Available online at www.banglajol.info

Bangladesh J. Sci. Ind. Res. **52(4)**, 273-280, 2017

BCSIR

BANGLADESH JOURNAL OF SCIENTIFIC AND INDUSTRIAL RESEARCH

E-mail: bjsir07@gmail.com

L*a*b* color model based road lane detection in autonomous vehicles

M. Kazemi* **and Y. Baleghi**

Electrical Engineering Department, Babol Noshirvani University of Technology, Babol, Iran

Abstract

Autonomous vehicles, as a main part of Intelligent Transportation Systems (ITS), will have great impact on transportation in near future. They could navigate autonomously in specific areas or highways and city streets using maps, GPS, video sensors and so on. To navigate autonomously or follow a road, intelligent vehicles need to detect lanes. This paper presents a method for lane detection in image sequences of a camera on top of a robotic vehicle. The main idea is to find the road area using the L*a*b* color space in consecutive frames. Subsequently, by applying this model in road area and equalization of histogram and calculation of gradient image using Sobel operator, the parameters of the lane can be calculated using a Hough transform. The proposed method is tested under various illumination conditions and experimental results indicate the good performance of the proposed method.

Keywords: Intelligent vehicle; Machine vision; Lane detection; Color segmentation; Hough transform

Introduction

Research of road detection techniques is mainly focusing on detecting lane markings. Traffic safety is becoming more and more popular these days due to increase in urban traffic (Bajwa and Kaur, 2013). Automating driving may help reduce this urban traffic. Lane detection and tracking is important to lateral vehicle guidance and lane departure warning which can eliminate many avoidable accidents (Wankhade and Shriwas, 2012). Autonomous navigation on different roads requires the knowledge of lane information, which is also an open problem for autonomous intelligent vehicles and driverless vehicles. To extract lane boundary information, vision is a natural and powerful tool. However, in an outdoor environment vision-based autonomous intelligent robots have many problems in the use of vision sensors. For example, illumination in video streams may change drastically because of entering into a tunnel. However, high curvature, occlusions, varying illumination, and unmarked or partly marked lanes in the image are still challenging situations for this task. Hence, the processing should be robust enough to adapt different road and weather conditions and to tolerate changes in illumination and contrast.

There are several useful technologies of lane detection which has achieved good results for application requirements (Deng *et al.,* 2013) such as, open uniform B-spline curve model (Xu *et al.,* 2009), multiple hyperbola road model (Bai and Wang, 2011) a K-means cluster algorithm (Miao and Shen, 2012) and Inverse Perspective Mapping (IPM) (Aly, 2008). Furthermore, the essential tracking technologies, like Kalman Filter and particle filter, are utilized frequently. Nearly all lane detection systems use the following three steps: lane feature extraction, outlier removal, and tracking (Yoo *et al.,* 2013). Feature extraction is a main step in lane detection. If the feature is not correctly detected, it is difficult to compensate during post processing. Many features such as colors (Wang and Zhang, 2004), corners, edges (Yim and Oh, 2003), and geometric shapes (Apostoloff and Zelinsky, 2003) can be used to represent lanes. Edges are one of the most significant features because lanes create strong edges on the road. In other words, large gradients exist between the road and the lane due to the difference in their intensities. Thus, many conventional methods use gradient-based features (Yoo *et al.,* 2013). Yoo proposed a linear discriminant analysis (LDA)-based gradient-enhancing conversion for illumination-robust lane detection (Yoo *et al.,* 2013). The method produces optimal RGB weights that maximize gradients at lane boundaries on the road to separate lanes from roads.

Aly proposed the algorithm that is called Aly's Method (Aly, 2008). It is based on two main parts, the first part producing an image based on the top view of the road, the

*Corresponding author e-mail: mohamadkazemi9595@gmail.com

so called Inverse Perspective Mapping (IPM). Another major part of algorithm uses RANSAC lane fitting that helps to detect curved lanes and avoid diagnosis false lanes. You proposed a method for road area extraction based on estimated ROI (region of interest) and presented a lane edge feature extraction algorithm on his proposed ROI (You *et al*., 2013).

Song proposed Canny edge and Hough transformation method of structured road lane detection for blind travel aid. Median Filter is used to develop image primarily, then mark off the region of interest in the initial image. Canny edge enhancement, thresholds to segment the image and road lane is fitted by modified Hough Transformation. The experimental results prove that this algorithm is very robust and real-time. In this paper a new improved lane detection algorithm is proposed. Initially, the input image is divided into two parts including road area and non-road area. Color information has been used to detect the road area. Color-Based Segmentation has been used for Road Detection Using the L*a*b* Color Space. Afterward edge detection is performed as a feature extraction method. Finally, Hough transform has been applied to detect lane markers after image noise filtering. This paper is organized as follows: Section II describes an overview of the proposed algorithm. Section III describes color segmentation method for road area detection. In Section IV, the detection (localization) of lane markings by extracting contextual features and modeling them with boosting in road area is discussed. Results and analyses are given in Section V, which introduces experimental results on different road situations. Finally the paper concludes and puts forth the future works in Section 4.

Over view

The proposed algorithm can be used for both still road image and video streams from a camera on intelligent robotic vehicle. Following is a five steps plan, as shown in Fig. 1.

Step 1: Extraction of the road area using an L*a*b* Color Space segmentation. (Also known as the Regions of Interest (ROI)).

Step 2: Removal of the non-road area using morphological operation.

Step 3: Contrast adjustment to facilitate the feature extraction

Step 4: Finally, Hough transformation is used to identify andmark the lanes.

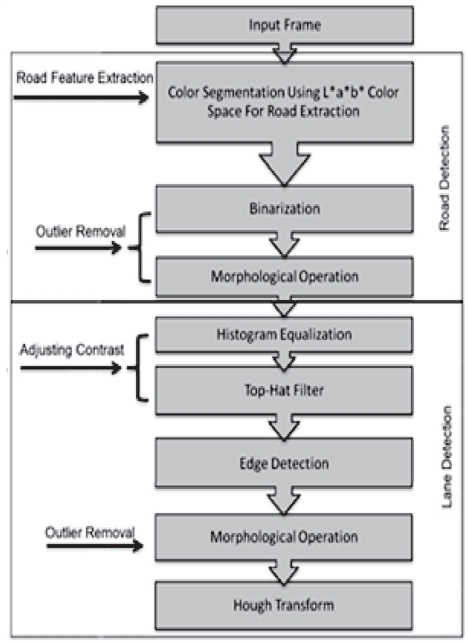


Fig. 1. Flowchart of the algorithm

Road extraction

*Color-Based Segmentation for Road Detection Using the L*a*b* Color Space*

The L*a*b* color space (also known as CIELAB or CIE L*a*b*) is one of the uniform color spaces with dimension L for lightness and a andb for the color-opponent dimensions (one color-three numbers) (Baldevbhai and Anand, 2012). The L*a*b* color space includes all perceivable colors, which means that its gamut exceeds those of the RGB and CMYK color models. This model is based on the colors red, green, yellow, blue, cyan and magenta, as shown in Fig. 2 (Baldevbhai and Anand, 2012).

Fig. 2. The six corner stones of the L*a*b* color space (Baldevbhai and Anand, 2012)

The three coordinates of CIELAB represent the lightness of the color (L* = 0 yields black and L* = 100 indicates diffuse white; specular white may be higher), its position between red/magenta and green (a*, negative values indicate green while positive values indicate magenta) and its position between yellow and blue (b*, negative values indicate blue and positive values indicate yellow), as shown in Fig. 3.

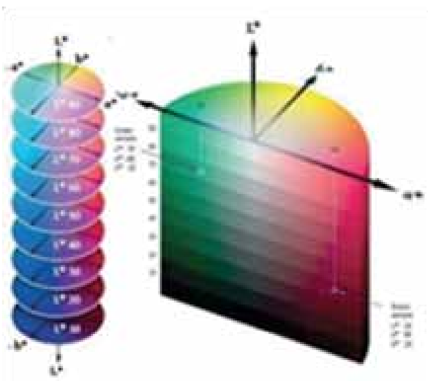


Fig. 3. Colors on each level of lightness (Baldevbhai and Anand, 2012)

The asterisk (*) after *L, a* and *b* are pronounced *star* and are part of the full name.

The values of L*, a*, and b* are calculated according to the formulas below:

$$L^* = 116\,\left(\frac{Y}{Y_n}\right)^{1/3} - 16 \quad (1)$$

$$a^* = 500\left[\left(\frac{x}{x_n}\right)^{1/3} - \left(\frac{Y}{Y_n}\right)\right] \quad (2)$$

$$b^* = 200\left[\left(\frac{y}{y_n}\right)^{1/3} - \left(\frac{z}{z_n}\right)\right] \quad (3)$$

Here, X_n, Y_n and Z_n are the CIE XYZ Tristimulusvalues of the reference white point (the subscript n suggests "normalized") (Rathore *et al.,* 2012). This approach is to choose a small sample region for each color and to calculate each sample region's average color in L*a*b* space. We will use these color markers to classify each pixel. The mean 'a*' and 'b*' values are calculated for each area that are extracted within the RGB image. These values will be calculated with the formula of 1, 2 and 3 and serve as our color markers in 'a*b*' space. Each color marker now has an 'a*' and a 'b*' value. We can classify each pixel in the L*a*b* image by calculating the Euclidean distance between that pixel and each color marker. The smallest distance will tell us that the pixel most closely matches that color marker. For example, if the distance between a pixel and the red color marker is the smallest, then the pixel would be labeled as a red pixel (Baldevbhai and Anand, 2012). Creating an array that contains the color labels, i.e., Blue/Purple Band = 1, Green Band = 2, Magenta Band = 3, Cyan Band = 4, Yellow Band = 5 and Red Band = 6 will result in Bands shown in Fig. 4.

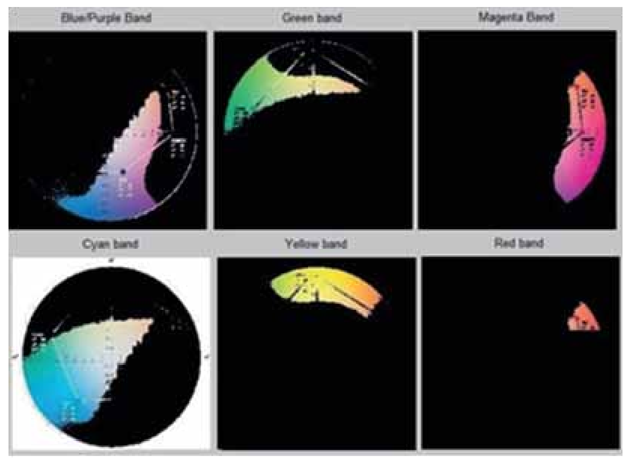


Fig. 4. This picture is showing the region of each band color (Baldevbhai and Anand, 2012)

Binarization and outlier removal

After the detection of road area, a binary image is created by applying a threshold value, So that only the pixels of the road are one and the other pixels are zero, as illustrated in Fig.5 (a). Here the binary image is divided into several areas and road area is one of the largest areas in the region. We will try to fill the holes of the remaining areas with the morphological operations. The largest area is kept as Road area in Fig.5 (b).

Urban roads in different weather conditions such as sunny or cloudy or inside tunnels have different colors. In Table 1 some examples of these colors can be seen which can vary from gray to purple and blue.

According to Road colors as shown in Table 1 and L*a*b* color Banding in Fig. 4, it can be concluded that Road color pixels are placed in the Blue/Purple Band , so in thisL*a*b* color space Image , it just keeps the Blue/Purple Band colors and removes all other colors. The result is shown in Fig.6 (b).

Fig. 5. (a) Original image (b) Road extraction from original image

Table I. Range of the road area colors

Color	HTML/CSS Name	Color	HTML/CSS Name
	Dark slate blue		Light slate gray
	Slate blue		Light steel blue
	Medium slate blue		Dim gray/dim grey
	Medium purple		Gray/grey
	Slate gray		Dark grey/dark grey
	Tuna		silver

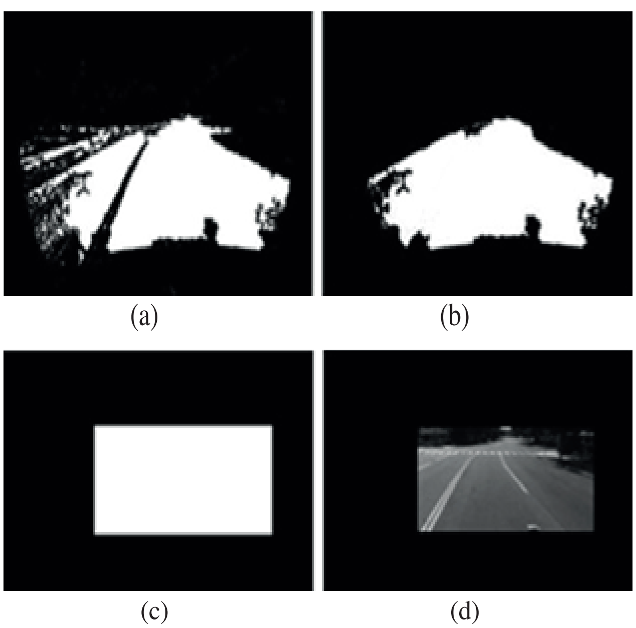


Fig. 6. (a) Result of road area binarization (b) Outlier removal (c) Road position (d) An area that is recognized as a road.

Lane detection stage

Histogram equalization

Intuitively, white lanes have high intensity values, and roads have low intensity values. Histogram equalizationwhich is an algorithm for contrast adjustment can be used to enhance gradients between white lanes and roads (Yoo *et al*., 2013).

The method is useful in images with backgrounds and foregrounds that are both bright or both dark. Histogram Equalization should be applied on the gray level image as shown in Fig. 7(b).

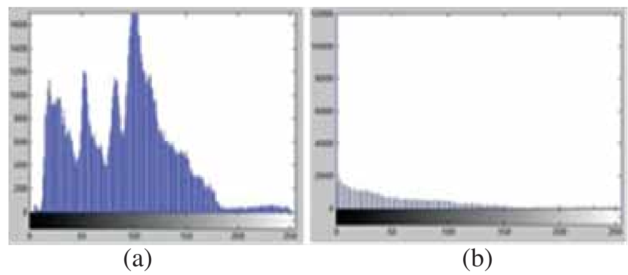
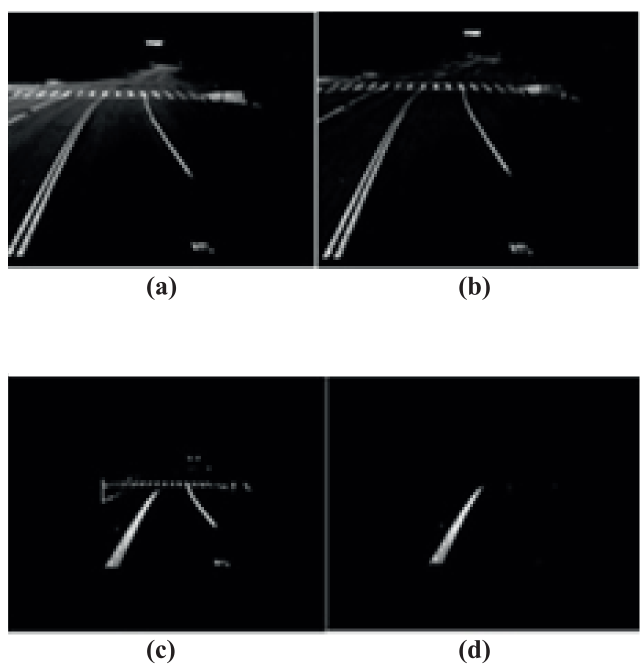


Fig. 7. (a) Histogram of the original image (b) Histogram image with improved contrast

Result of use of Histogram Equalization on image is shown in Fig. 8(a).



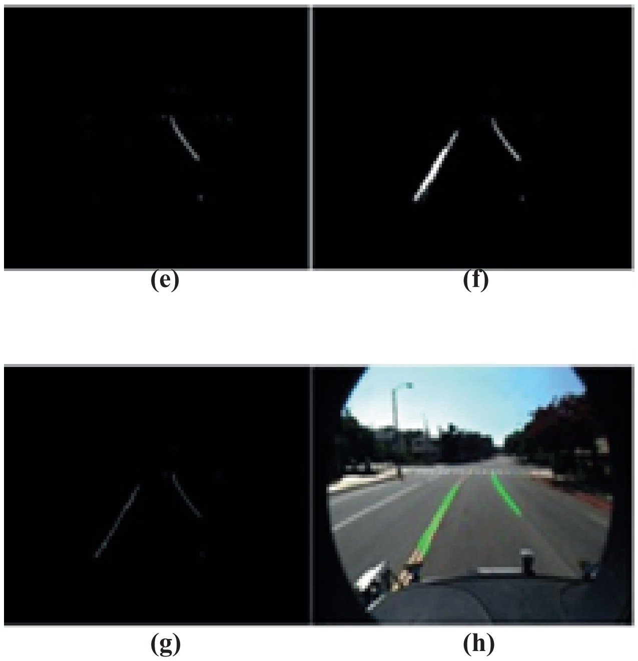


Fig. 8. (a) Result histogram equalization on image. (b) Result of applying top hat filter. (c) Image after applying the sobel operator. (d) Left lane detection. (e) Right lane detection. (f) Sum of two images of Left lane detection and Right lane detection. (g) Skeleton of the image. (h) Lane diagnosed and labeled in original image using Hough transform.

Top hat filter

Top-hat filter is an operation that extracts small elements and details from given images and is defined as the difference between the input image and its opening by some element; Top-hat transforms are used for various image processing tasks, such as feature extraction, background equalization,image enhancement, and others.

Then, the top-hat filter of f with structure element b is given by:

$$T_W(f) = f - f \circ b \quad (4)$$

Thus, these filters are used to correct uneven lighting (eliminating the uneven illumination) when the background is dark and hence the result of applying this filter is shown in Fig. 8(b).

Edge detection

The overall goal of this step is to identify and extract features from the image which allows us to use them for the intended application. As mentioned previously, identification of Lane Edges, Lane colors, Lane texture, direction of Lane and Lane geometry are important features for lane detection. In our work we use edge feature for lane detection. There are several operators for edge detection which are applied to the image, and each will have different results. The Sobel operator, in Lane detection operator, results in much better images.

Sobel operator should be applied only in the vertical direction to the image. The result is a strengthening of the vertical lanes and attenuates the irrelevant horizontal lines in the picture.

To eliminate the irrelevant edges, only the first 15% strongest edges are considered and the rest of the edges are not considered. Fig. 8(c) illustrates the image after applying the Sobel operator.

Outlier removal (Morphological operation)

In this section, for better Lane diagnosis, according to Lane, each left and right angles are diagnosed separately in two images and finally the sum of two images is obtained.

Fig. 8(d) and (e) and (f) illustrate this process. Finally, using the skeleton of the image, it will be easier to diagnose Lane as shown in Fig.8 (g).

Hough transform

The Hough transform is a feature extraction technique used in image analysis, computer vision, and digital imageprocessing. The purpose of the technique is to find imperfect instances of objects within a certain class of shapes by a voting procedure. The classical Hough transform was concerned with the identification of lines in the image, but later the Hough transform has been extended to identifying positions of arbitrary shapes, most commonly circles or ellipses. The Hough transform (HT) is used for initial lane estimation in this algorithm, and the result of applying (HT) is shown in Fig. 8(h).

Experimental result

The proposed algorithm has been simulated by MATLAB codes and tested on more than 1200 frames in various illumination conditions from 4 different databases (Cordova1,

Fig. 9. Lane detection results of the proposed method under various driving conditions. (a), (b), (c), are related to the Cordova 1 database. (d), (e), (f) are related to the Cordova 2 database. (g), (h), (i), are related to the Washington 1 database. (j), (k), (l) are related to the Washington 2 database.

Fig. 10. False detection samples result. (a) is related to the Cordova 1database and edge of the car misdiagnosed. (b) is related to the Cordova 2 database and edge of the car misdiagnosed. (c) is related to the Washington 1 database and not a complete diagnosis. (d) is related to the Washington 2 database and object along the street is misdiagnosed.

The average detection rate is 85.94%, as summarized in Table II.

Table II. Lane detection rate of comparison

		Aly's Method			Proposed Method		
Data Set	Total	Detected	Accuracy	Average Run Time	Detected	Accuracy	Average Run Time
	Frame	Frame		For Each Frame	Frame		For Each Frame
Cordova 1	250	219	87.60 %	3.5 s	230	92.00 %	3.2 s
Cordova 2	406	304	74.87 %	4.3 s	356	87.68 %	3.8 s
Washington 1	336	273	81.25 %	3.8 s	260	77.38 %	4.3 s
Washington 2	232	191	82.32 %	4.1 s	206	88.79 %	4 s
Total	1224	987	80.63 %	3.92 s	1052	85.94 %	3.82 s

Cordova 2, washington1, Washington 2). These 4 databases are presented by Aly's Method (Aly, 2008). We manually count the number of correct detection frames. The detection frames are considered correct if detection lanes are on real lane markings and their bending directions are correct, as shown in Fig. 9. Fig. 10 shows examples of false detection frames. In most illumination conditions of the proposed road detection, the rates were good, even under poor illumination conditions. In addition, proposed detection method is compared with Aly's Method lane detection (Aly, 2008).

Conclusion

In this study, we proposed a robust algorithm for detecting roads and lanes in urban streets using images from driving scenes of autonomous intelligent robots. The algorithm is based on L*a*b* Color Space for detecting roads, adjusting road contrast, filtering with Sobel operators, outlier removal with morphological operation and then using line detection Hough transform technique to detect lanes in the street, which is followed by a post-processing step. We compare the lane detection results under various illumination conditions with Aly's method in the experimental section. In addition, the proposed method does not involve high computational complexity. However, the proposed method does not work well in extremely different multi-illumination conditions, such as presence of shadows and water reflection in heavy rainfall at night and it has been assumed that the environment does not contain so different illuminations. To overcome this limitation, we will establish a model that has the ability to work in difficult illumination conditions and apply the lane detection algorithm.

The proposed method is simple and fast. The processing run on a PC with 2.6 GHs Pentium 4 processor and 4.00 GB RAM.

References

Aly M (2008), Real time detection of lane markers in urban streets ***In:*** Proc. Intelligent Vehicles Symposium, 2008, IEEE, pp 7-12.

Apostoloff N and Zelinsky A (2003), Robust vision based lane tracking using multiple cues and particle filtering ***In:*** Proc. Intelligent Vehicles Symposium, 2003, IEEE, pp 558-563.

BaiL and Wang Y (2011), Road tracking using particle filters with partition sampling and auxiliary variables, *Computer Vision and Image Understanding* **115**(10): 1463-1471.

Bajwa AK and Kaur R (2013), Fast Lane Detection Using Improved Hough Transform, *Journal of Computing Technologies* **2**(5): 10-13.

Baldevbhai PJ and Anand RS (2012), Color image segmentation for medical images using L* a* b* color space, *IOSR Journal of Electronics and Communication Engineering* **1**(2): 24-45.

Deng J, Kim J, Sin H and HanY (2013), Fast lane detection based on the B-spline fitting, *International Journal of Research in Engineering and Technology* (IJRET) **2**: 134-137.

He Y, Wang H and Zhang B (2004), Color-based road detection in urban traffic scenes, *IEEE Transactions on intelligent transportation systems* **5**(4): 309-318.

Liu G, Worgotter F and Markelic I (2013), Stochastic lane shape estimation using local image descriptors, *IEEE Transactions on Intelligent Transportation Systems* **14**(1): 13-21.

Miao X, Li S and Shen H (2012), On-board lane detection system for intelligent vehicle based on monocular vision, *International journal on smart sensing and intelligent systems* **5**(4): 957-972.

Rathore MVS, Kumar MMS, and Verma MA (2012), Colour based image segmentation using L* a* b* colour space based on genetic algorithm, *International Journal of Emerging Technology and Advanced Engineering* **2**(6).

Wankhade T and Shriwas P (2012), Design of Lane Detecting and Following Autonomous Robot, *IOSR Journal of Computer Engineering (IOSRJCE) ISSN, 2278-0661*.

Xu H, Wang X, Huang H, Wu K and Fang Q (2009), A fast and stable lane detection method based on B-spline curve ***In:*** Computer-Aided Industrial Design & Conceptual Design, CAID & CD, IEEE 10th International Conference, pp 1036-1040.

Xu S, Ying J and Song Y (2005), Research on road detection based on blind navigation device ***In:*** Cyber Technology in Automation, Control, and Intelligent Systems (CYBER), 2012 IEEE International Conference, pp 69-71.

Yim YU and Oh SY (2003), Three-feature based automatic lane detection algorithm (TFALDA) for autonomous driving, *IEEE Transactions on Intelligent Transportation Systems* **4**(4): 219-225.

Yoo H, Yang U and Sohn K (2013), Gradient-enhancing conversion for illumination-robust lane detection, *IEEE Transactions on Intelligent Transportation Systems* **14**(3): 1083-1094.

You F, Zhang R, Zhong L, Wang H and Xu J (2013), Lane detection algorithm for night-time digital image based on distribution feature of boundary pixels, *Journal of the Optical Society of Korea* **17**(2): 188-199.

Received: 20 February 2017; Revised: 03 April 2017; Accepted: 29 May 2017.