A Lane Detection Algorithm Based on Reliable Lane Markings

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***Abstract*— This paper proposes a robust and effective vision-based lane detection approach. First, two binary images are obtained from the region of interest of gray-scale images. The obtained binary images are merged by a novel neighborhood AND operator and then transformed to a bird's eye view (BEV) via inverse perspective mapping. Then, determine the left and right regions of a histogram image acquired from the BEV. Finally, a polynomial lane model is estimated from the identified regions.**

Keywords—Vision-based lane detection; neighborhood AND operator; maximum likelihood estimation; parallelism of lanes.

I. INTRODUCTION

Advances in the field of autonomous and semi-autonomous vehicles such Lane Departure Warning (LDW) and Lane Keeping Assist System (LKAS) have a high potential to decrease the number of vehicle crashes [1, 2]. In order to realize LDW or LKAS, lane detection has to be performed, whereby vision-based lane detection is one of the main enablers for the lane detection [2, 3, 4, 5].

This paper develops a robust and effective vision-based lane detection approach. In the proposed method, gray-scale images are converted to two binary images from a fixed region of interest (ROI). These images are then merged using a novel neighborhood AND operator and then transformed to a bird's eye view (BEV) via inverse perspective mapping (IPM). A histogram image is extracted from the BEV and two gaussian probability density functions are fit to its left and right regions to determine the variance of the left and right lane markings. Finally, a polynomial lane model is estimated from the identified regions. Experimental results show that the proposed method accurately detects lanes in complex situations including worn-out and curved lanes. The novel neighborhood AND operator increases the robustness of the method.

II. PROPOSED METHOD

STEP-1

In this section, we summarize basic image processing techniques. We assume that images are given in RGB format and camera calibration has been performed.
Grayscale images carry enough information to detect lanes and can be handled with smaller computational times.Hence, we convert the images in RGB format to grayscale format.

$$I_G(i,j) = 0.299\, I_{RGB}(i,j,R) + 0.587\, I_{RGB}(i,j,G) + 0.114\, I_{RGB}(i,j,B) \tag{1}$$

Sobel operators perform gradient measurements on grayscale images using convolution kernels for finding edges. An example of 3x3 Sobel operators for finding vertical and horizontal lines are given as follows.

$$\text{Vertical Line: } \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}, \text{ Horizontal Line: } \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

(2)

Global thresholding is used to binarize images for lane pixels in this work.

$$I_B(i,j) = \begin{cases} 1, & if\ I_G(i,j) \geq th \\ 0, & if\ I_G(i,j) < th \end{cases}$$

(3)

The undistorted RGB image after calibration is first converted to a grayscale image as in (1). After that, to focus onthe lanes and to reduce the image processing time, the ROI is selected on grayscale image. Then, two binary images Ib1 and Ib2 are acquired, applying (2) to the grayscale image Ig itself and to the gradient magnitude image after applying the Sobel operator.

The binary images are then merged via the novel neighborhood AND operator

$$I(i,j) = \begin{cases} 0 & \text{if } \left(\sum_{l=i-k}^{i+k} \sum_{m=j-k}^{j+k} I_{B1}(l,m) \right) \cdot \left(\sum_{l=i-k}^{i+k} \sum_{m=j-k}^{j+k} I_{B2}(l,m) \right) = 0 \\ 1 & \text{otherwise} \end{cases}$$

Ib1 Ib2 And Operator

STEP-2

To make use of the parallelism of the lanes, the images are transformed to the BEV via IPM.

First we need to create the transformation matrix(5) .This matrix is 8x8 in size. Thanks to this matrix, we remove the perspective view in all our visuals(6).

$$\begin{bmatrix} X_1 \\ Y_1 \\ X_2 \\ Y_2 \\ X_3 \\ Y_3 \\ X_4 \\ Y_4 \end{bmatrix} = \begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1X_1 & -y_1X_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -x_1Y_1 & -y_1Y_1 \\ x_2 & y_2 & 1 & 0 & 0 & 0 & -x_2X_2 & -y_2X_2 \\ 0 & 0 & 0 & x_2 & y_2 & 1 & -x_2Y_2 & -y_2Y_2 \\ x_3 & y_3 & 1 & 0 & 0 & 0 & -x_3X_3 & -y_3X_3 \\ 0 & 0 & 0 & x_3 & y_3 & 1 & -x_3Y_3 & -y_3Y_3 \\ x_4 & y_4 & 1 & 0 & 0 & 0 & -x_4X_4 & -y_4X_4 \\ 0 & 0 & 0 & x_4 & y_4 & 1 & -x_4Y_4 & -y_4Y_4 \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{21} \\ a_{22} \\ a_{23} \\ a_{31} \\ a_{32} \end{bmatrix}$$

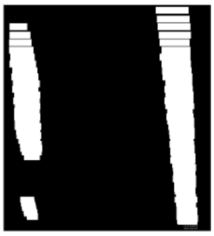
(5)

$$\mathbf{X} = \frac{a_{00}\mathrm{x} + a_{01}\mathrm{y} + a_{02}}{\mathrm{z}}$$

$$\mathbf{Y} = \frac{a_{10}\mathrm{x} + a_{11}\mathrm{y} + a_{12}}{\mathrm{z}}$$

(6)

Perpespective Image



Interpolated Perspective Image

The reason for our interpolation is because we rounded the numbers with commas during the transfer process. A 5x5 core is used for this process. Core dot multiplication is done with the corresponding 5x5 pixels of the image.

STEP -3

We next determine regions on the binary BEV that should be used for lane detection. Firstly, a histogram plot of the binary BEV along the x-axis is obtained. The y-axis represents the number of candidate lane pixels for each column of the binary BEV. the histogram plot of the binary image for is given and is divided in a left and right region with respect to the vehicle center. Since the proximity of lane pixels to each other play an important role for a good lane detection, standard deviations Sigmaleft, Sigmaright by using mean values , on the left (l) and right (r) region of the histogram plot are computed. To determine the parameters, we fit a Gaussian probability density function (pdf) to the candidate lane pixels in the left and right regions via maximum likelihood estimation (MLE):

$$\mu_l = \frac{2}{N}\sum_{j=1}^{N/2}\sum_{i=1}^{M} j \cdot I(i,j);\ \sigma_l^2 = \frac{2}{N}\sum_{j=1}^{N/2}\sum_{i=1}^{M} \mathrm{I(i,j)} \cdot (\mathrm{j} - \mu_l)^2$$

$$\mu_r = \frac{2}{N}\sum_{j=N/2+1}^{N}\sum_{i=1}^{M} j\, I(i,j);\ \sigma_r^2 = \frac{2}{N}\sum_{j=N/2+1}^{N}\sum_{i=1}^{M} \mathrm{I(i,j)}(\mathrm{j} - \mu_r)^2$$

(7)

In this paper, we propose to perform the lane detection using the most reliable lane. The criterion to determine which region is selected for the lane detection is as follows:

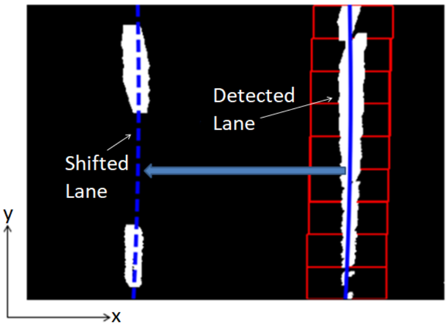
$$\text{Choose left region, if } (t\,P_l - \sigma_l) \geq (t\,P_r - \sigma_r)$$

$$\text{Choose right region, if } (t\,P_l - \sigma_l) < (t\,P_r - \sigma_r)$$

Pl, Pr denote the peak values in the left/right region of the histogram and t is a trade-off parameter between peak value and standard deviation. The proposed criterion determines the more distinctive peak, whereby more importance can be given to the peak value or the standard deviation by t. In this work, t is determined experimentally.

STEP -4

Up to this point, we found the column index of Pl or Pr as the basic location of the lane marking to be detected. In this step, we precisely determine the shape of the lane pixels along the column indexes by scanning the BEV row by row (respecting the fact the lane might be curved). This step is visualized in Figure 8, where the right region was selected for lane detection based on (7). Intuitively, the red rectangles scan the BEV from bottom to top along the y-axis. The x-position of each red rectangle is determined by the mean of the x coordinates of the lane pixels in the respective previous rectangle starting from column index of ⍰⍰. In this work, the height ⍰ and width ⍰ of the rectangle are fixed experimentally. The parameters of the polynomial in (9) for the detected lane are finally computed by applying the LSE method to all the pixels covered by red rectangles. The computed lane polynomial is then shifted to the column position of the peak value in the other region to obtain the second lane marking.



(8)

$$ai^2 + bi + c = j$$

Then, the LSE formulation determines a, b, c as

$$\bar{x} = (A^T A)^{-1} A^T \bar{\jmath}$$

With the matrices and vectors

$$A = \begin{bmatrix} {i_1}^2 & i_1 & 1 \\ {i_2}^2 & i_2 & 1 \\ \vdots & \vdots & \vdots \\ {i_N}^2 & i_N & 1 \end{bmatrix},\ \bar{x} = \begin{bmatrix} a \\ b \\ c \end{bmatrix},\ \bar{\jmath} = \begin{bmatrix} j_1 \\ j_2 \\ \vdots \\ j_N \end{bmatrix},$$

(9)

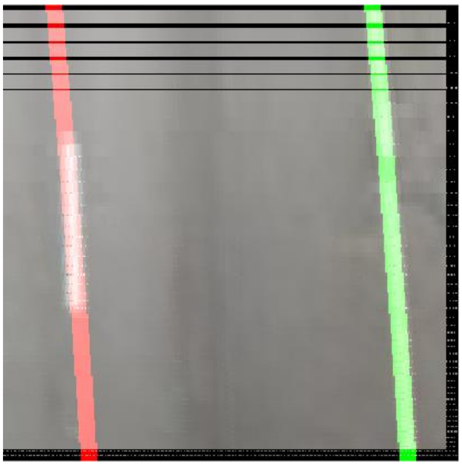


Figure 10 shows result lane detection image

CONCLUSIONS

This paper proposes a robust lane detection method under the assumption that lane markings are parallel. Experiments show that detecting the more reliable lane marking and estimating the other one performs very well even in complex conditions. Since the algorithm only performs basic operations on gray-scale images and uses least-square error and maximum likelihood estimation methods on histogram plots, it has a high potential for real time applications. In the future, we intend to extend the algorithm by lane tracking.

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