Lane Detection Using Labeling Based RANSAC Algorithm

Yeongyu Choi, Ju H. Park, Ho-Youl Jung

***Abstract*—**In this paper, we propose labeling based RANSAC algorithm for lane detection. Advanced driver assistance systems (ADAS) have been widely researched to avoid unexpected accidents. Lane detection is a necessary system to assist keeping lane and lane departure prevention. The proposed vision based lane detection method applies Canny edge detection, inverse perspective mapping (IPM), K-means algorithm, mathematical morphology operations and 8 connected-component labeling. Next, random samples are selected from each labeling region for RANSAC. The sampling method selects the points of lane with a high probability. Finally, lane parameters of straight line or curve equations are estimated. Through the simulations tested on video recorded at daytime and nighttime, we show that the proposed method has better performance than the existing RANSAC algorithm in various environments.

***Keywords*—**Canny edge detection, k-means algorithm, RANSAC, inverse perspective mapping.

I. Introduction

RECENTLY, a variety of IT technologies have been applied into vehicles for the purpose of increasing the convenience and safety of drivers. Since automobile accidents can directly cause fatal, safety is the most important. ADAS has been widely researched to provide drivers perceptual and visual information for the safety and convenience. Lane detection is essential task for lane keeping assist (LKA), lane departure warning (LDW) [1]. Hough transform [2] and RANSAC [3] based lane parameter estimation have been developed and widely used. In addition, B-Snake method [4] and spline have also been used for the lane detection in complicated environments such as curved lanes [5]. In general, video is captured by monocular camera mounted behind room mirror. In order to detect lanes efficiently in the image captured from the camera viewpoints, IPM has been often used [6]. We also use IPM to generate top-view image in pre-processing step.

In this paper, we present vision based lane detection system which consists of Canny edge detection [7], IPM, morphology operation [8], K-means algorithm [9] for division of region of left and right lanes and RANSAC [10]. Here, labeling based RANSAC algorithm is proposed and used in the lane detection.

The rest of this paper is organized as follows. In section II, the proposed vision based lane detection system is introduced. Section III shows the simulation results. Section IV concludes this paper.

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II. The Proposed Lane Detection

The camera mounted behind room mirror observes forward. Therefore, on the image obtained from the camera, lanes appear the shape projected according to the position and orientation of the camera. In the proposed lane detection, input image is transformed into top-view image using IPM. Since the shape of lane in top-view image is shown as similar to the actual lane, we can estimate lane parameter more correctly.

Fig. 1 shows the system flow chart of the proposed method. Generally, a camera has radial distortion of the lens and tangential distortion that occur from nonparallel of the image sensor and lens. Therefore, the proposed method performs lens distortion correction processes at the first step. Input RGB color image is converted to gray-scale image and edge points are extracted by using Canny edge detector. The remaining processing is described in details step by step in the following subsections.

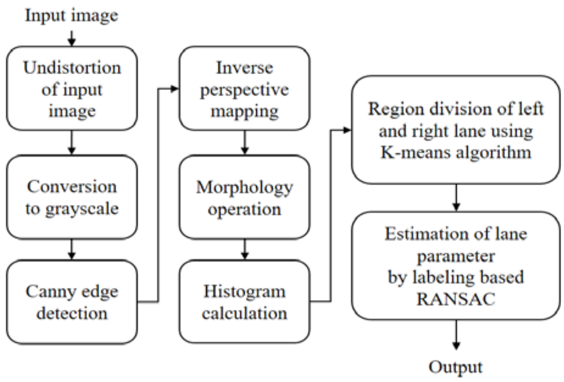


Fig. 1 System flow of the proposed lane detection

A. Inverse Perspective Mapping

Fig. 2 shows examples of top-view images. Fig. 2 (a) shows the original input image where green colored parallelogram area indicates the region to be inversely projected using IPM. To realize IPM, four corner points in input image and four corresponding points in projected top-view image are needed at least [6]. Because of different size between input and top-view images, interpolation is required after transformation. For such purpose, linear interpolation is applied.

B. Morphology Operation

For the purpose of labeling lanes as well as eliminating noise, we apply successively two mathematical morphology operations such closing and erosion [8]. The closing result from edge IPM image is shown in Fig. 3 (a) and erosion of (a) is shown in Fig. 3 (b).

(a) Region for IPM

(b) IPM image

(c) Edge image

(d) Edge IPM image

Fig. 2 Example of IPM transformation

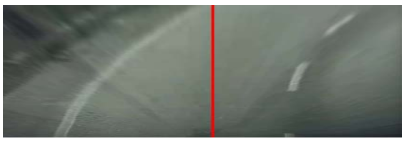
(a) Closing of edge IPM image

(b) Erosion of (a)

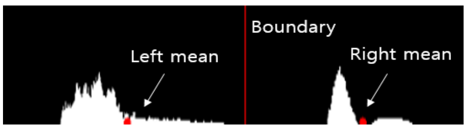
Fig. 3 Closing and erosion of morphology operation

C. Region Division using K-means Algorithm

As shown in Fig. 2, IPM image shows only forward area which includes mainly two lanes, one left and one right lane. Edge points are divided into two groups using K-means algorithm for the next processing, RANSAC sampling. The number of edge pixels is accumulated along the vertical axis. One-dimensional histogram is obtained as shown in Fig. 4. By applying K- means algorithm (K = 2) to the histogram, the boundary to divide two groups, left and right lane candidates as shown in Fig. 4 (a).



(a) Region division of curved lane



(b) Histogram accumulating the number of edge pixels along the vertical axis where left and right lane candidate regions are divided

Fig. 4 Region division example of curved lane

D. Labeling Based Sampling

Even if some noise is removed by the morphology operations as shown in Fig 3, there exists still edge points not related to lane. The edge points are re-grouped into distinct labels that are used to estimate lane parameters using RANSAC algorithm. The proposed RANSAC selects samples based on label unit. The traditional RANSAC selects samples randomly from whole edge points. Then, the method may also select noise points as well as lane points.

The proposed labeling based RANSAC determines the labels to be used in advance. RANSAC parameters are estimated by using the edge points in the determined labels and inliers are decided. These processes perform iteratively, until every combination is investigated. For given N labels, the combination of selecting less than or equal to k labels is $\sum_{i=1}^{k} {}_N C_i$. Fig. 5 shows k determined labels for the case $k = 2$, when the right lane candidate labels are considered in Fig. 3 (b).

1 Labels 2 Labels

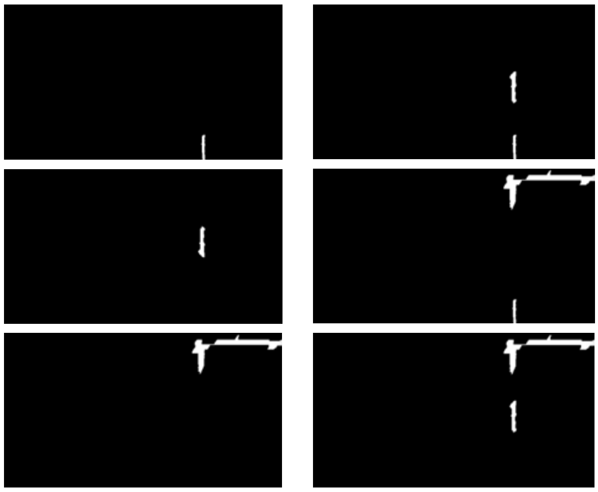


Fig. 5 Labeling based sampling region

E. Lane Parameter Estimation

In the IPM edge image, the shape of the lane is assumed to be straight line or circle. Lane parameters are estimated using the Gauss-Newton method which carries out geometric analysis with minimal Euclidean distance. For given n samples (x_1, y_1), $(x_2, y_2), \dots, (x_n, y_n)$, (1) and (2) determine the parameters for the straight line equation $ax - y + b = 0$ and for the circle equation $x^2 + y^2 + cx + dy + e = 0$, respectively.

$$\begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} x_1 & y_1 & 1 \\ x_2 & y_2 & 1 \\ \vdots & \vdots & \vdots \\ x_n & y_n & 1 \end{bmatrix} \begin{bmatrix} c \\ d \\ e \end{bmatrix} = \begin{bmatrix} -x_1^2 - y_1^2 \\ -x_2^2 - y_2^2 \\ \vdots \\ -x_n^2 - y_n^2 \end{bmatrix} \quad (2)$$

Next, Gauss-Newton method is used to find parameters minimizing non-linear Euclidean distance [11].

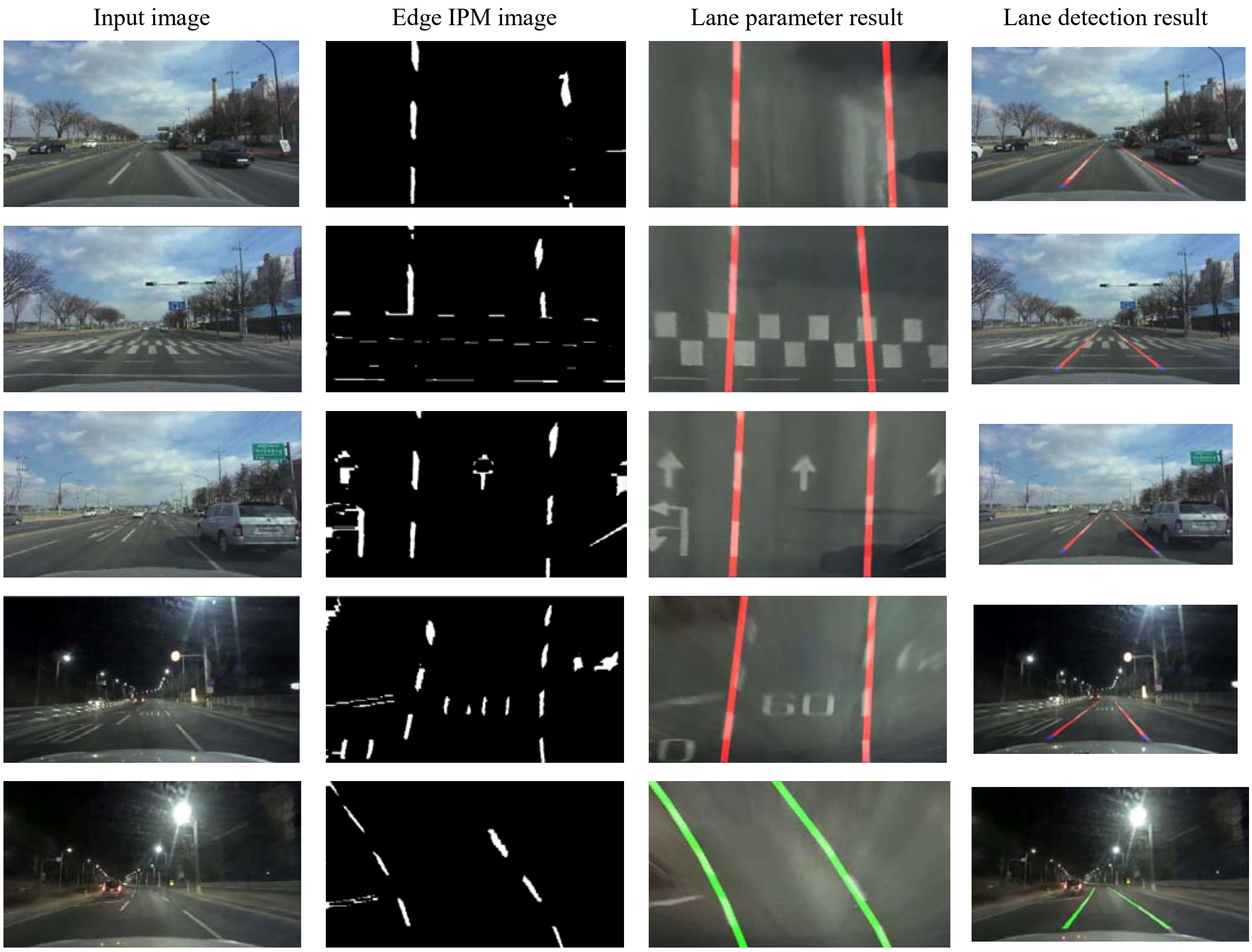


Fig. 6 Experimental environments and detection results

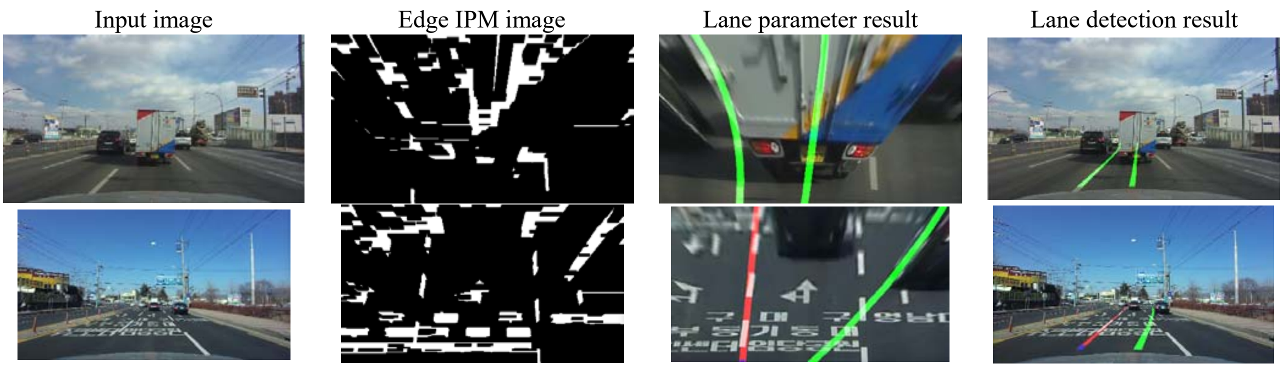


Fig. 7 Example of incorrect detection

III. Experimental Results

The proposed method is implemented and tested on video recorded at daytime and nighttime. This video includes various road marking, other vehicles as well as various types of lanes.

Table I shows the comparison of two methods. Labeling based sampling method has better performance than the conventional method that randomly selects samples from every data.

Fig. 6 shows the day/night original images and lane detection results. Fig. 7 shows some examples of incorrect detection.

TABLE I
THE PERFORMANCES OF THE PROPOSED METHOD AND EXISTING METHOD

Method	Existing sampling	Labeling based sampling
Detection rate	82.5%	90.9%

As shown in Fig. 6, the proposed lane detection method can detect the lane correctly even though there are various edge noises due to road markings or crosswalks. However, the proposed method has some limited detection performances in the case of very complicated edge noises as shown in Fig. 7.

IV. Conclusion

In this paper, we proposed labeling based RANSAC algorithm which can estimate more efficiently lane parameters. Through the simulations, we show that the proposed method has more robust performance than the conventional RANSAC in various environments such as the road brightness changes. Also, it is shown that the proposed have some limited detection performances in the case of very complicated environments.

Acknowledgment

This work was supported in part by the Creative Economy Leading Technology Development Program through the Gyeongsangbuk-Do and Gyeongbuk Science & Technology Promotion Center of Korea (SF317002A).

This work was supported in part by Basic Science Research Programs through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (Grant number NRF-2017R1A2B2004671).

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