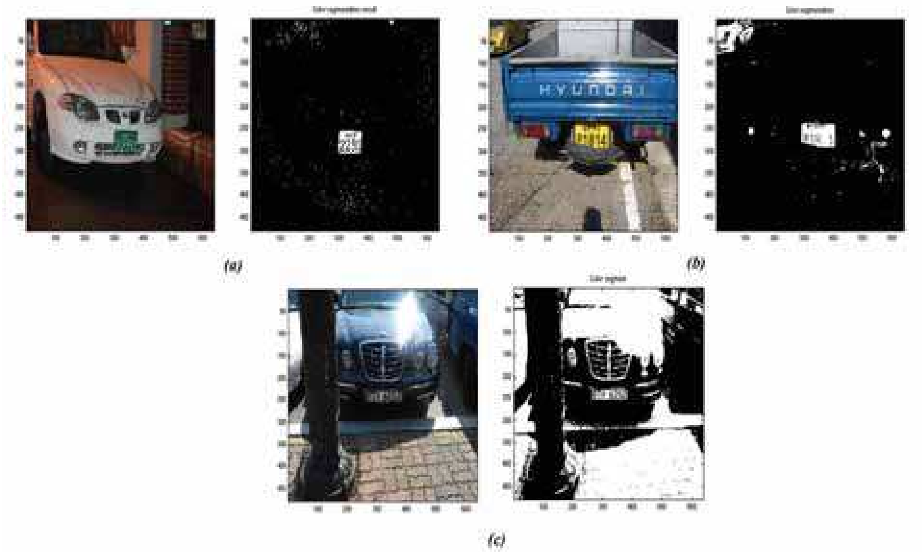

Fig. 4. An LP image *(left)* and its color segmentation results *(right)* using HSI color model

Color segmentation parameters are very sensitive in order to detect as many candidates as possible. All false candidates will be filtered out on the next stages. According to the prior knowledge of vehicle LP inspection, all license plates must be rectangular in shape and have the dimensions and have all alphanumeric characters written in one or two rows, in LP region. After the segmentation, there may still exist noises in the image and that is not ideal. These noises have many types, such as small holes or/and bulges of the target candidate regions. The problem may be resolved by using mathematical morphology processing method. Mathematical morphology is used as a potent tool for image analysis which is based on shapes in the image, not pixel intensities. The two principal morphological operations are dilation and erosion. Dilation allows objects to expand and erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded. Dilation and erosion are combined into other two operations: opening and closing. In this part of the application, we use the closing operation which is dilation followed by erosion to fill in holes and gaps smaller than the structuring element on the plate image. Removal of those holes plays an important role in calculating bounding box region. Implementation of morphological closing operation is depicted in Fig. 5(c) – 7(c), respectively.

5.2 Labeling and filtering

After the candidate regions are obtained by applying color segmentation, features of each region are to be extracted in order to correctly differentiate the LP regions from others. Next step of proposed algorithm is labeling the connected components. In the proposed method, a recursive algorithm is implemented for connected component labeling operation. Recursive algorithm (Shapiro et al., 2001) works on one component at a time, but can move all over the image. In this step we extract candidate regions which may include LP regions from the binary mask obtained in the previous step. During this step, main geometrical properties of LP candidate such as area, bounding box, and aspect ratio are computed.
Following the successful connected component labeling operation in image, measurements such as the area, the bounding box and the aspect ratio for every binary object in the image are performed.
A bounding box is a rectangle whose horizontal and vertical sides enclose the region and touch its topmost, bottommost, leftmost, and rightmost points. Rectangularity is defined as the ratio of the area of candidate object's MER (minimum enclosing rectangle) and the area of the object. Here, the area is measured in pixels and indicates the relative size of the object.
The aspect ratio (also called elongation or eccentricity), is defined by the ratio of the bounding box of an object. This can be found by scanning the image and the minimum and maximum values on the row and the columns, where the object lies. This ratio is defined by

$$\rho_A = \frac{c_{\max} - c_{\min} + 1}{r_{\max} - r_{\min} + 1} \tag{11}$$

where c and r indicate columns and row, respectively. Objects which satisfy ρ_A (aspect ratio) bounds 1 to 3 for green, 1 to 2 for yellow, and 1 to 6 for white LPs are considered as candidate regions. These parameters are used for filtering operation to eliminate LP-like objects from candidate list. Filtering operation is done on geometrical properties of LP regions. Figs. 5 - 7 illustrate the steps for license plate segmentation: (a) an LP image, (b) color segmentation result, (c) implementation of morphological closing operation for removing small holes in candidate region, (d) detected candidate after filtering, and (e) candidate region detection. The most important LP-parameters are grouped in Table 2.

Filtering parameter	CR (green)	CR (yellow)	CR (white)
Bounding box	[0.6, 1.0]	[0.7, 1.0]	[0.7, 1.0]
Aspect ratio	[1.0, 3.0]	[1.0, 2.0]	[1.0, 6.0]
Possible shapes	Rectangle		

Table 2. Filtering properties

Here CR indicates candidate region.

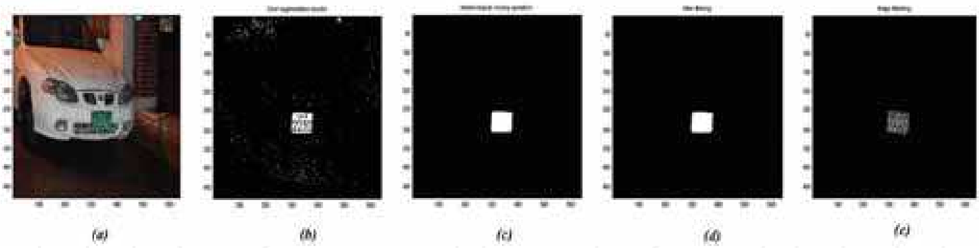

Fig. 5. Illustration of license plate segmentation: (a) an LP image in a night time, (b) color segmentation result, (c) implementation of morphological closing operation for removing small holes in candidate region, (d) detected candidate after filtering, and (e) candidate region detection

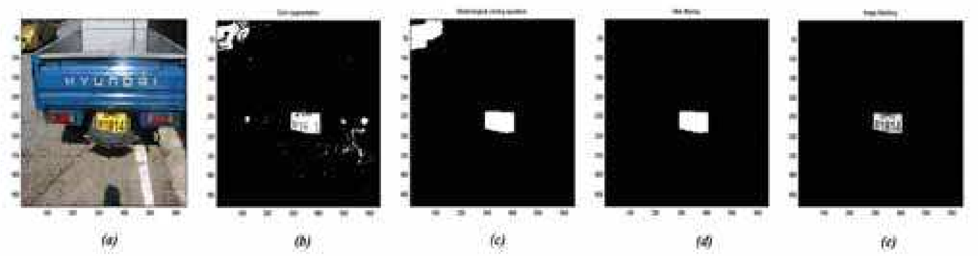

Fig. 6. Illustration of license plate segmentation: (a) an LP image in a strong sunshine, (b) color segmentation result, (c) implementation of morphological closing operation for removing small holes in candidate region, (d) detected candidate after filtering, and (e) candidate region detection

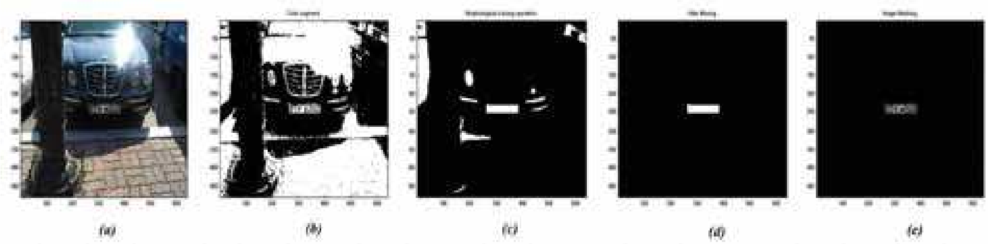

Fig. 7. Illustration of license plate segmentation: (a) an LP image in a strong sunshine reflected by vehicle mirror and also a light post located in front of vehicle, (b) color segmentation result, (c) implementation of morphological closing operation for removing small holes in candidate region, (d) detected candidate after filtering, and (e) candidate region detection

5.3 Determining the angle of the candidate - rotation adjustment

As license plates can appear at many different angles (in our experiment is more robust when LP is rotated from -15 to +15 degree) to the camera's optical axis, each rectangular candidate regions is rotated until they are all aligned in the same way before the candidate decomposition. Following the successful filtering operation in image, measurements such as center of area and the axis of least second moment are employed to solve the rotation adjustment problem.

The center of area (centroid), is the midpoint along each row and column axis corresponding to the "middle" based on the spatial distribution within candidate object. This feature used to locate an object in the 2D image plan is defined by the pair $\left(\overline{r_i}, \overline{c_i}\right)$:

$$\overline{r_i} = \frac{1}{A_i} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} r\, I_i(r, c) \tag{12}$$

$$\overline{c_i} = \frac{1}{A_i} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} c\, I_i(r, c) \tag{13}$$

where $\overline{r_i}$ and $\overline{c_i}$ indicates row and column coordinate of the center of area for the ith object. The area, A_i, is measured in pixels and indicates the relative size of the object.

The least second moment provides the principal axis as the orientation with the candidate object. For getting principal axis of detected candidate region, we compute central moments of detected candidate region. The central moments are defined as

$$\mu_{pq} = \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} \left(r - \overline{r}\right)^p \left(c - \overline{c}\right)^q I\,(r, c) \tag{14}$$

We apply this result to obtain a direction of principal axis by centroid of detected candidate region. Angle of principal axis moments is obtained as

$$\theta = \frac{1}{2} \arctan\left(\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right) \tag{15}$$

where θ denotes an angle between basis horizontal coordinate and principal axis of region. Figure 8 portrays a sequence of successful license plate identification.

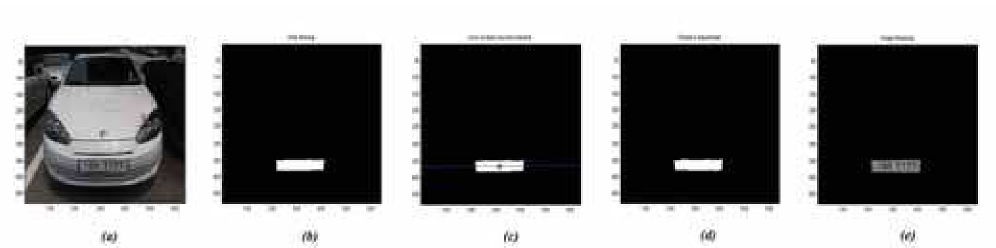

Fig. 8. Illustration of license plate segmentation: (a) an LP image (b) detected candidate after filtering (c) principal axis (d) rotation adjustment, and (e) extracted candidate

5.4 Decomposing candidate's

Information extracted from image and intensity histograms plays a basic role in image processing, in areas such as enhancement, segmentation, and description. In this section,

verification and detection of the VLP region as well as character segmentation are considered and discussed in this study. The algorithm scheme for candidate decomposition is shown in Fig. 9.
Once the candidate area is binarized, the next step is to extract the information. At first, regions without interest such as border or some small noisy regions are eliminated; the checking is made by height comparison with other plate characters height. Following procedure is performed when LP color is green and yellow: first we proceed by performing horizontal position in the histogram; two objects are found where each object corresponds with one row. Then the rows are isolated and processed separately. As mentioned before in Sect. 3, two types of plate are considered.

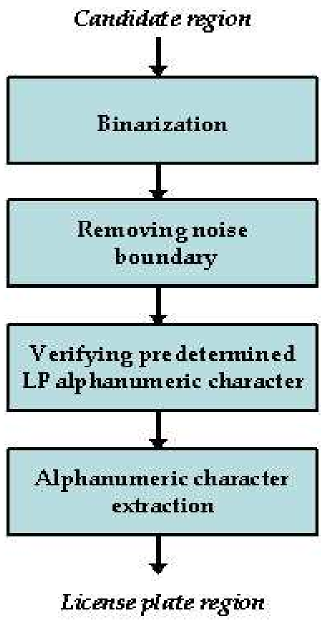

Fig. 9. Algorithm scheme for candidate decomposition

Processing of the upper row: first filter phase is performed to eliminate the regions without interest. Then vertical position histogram is processed. The upper row also has two different types as we mentioned in Sect. 3. As it can be observed, usually in the upper row we can find two plate-fixing dots as shown in Fig. 1. The right plate-fixing dot does not even appear in the binarization process due to the fact that it is printed green. The left plate-fixing dot is also eliminated. The checking is made by height comparison. From the vertical position in the histogram we can find isolated alphanumeric characters.

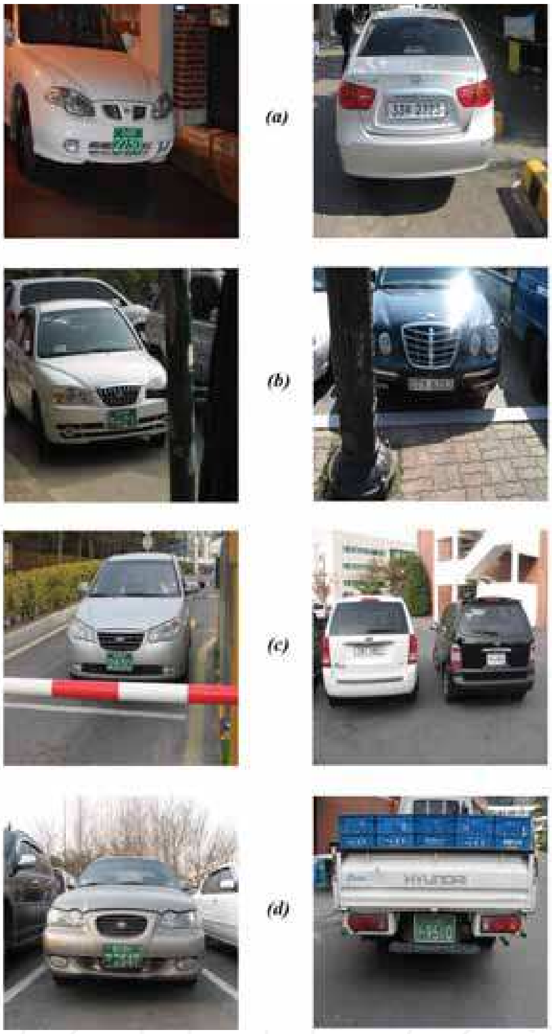

Fig. 10. Example images: (a) different illuminations, (b) complex scenes, (c) various environments, and (d) damaged license plates

Processing of the lower row: first filter phase is performed to eliminate the regions without interest. Then vertical position histogram is performed and from the vertical position histogram the alphanumeric characters are isolated.
According to the prior knowledge of vehicle LP inspection, all white LPs contain seven alphanumeric characters as well as written in a single row. The following procedure is performed for character segmentation: After eliminating border area, vertical position in the histogram is performed for segmenting predetermined alphanumeric characters. As it can be observed, usually we can find also two plate-fixing dots in upper area of plate region. The right plate fixing dot or both plate-fixing dots do not even appear in the binarization

process due to the fact that it is printed white. The left plate-fixing dot is also eliminated; this checking is made by height comparison.
Figure 11 shows the following steps for verifying predetermined alphanumeric characters (white back ground LP): (a) extracting candidate region, (b) vertical position histogram with LP border, (c) horizontal position histogram with LP border, (d) horizontal position histogram without LP border,(e) view of normalization candidate region after removing border and noisy area, (f) vertical position histogram (seven peaks for predetermined seven alphanumeric characters in LP region), and (g) character extraction.

6. Experimental results

All experiments have been done on Pentium-IV 2.4 GHz with 1024 MB RAM under Matlab environment. In the experiments, 150 images were used the size is 640 × 480 pixels, some images which are shown in Fig. 10. The images are taken from (a) different illuminations (night time, strong sunshine, and shadow), (b) complex scenes where several objects such as trees, light post in front of vehicles, (c) various environments in campus parking, access areas and more than one license plates in the same image, and (d) damaged LP as bent or old. They were taken in distance from 2 up to 8 m and the camera was focused in the plate region. Under these conditions, success of LP detection has reached to more than 94%. Results of candidate region detection are shown in Table 3.

Image group	Total images	Detected LPs	Success rate (%)
Different illuminations	57	53	92.98%
Complex scenes	15	14	93.34%
Various environmants	73	69	94.52%
Damaged LP	5	5	100%
Total	150	141	94%

Table 3. Detection results

A common drawback of the proposed VLPD system is the failure to detect the boundaries or border of license plates. This occurs when vehicle bodies and their license plate possess similar colors. The average computational time for the color segmentation and filtering operations of the proposed method are shown in Table 4.

Stage	Avg time (s)	Std. deviation (s)
Color segmentation	0.16	0.07
Filtering	0.07	0.02

Table 4. Average computation time

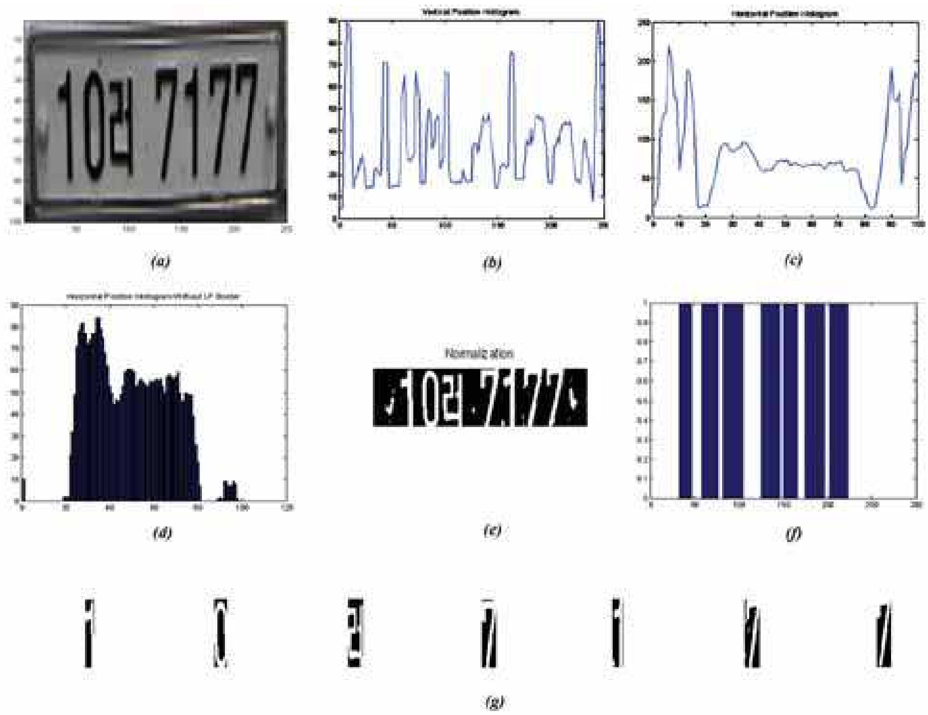

Fig. 11. Steps for verify predetermined alphanumeric characters (white back ground LP): (a) extracting candidate region, (b) vertical position histogram with LP border, (c) horizontal position histogram with LP border, (d) horizontal position histogram without LP border,(e) view of normalization candidate region after removing border and noisy area, (f) vertical position histogram (seven peaks for predetermined seven alphanumeric characters in LP region), and (g) character extraction.

7. Conclusion

In conclusion, a new method is adopted in this paper to select statistical threshold value in HSI color model. In the proposed method candidate regions are found by using HSI color model. These candidate regions may include LP regions; geometrical properties of LP are then used for classification. The proposed method is able to deal with candidate regions under independent orientation and scale of the plate. Finally, VLP regions containing predetermined LP alphanumeric character are verified and detected by using position histogram. Color arrangement and predetermined LP alphanumeric character of the Korean license plate are important features for verification and detection of license plate regions.
While conducting the experiments, different illumination conditions and varied distances between vehicle and camera often occurred. In that case, the result that has been confirmed is very much effective when the proposed approach is used. However, the proposed method is sensitive when vehicle bodies and their license plates possess similar colors. We leave these issues to be considered in future studies.

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For more than 40 years, pattern recognition approaches are continuingly improving and have been used in an increasing number of areas with great success. This book discloses recent advances and new ideas in approaches and applications for pattern recognition. The 30 chapters selected in this book cover the major topics in pattern recognition. These chapters propose state-of-the-art approaches and cutting-edge research results. I could not thank enough to the contributions of the authors. This book would not have been possible without their support.