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An Efficient Method for Correcting Vehicle License Plate Tilt

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***Abstract*—Tilt correction is a very crucial and inevitable task in the automatic recognition of the vehicle license plate (VLP). In this paper, according to the least square fitting with perpendicular offsets (LSFPO) the VLP region is fitted to a straight line. After the line slope is obtained, rotation angle of the VLP is estimated. Then the whole image is rotated for tilt correction in horizontal direction by this angle. Tilt correction in vertical direction by inverse affine transformation is proposed for removing shear from the LP candidates. Despite the success of VLP detection approaches in the past decades, a few of them can effectively locate license plate (LP), even when vehicle bodies and LPs have similar color. A common drawback of color-based VLP detection is the failure to detect the boundaries or border of LPs. In this paper, we propose a modified recursive labeling algorithm for solving this problem and detecting candidate regions. According to different colored LP, these candidate regions may include LP regions. Geometrical properties of the LP such as area, bounding box and aspect ratio are then used for classification. Various LP images were used with a variety of conditions to test the proposed method and results are presented to prove its effectiveness.**

***Keywords*-tilt correction; least square fitting with perpendicular offsets (LSFPO); affine transformation; and recursive labeling algorithm**

I. INTRODUCTION

As license plates can appear at many different angles to the camera's optical axis, each rectangular candidate region is rotated (i.e. correcting tilt) until they are all aligned in the same way before the candidate decomposition. License plate tilt correction and detection are crucial and indispensable components of the character segmentation and automatic recognition of the VLP. Humans can perform the usual target recognition without too much effort. However, by computer the task of recognizing a specific object in an image is one of the most difficult topics in the field of computer vision or digital image processing. The vehicle license plate detection (VLPD) task is quite challenging from vehicle images due to the view point changes, when vehicle bodies and LP have similar color, multi-style plate formats, distance changes, complex background and the nonuniform outdoor illumination conditions during image acquisition in [2]. In addition, a VLPD system should operate fast enough to be real time to satisfy the needs of intelligent transportation system (ITS) and not miss a single object of interest from the vehicle image. Vehicle license plate detection is also very interesting in finding an LP area from a vehicle image. Detecting speeding cars, security control in restricted areas, unattended parking zones, traffic law enforcements, and electronic toll collection are some applications for a VLPD 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.

As far as tilt correction and detection of the license plate region are concerned, researchers have found various methods of correcting tilt and locating license plate. For example, Karhunen-Loeve (K-L) transformation method has been introduced for correcting a VLP tilt in [1]. However, no explanation of extracting LP region has been given in the paper. A method for multi-style LP recognition has been presented in [2]. This method has introduced the density-based region growing algorithm for detecting LP location. In [3], a technique based on extract 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. A region-based LP detection method has been presented in [4], which first applies a mean shift procedure in a spatial-range domain to segment a color vehicle image in order to get LP regions. Fuzzy logic has been applied in detecting license plates in [5].

The emphasis of this paper is on the implementation of a line fitting method based on least square fitting with perpendicular offsets (LSFPO) for correcting a VLP tilt in horizontal direction. Tilt correction in vertical direction by reorientation of the titled LP candidate through inverse affine transformation is propose and implement for removing shear from the LP candidates. Horizontal tilt correction performance of LSFPO is evaluated in comparison with other representative method such as, the least square fitting with vertical offsets (LSFVO) of [1] and the principal axis method. This paper explores the line fitting method based on LSFPO that outperforms other two correction methods

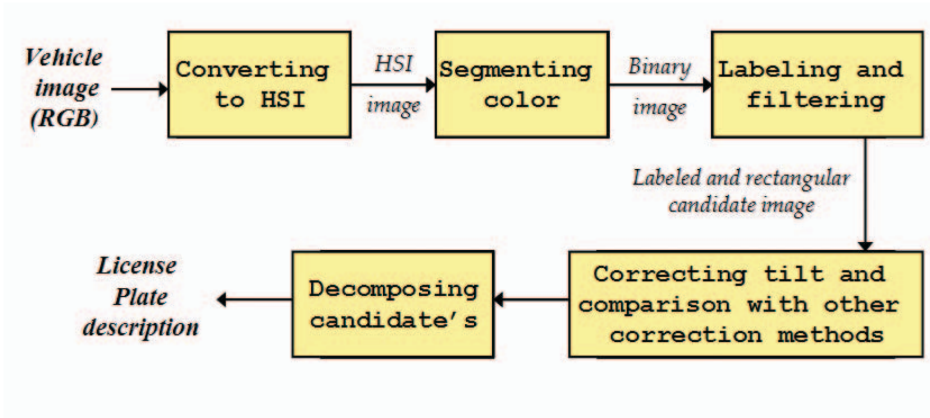

Figure 1. Proposed vehicle license plate tilt correction and detection framework.

because of faster processing time, more precise tilt angle, and easily implemented.

In addition, we focus on the consolidation of a new method to detect candidate regions when vehicle bodies and LPs have similar color. A common drawback of color-based VLPD is the failure to detect the boundaries or border of LPs. This occurs when vehicle and LPs have similar colors. To overcome the common drawback, in this paper, we propose and implement a new method named as modified recursive labeling algorithm. Finally, decomposing of a candidate region which contains a predetermined LP alphanumeric character, by using position in the histogram to verify and detect VLP regions.

II. Proposed Framework

In the author's previous work [6], VLP detection algorithm based on color space and geometrical properties was presented. We propose in this section, an enhanced version of the framework for VLP tilt correction and detection as shown in Figure 1. To improve 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. For correcting a VLP tilt in horizontal direction, a line fitting method based on LSFPO is introduced. Horizontal tilt correction performance of LSFPO is evaluated in comparison with other correction methods such as line fitting based on LSFVO [1] and principal axis. Tilt correction in vertical direction by reorientation of the tilted LP candidate through inverse affine transformation is propose and implement for removing shear from the LP candidates. Furthermore, a common drawback of color-based VLPD is the failure to detect the boundaries or border of LPs. This occurs when vehicle and LP have similar colors. It is important to mention here that some previous researches [4] and [5] doesn't solve this problem and they assert leave these issues to be considered in future study. To overcome this common drawback, we propose and implement a new method named as modified recursive labeling algorithm for detecting candidate regions.

III. VLP Tilt Correction and Detection Module

In this section, the four primary stages of the proposed VLP tilt correction and detection framework, i.e., segmenting color, labeling and filtering, correcting tilt, and decomposing candidates have been discussed in details. Color arrangement of the Korean LPs are well classified. Standard LP contains Korean alphabets and number which are shown in Figure 2. A More detailed explanation for color arrangement and outline of the Korean VLPs could be found in [6].

A. Segmenting color

Color is a distinctive feature which can be used for VLPD. Representation of plate color in an invariant manner is of main objectives for our color-based LP detection method. In the proposed framework, input vehicle images are converted into HSI color images. Then the candidate regions are found by using HSI color space on the basis of using hue, saturation and/or intensity. Many applications use the HSI color model. Machine vision uses HSI color model in identifying the color of different objects. Plate color information is used to detect candidate regions in our experiments, and

Figure 2. Outline of the Korean VLPs and LP images of one nation with different style.

shape properties of LP allow reducing number of LP-like candidates. A More detailed explanation could be found in [6] for detecting green, yellow, and white license plate pixels. Color segmentation parameters are very sensitive in order to detect as much candidates as possible. All false candidates will be filtered out on the next stages. Examples of proposed color segmentation method is depicted in Figure 3.

B. 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. The next step of proposed framework is labeling the connected components. In the proposed method, a recursive algorithm is implemented for connected component labeling operation. A common drawback of color-based VLPD is the failure to detect the boundaries or border of LPs. This occurs when vehicles and LPs have similar colors. To overcome this common drawback, we proposed and implemented a new method named modified recursive labeling algorithm. If we investigate carefully, when vehicle bodies and LPs have a similar color, we can find there is little color differences between LPs and vehicle color. Based on this idea, we overcome this problem, by trying to find those color difference parameters. Two four-connected pixels are grouped if $Dist(I_{i,j}, I_{m,n}) < D_{min}$.

$$Dist\left(I_{i,j}, I_{m,n}\right) = \sum_{k=\{R,G,B\}} \left|I_{i,j}^{k} - I_{m,n}^{k}\right| \quad (1)$$

In this step we extract candidate regions that 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. A more detailed explanation could be found in [6]. These parameters are used in the filtering operation to eliminate LP-like objects from candidate list. Figure 3 illustrates the step for LP segmentation.

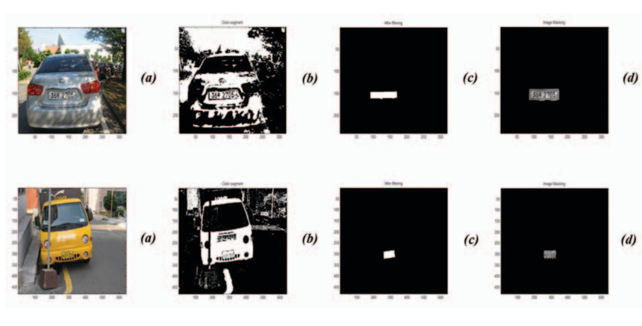

Figure 3. Successful license plate identification sequence in two unmoving vehicle: (a) an LP images, when vehicles and LPs have similar colors, moreover an LP image (first row) in the sunshine with shadow and also a obstacle located in front of vehicle (second row), respectively, (b) color segmentation results, (c) detected candidate after implementation of morphological closing operation and filtering, and (d) extracted candidate after tilt correction in horizontal direction.

C. Correcting tilt

In order to facilitate character segmentation and recognition in a VLPR system, the tilted LPs in the located image should be corrected in both the horizontal and vertical directions. In this subsection correcting tilt in horizontal and vertical direction have been discussed in details.

1) Correcting horizontal tilt:: Following the successful filtering operation of the image, in this paper, according to the LSFPO, the VLP candidate region is fitted to a straight line. After the line slope is obtained, tilt or rotation angle is estimated. Figure 4(a, b) depicts rotation angle α between the principal axis X' of and the the horizontal axis X of the tilt VLP region. Then, the whole image is rotated for tilt correction in horizontal direction by this angle. Tilt correction performance of LSFPO is evaluated in comparison with other correction methods such as the least square fitting with vertical offsets (LSFVO) and the principal axis that are considered in this study are described.

Fitting the straight line based on LSFPO: The least square method is a commonly used fitting method. Fitting requires a parametric model that relates the response data to the predictor data with one or more coefficients. To obtain the coefficient estimates, the least square method minimizes the summed square of residuals or offsets. The residual for the ith data point d_i is defined as the difference between observed response value y_i and the fitted response value $\hat{y}_i$ and is identified as the error associated with the data. The residual of the best-fit line for a set of n points using squared perpendicular distances d_i of points $(x_i,\ y_i)$ are given by $G = \sum_{i=1}^{n} d_i^2$. The perpendicular distance as shown in Figure 5(a) from a line $y = b + a_1 x$ to point i is given by $d_i = \frac{[y_i-(b+a_1 x)]}{\sqrt{1+a_1^2}}$. The objective function to be minimized is $G = \sum_{i=1}^{n} d_i^2 = \sum_{i=1}^{n} \frac{[y_i-(b+a_1 x_i)]^2}{1+a_1^2}$. From objective function, partial derivative with respect to a_1 is obtained as follows:

$$\frac{\partial G}{\partial a_1} = \frac{2}{1+a_1^2} \sum_{i=1}^{n} \left[y_i - (b + a_1 x_i)\right](-x_i) +$$

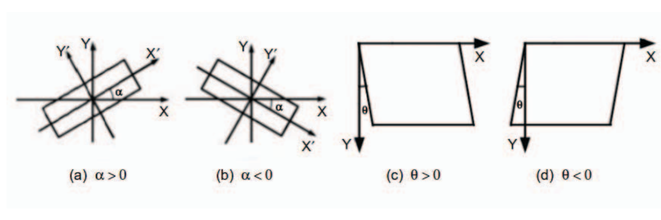

Figure 4. VLP tilt image in horizontal direction: (a) tilt angle $\alpha > 0$ and (b) tilt angle $\alpha < 0$. VLP tilt image in vertical direction: (c) tilt angle $\theta > 0$ and (d) tilt angle $\theta < 0$.

$$\sum_{i=1}^{n} \frac{[y_i - (b + a_1 x_i)]^2 (-1)(2b)}{(1+b^2)^2} = 0 \tag{2}$$

Solving the above equation, a_1 is obtained:

$$A = \frac{1}{2} \frac{\sum\limits_{i=1}^{n} y_i^2 - n\bar{y}^2 - \sum\limits_{i=1}^{n} x_i^2 - n\bar{x}^2}{n\bar{x}\bar{y} - \sum\limits_{i=1}^{n} x_i y_i};$$

$$a_1 = -A \pm \sqrt{A^2 + 1} \tag{3}$$

Fitting the straight line based on LSFVO: Given a set of data points. It is desired to find the best fitting line from a given set of data points. In principle, deviation between data and fitting line should be minimized. The deviation $d_i = y_i - \hat{y}_i$ is commonly called offsets or residue. The vertical distance as shown in Figure 5(b) from a line $y = b + a_1 x$ to point i is given by $d_i = [y_i - (b + a_1 x_i)]$. LSFVO enable the sum of the d_i^2 to achieve the minimum, namely objective function $G = \sum_{i=1}^{n} d_i^2$ is the minimum. The objective function is $G = \sum_{i=1}^{n} d_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} [y_i - (b + a_1 x_i)]^2$. From the objective function, partial derivative with respect to a_1 is obtained as follows:

$$\frac{\partial G}{\partial a_1} = -2 \sum_{i=1}^{n} [y_i - (b + a_1 x_i)](x_i) = 0 \tag{4}$$

Solving the above equations, a_1 is obtained:

$$a_1 = \frac{n \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2} \tag{5}$$

x_i and y_i are inserted into (3) and (5), to get the fitting slope a_1. Let $tan\ \alpha = a_1$, and get the tilt angle α. Rotate the entire image with α from centroid rectangular candidates region of LP image and perform the tilt correction. Figures 6(d1-e1) and 6(d2-e2) portrays a sequence of successful horizontal tilt correction by LSFPO and LSFVO, respectively.

Determining the rotation angle using principal axis: Following the successful filtering operation of the image, measurements such as center of area and the axis of least second moment are employed to solve the rotation adjustment problem. A more detailed explanation could be found in [6]. Figures 6(d3) and 6(e3) portrays a sequence of successful horizontal tilt correction by the principal axis (PA) method.

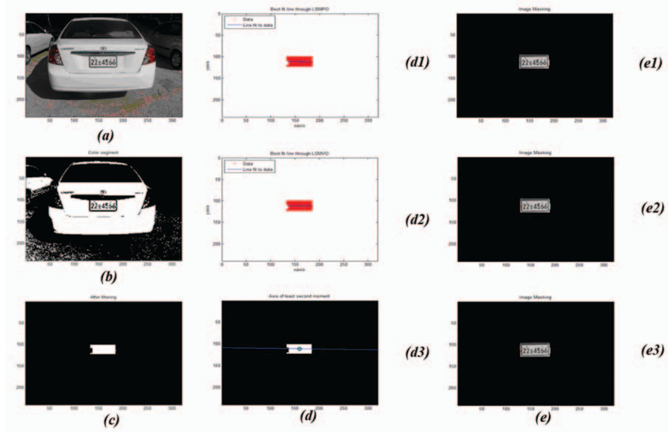

Figure 6. Illustration of license plate segmentation : (a) an LP image, (b) color segmentation results, (c) detected candidate after filtering, (d) finding best fitting line through LSFPO (d1), LSFVO (d2), and principal axis (d3), and (e) extracted candidate after horizontal tilt correction, respectively.

2) Correcting vertical tilt: The purpose of correcting tilt in vertical direction is to correct VLP shear left and right in horizontal axis X as shown in Figure 4(c, d). Vertical tilt correction is also essential to facilitate character segmentation and to recognize VLP character accurately. Tilt correction in vertical direction by reorientation of the tilted LP candidate through inverse affine transformation is proposed and implemented for removing shear from the LP candidates.

Shear correction through general affine transformation: A general affine transformation (AT) from 2D to 2D as in (6) requires six parameters and can be computed from only 3 matching pairs of points $\left(([x_j,\ y_j],\ [u_j,\ v_j])_{j=1,\ 3}\right)$.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{6}$$

We use Hough transform for getting 4 vertexes from candidate LP regions. Boundary of candidate LP (i.e. contour) and vertexes are detected by intersection of hough line. After

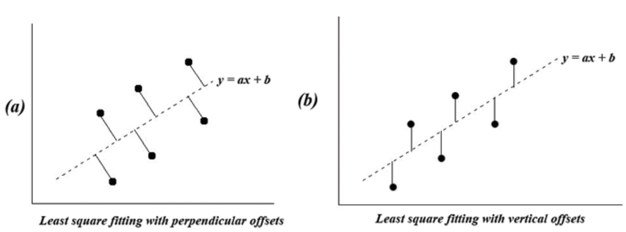

Figure 5. Least squares fitting for finding a straight line: (a) perpendicular offsets and (b) vertical offsets.

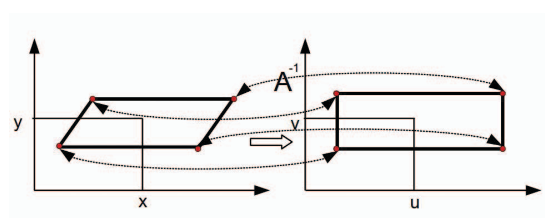

Figure 7. Reorientation of 4 points by using inverse general affine transformation.

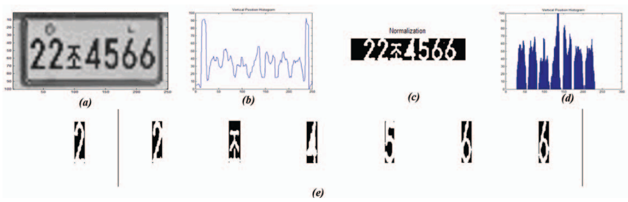

Figure 8. Steps for verifying predetermined alphanumeric characters: (a) extracting the candidate region, (b) vertical position histogram with LP border, (c) view of normalization candidate region after removing border and noisy area, (d) vertical position histogram (seven peaks for predetermined seven alphanumeric characters in LP region), and (e) character extraction.

determining the 4 points (vertexes) from LP candidate, the inverse general affine transformation (A^{-1}) is applied for rectifying candidate LP region as shown in Figure 7.

D. Candidate decomposition

Information is extracted from the image by intensity histograms that play 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. 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. Figure 8 shows the results for verifying predetermined alphanumeric characters.

IV. Experimental results and conclusions

All experiments were done on Pentium-IV 2.4 GHz with 1 GB RAM under MATLAB environment. Images of size 640*480 and 320*240 pixels were used. The image database consists of 200 digital images from different two groups. Some images are shown in Figures 9 and 10. In order to evaluate the proposed framework, two groups of experiment were conducted. First group was used to compare the proposed framework with sliding concentric windows (SCW) method of [3] and mathematical morphology (MM) method of [7]. Korean VLP images of in this group (see Figure 9) were taken when limitations in distance, angle of view, and illumination conditions were set, and background complexity was low. These images are easy for detection, thus the LP detection rate of the proposed method (LSFPO method and AT) is 100%. A comparison between the proposed method and some well-reported methods in the literature is given in Table I. From Table I it can be seen that the proposed method outperforms the method report in [3] and [7] from the detection rate points of view.

Figure 9. Some sample vehicle images in first group: (a) frontal view and (b) back view.

Figure 10. Example VLP images from second group: (a) different illuminations, (b) complex scenes, (c) various environments, and (d) damaged License plates.

Table I
Comparison of detection rates.

Reference number	Detection rate	Detection method
3	82.5%	SCW and histogram
7	80.4%	MM
The proposed	100%	LSFPO and AT

The second group contains 175 images. Some images which are shown in Figure 10. All images in that group represents South Korean license plates from the natural scenes obtained in the nonuniform outdoor illumination conditions, multi-style and color of license plates, and various angles of vision. They were taken in distance of 3 to 15 m. Under these conditions, the success of LP detection has reached to more than 96%.

In tilt correction experiments, we compare the tilt performance results of LSFPO with those of LSFVO and principal axis. For comparing tilt performance, initially we take 9 sample images, where rectangular candidate region is rotated in various angle. Figure 11 illustrates the steps for finding best fitting line and principal axis from among one sample image, when rectangular candidate region rotated by $45°$. In this implementation, after obtaining line slope and principal axis, rotation angle error is estimated as follows through LSFPO $(0.0200°)$, LSFVO $(6.9187°)$ and principal axis $(0.0249°)$, respectively. Experimental result indicate that, less tilt error and the top and bottom line are basically horizontal in Figures $11(c1)$, and $11(c3)$. However, $11(c2)$ (i.e. LSFVO), have some tilt, and the rotation angle is either small or large. The average processing time for tilt estimation (TE) and rotation adjustment (RA) operations of

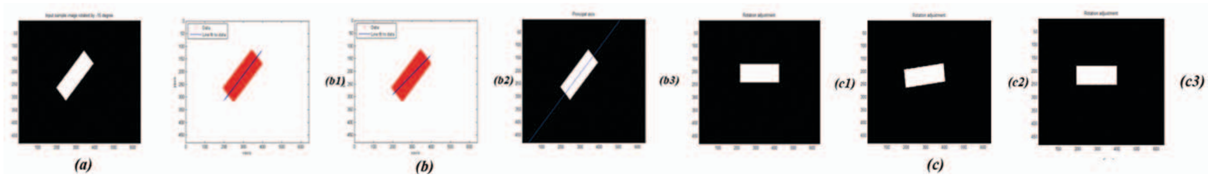

Figure 11. Illustration of finding best fitting line and principal axis from sample image: (a) input image, (b) finding best fitting line through LSFPO (b1), LSFVO (b2) and principal axis (b3), and (c) extracted candidate after rotation adjustment, respectively.

Table II
AVERAGE COMPUTATIONAL TIME FOR TILT ESTIMATION AND ROTATION ADJUSTMENT.

Correction method	Average computational time (s) for TE	Average computational time (s) for RA
LSFPO	0.0146	0.2207
LSFVO	0.0174	0.2209
Principal axis	0.0280	0.3236

the proposed method are shown in Table II.

To overcome common drawbacks of color-based VLP detection, we implemented a modified recursive labeling algorithm. In our experiments, in 27 images vehicle bodies and LPs have similar color. Among them in 26 images, LPs were detected successfully. Figures 3 and 6 show successful plate identification, where vehicle bodies and their LPs possess similar colors. The average computational time for the color segmentation and filtering operations of the proposed method are 0.16 and 0.07 s, respectively.

In conclusion, a method is adopted in this paper for correcting tilt which is a very crucial part of the VLP automatic recognition. In the vehicle horizontal tilt correction process, three correction methods are implemented for comparing the tilt performance results. Analysis and simulation results suggest that LSFPO and principal axis method tilt correction are more precise than LSFVO. However, LSFPO outperforms than principal axis because of faster computational time, easily implemented and more precise tilt correction.

In this paper, tilt correction in vertical direction by inverse affine transformation is proposed for removing shear from the LP candidates. In addition, the emphasis of this paper is on the implementation of a new method to detect candidate regions when vehicle bodies have similar color. Finally, VLP regions containing predetermined alphanumeric character that are verified and detected by using position in the histogram. Color arrangement and predetermined alphanumeric character of the Korean license plate are important features for verification and detection of license plate regions. While conducting the experiments, different view point, illumination conditions, and varied distances between vehicle and camera often occurred. In such cases, confirmed the result is very effective when the proposed method is used. However, the proposed method is sensitive with motion blur in the input image. We leave these issues for consideration in future studies.

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