Automatic Lane Detection and Navigation using Pattern Matching Mode

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Abstract: - Automatic navigation for autonomous vehicle requires information of outdoor surroundings, especially information of the road. Such system must acknowledge the changing of environment to achieve significant and consistent road information. This paper presents automatic lane detection and navigation using pattern matching model. The parabola model is deployed for lane modeling and lane type classification with optimal parameters. The proposed system shows desirable performance for lane detection and classification. It is also less sensitive to unexpected conditions such as noise in the image, shadow, and obscured lane.

Keyword: - Pattern matching model, lane detection, lane classification, automatic navigation

1 Introduction

Nowadays lane detection systems have been widely deployed in automatic driving systems for outdoor vehicle and driver assistance system. The main purposes are for safety and aid for a driving. There have been various lane detection systems which can mainly be categorized in two groups: using a single camera and using multiple cameras. In the first category, the artificial neural network has been applied for detecting lane. Earlier, most of researches emphasized on using edge detection for lane segmentation from other environments. Also, image transformation for detecting lines were also considered, such as, Hough transform. Later, matching techniques had become more focused. These techniques can be performed by matching salient features to lane features, for examples, the LOIS in [1]. Following that, lane modeling had been introduced and become more popular. The models can be described by 1st and 2nd order polynomial functions [2] and B-spline function [3]. For automatic lane detection, a sequence of images is processed to calculate for model's parameters using various optimization techniques. These techniques, however, depend on accuracy of sensors in the system such as wheel velocity sensors. Prediction techniques, for examples, Kalman filter or particle filter [4], are then required together with optimization approaches in order to efficiently estimate camera positions at each time step. This is to minimize error in 3D lane model in time varying. Consider the second category, stereo vision had been utilized for lane detection. Additional special equipments have been developed to increase performance of the system but at the cost of complexity. In [5], active vision system had been developed to capture sequences of images at both near and far distances. Both data had been computationally combined to boost performance of decision making at different distances. The lane detection system in this work composes of 3 main parts: i) lane segmentation, ii) lane type classification and iii) lane navigation. Details of each part are described in the following sections.

2 Lane Segmentation

A segmentation of lane from other environments is required in order to classify lane type. This work focuses on examination the image to extract the significant information of the lane images which are the sky, trees (or other constructions) and lanes. This can be accomplished by locating the vanishing line and the line of lane boundary. The details are discussed next.

2.1 Vanishing line pre-computation

In order to segment the sky, trees and lanes from an image, the possible location of the vanishing line is computed. Using simple 3-level gray-scale value thresholding, the corresponding area of the sky, trees and lanes in the image can be roughly segmented as shown in Fig. 1. The result of segmentation shows that the vanishing line can be assumed to appear in the same horizontal line of the tree area in the image (see Fig. 2). This is because it is the connected area between the sky and the lanes.

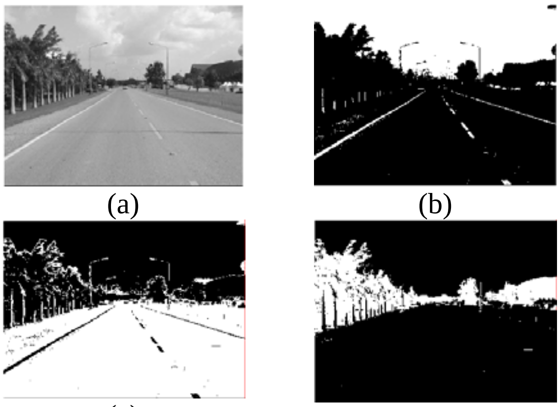


Figure 1 Three main components in the image of a lane (a) original image (b) sky (c) lane and (d) trees

Figure 2 Vanishing line estimation

2.2 Lane boundary computation

The lane boundary in the image can be used to separate an area of the tree and the lane. It can be considered as a straight line with different slopes. It can also be described using a parabolic equation (by using only first order). This information from the parabolic equation will be used later for lane classification. Consider the linear equation (1) for describing the lane boundary,

$$c = Br + M \quad (1)$$

where c is the image column, r is the image row, B is the proportional direction, and M is the proportional compensation. From the equation above, the negative and positive values of B can be assigned for the left side and the right side of the lane boundary, respectively as described in equation (2.1) and (2.2).

$$c_L = B_L r_L + M_L, B_L < 0 \quad (2.1)$$

$$c_R = B_R r_R + M_R, B_R > 0 \quad (2.2)$$

The information from these equations will later be considered in the classification of the lane. Fig. 3 demonstrates the computed boundary of the lane.

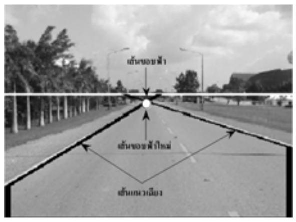


Figure 3 Lane boundary

2.3 Vanishing line computation

The vanishing line is the most important information in the image for the lane detection system. It defines the horizontal line that divides the sky and the lane in the image. The image area above the vanishing line is simply discarded which can reduce the area of interest. The vanishing line is also the intersection of the left and right lane boundary. This intersection point can be calculated by considering $c_L = c_R$ and $r_L = r_R = r$ as described in equation (3).

$$B_L r + M_L = B_R r + M_R \quad (3)$$

Rearrange equation (3) then,

$$r = \frac{M_R - M_L}{B_L - B_R} \quad (4)$$

The resulting r from equation (4) is the exact position of the vanishing line as shown in Fig. 4.

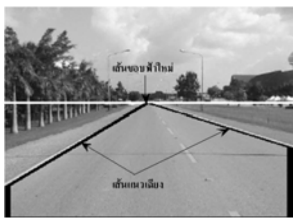


Figure 4 Exact vanishing line positions

3 Lane Type Classification

Types of the lane can be roughly classified into straight lane, T-junction, and intersection. In this work, a statistical approach is deployed in the analysis of the lane type. Consider each segments of the image in Fig. 5, functions in equation (5.1) and (5.2) are plotted and analyzed.

$$F_L(i_1) = \sum_{j_1=1}^{m_1} B(i_1, j_1)\,,\ i_1 = 1,\ldots,n_1 \qquad (5.1)$$

$$F_R(i_2) = \sum_{j_2=1}^{m_2} B(i_2, j_2)\,,\ i_2 = 1,\ldots,n_2 \qquad (5.2)$$

where F_L is a summation of pixels of i_1 th row, F_R is a summation of pixels of i_2 th row, and $B(i, j)$ is edge pixel with value of 0 and 1.

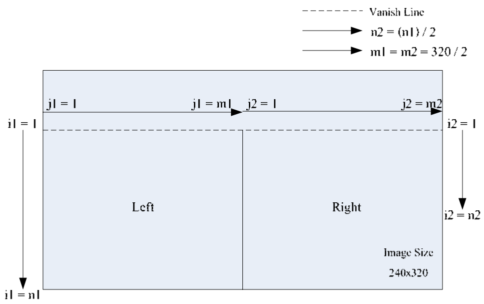


Figure 5 Segment of image for analysis

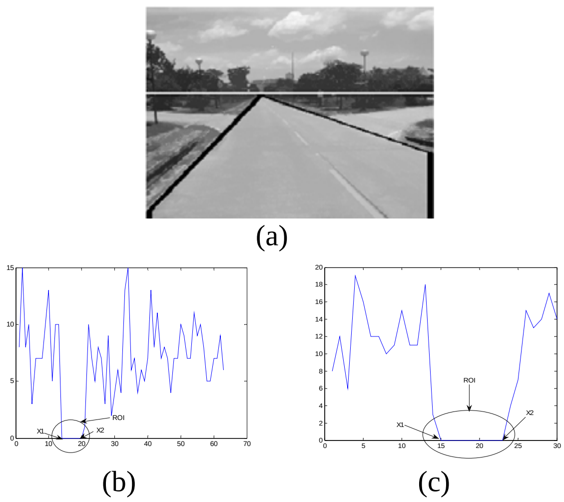


Figure 6 (a) Image of the road with vanishing line and lane boundary (b) profile of F_L (c) profile of F_R

The plots of F_L and F_R from Fig. 6-(a) are displayed in Fig. 6-(b) and (c), respectively. It is interesting that the zero values of the plots are physically agreed to the intersection of the lane, while the rest of the plot is corresponded to the straight parts or the curves of the road. This piece of information can be used to find the starting point of lane intersection and, hence, can be used to classify the type of the lane. For example, the left T-junction (see Fig. 7-(a)), is composed of the lane for left turn. The F_L profile in Fig. 7-(b) displays the corresponding points of that left-turn lane while no such point in the F_R profile of Fig. 7-(c) which indicates that no existing lane for a right turn. Table 1 summarizes the plot of F_L and F_R together with the possible types of lane. Note that the maximum number of such a point that indicates the starting point of the intersection is two. The greater number could appear but it should correspond to the intersection beyond our interests which should be dealt with when the car approaches after passes the current intersection.

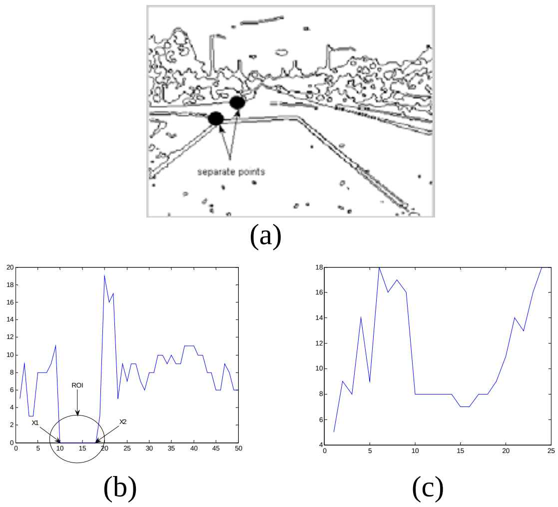


Figure 7 (a) Image of the road with left T-junction (b) profile of F_L (c) profile of F_R

Number of starting points of the left-turn lane	Number of starting points of the right-turn lane	Type of lane
0	0	straight or curve
1	0	left turn
0	1	right turn
1	1	T-junction or intersection
2	0	left-turn or T-junction
0	2	right-turn or T-junction
2	1	intersection
1	2	intersection
2	2	intersection

Table 1 Type of lane and its corresponding number of starting points.

4 Lane Navigation

The lane navigation requires the system to be able to consistently detect the area of the lane. This can be accomplished using a lane modeling. The model that uses to describe the physical appearance of the road is a simple parabolic equation as shown in equation (6).

$$x = ky^2 + my + b \tag{6}$$

where k is a coefficient of curvature, m is a coefficient of direction, and b is a coefficient of compensation. By simple transformation, the corresponding relationship of equation (6) in image plane can be presented by equation (7).

$$c = K\frac{1}{r} + Br + M \tag{7}$$

where K is a proportional curvature, B is a proportional direction, and M is compensation. The parameters from equation (7) are related to the lane types. Matrices of these parameters for both left and right side of the road are presented in equation (8).

$$P_L(k_L) = \begin{bmatrix} K_{L1} & B_{L1} & M_{L1} \\ \vdots & \ddots & \vdots \\ K_{Lk_L} & B_{Lk_L} & M_{Lk_L} \end{bmatrix}_{k_L \times 3}$$
$$P_R(k_R) = \begin{bmatrix} K_{R1} & B_{R1} & M_{R1} \\ \vdots & \ddots & \vdots \\ K_{Rk_R} & B_{Rk_R} & M_{Rk_R} \end{bmatrix}_{k_R \times 3} \tag{8}$$

where k_L and k_R are size of $K_L \times B_L \times M_L$ and $K_R \times B_R \times M_R$, respectively.

The matching of the lane model and the actual lane in the image is performed by optimizing the maximum likelihood function of the equation (9).

$$L(P(k)) = \sum_{r=\upsilon}^{m}\left[B(r,c(P(k))-1) + B(r,c(P(k))) + B(r,c(P(k))+1)\right] \tag{9}$$

where m is number of rows of the image, υ is vanishing line, and $B(r,c)$ is edge pixel with value of 0 and 1. The optimization is done by searching for the parameters of which

$$P_{best} = \max[L_k],\ k = 1,2,3,\cdots,n_{L,R} \tag{10}$$

where $n_{L,R}$ is a size of left and right matrix of parameters.

5 Results and Discussion

The presented system has been tested with 320x240 pixels images. There are two categories of these images. The first group is the images with

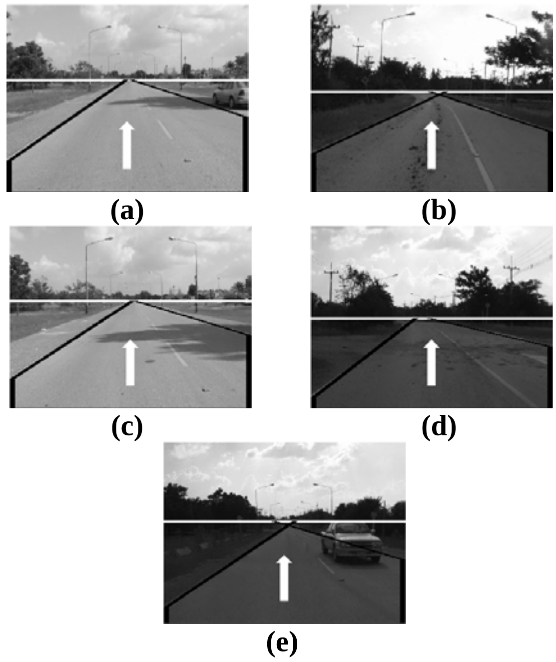


Figure 8 (a) road with normal light condition (b) low light condition road (c) shadow on the road (d) and (e) partially obscured road

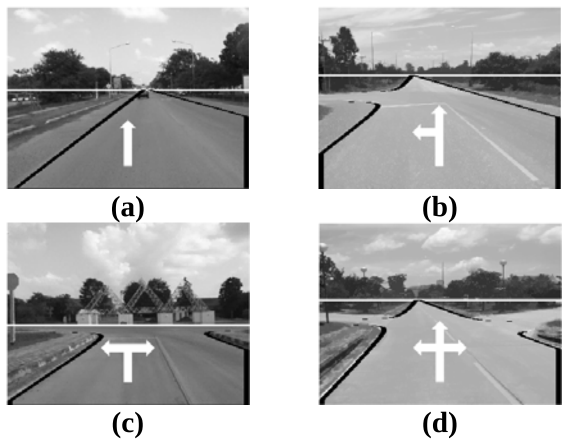


Figure 9 Classification of lane type (a) straight lane (b) left T-junction (c) T-junction (d) intersection

light and environment conditions. Results are displayed in Fig. 8. The results show desirable performance at different illuminations from sun light, shadows on the road, and partially obscured lane. The second group is the images for testing the classification of lane types. Fig. 9 demonstrates the results of classifying a straight lane, T-junction, and intersection.

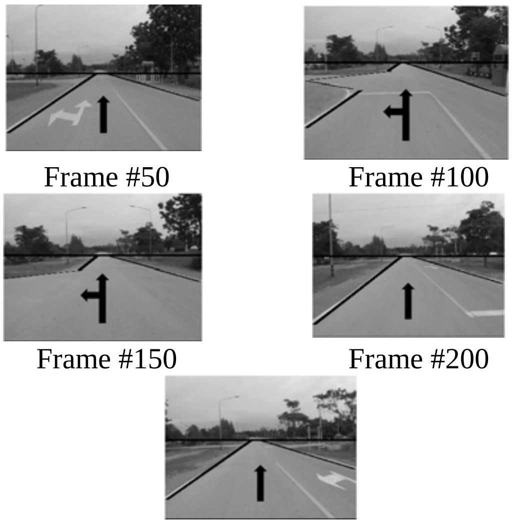
Performance of the proposed system has also been analyzed by investigating the resulting lane detection of a sequence of image taken from the vehicle on the road. Table 2 displays the accuracy percentage of the lane detection system measured from the vehicle passing various lane types. Fig. 10-13 shows examples of lane detection and navigation from experiments reported in Table 2. The average over 93% accuracy is very promising for any practical applications.

Lane Type	Video #	Correct detection (# of frame	False detection (# of frame)	% Accuracy
Vehicle moving through straight lane passing left T-junction	1	242	8	96.8
	2	240	10	96.0
	3	235	15	94.0
	4	235	15	94.0
	5	239	11	95.6
Vehicle moving through straight lane passing right T-junction	1	238	12	95.2
	2	236	14	94.4
	3	241	9	96.4
	4	235	15	94.0
	5	232	18	92.8
Vehicle moving through straight lane and turning left	1	225	25	90.0
	2	232	18	92.8
	3	228	22	91.2
	4	234	16	93.6
	5	222	28	88.8
Vehicle moving through straight lane and turning right	1	220	30	88.0
	2	230	20	92.0
	3	229	21	91.6
	4	228	22	91.2
	5	230	20	92.0

Table 2 Percent accuracy of lane detection in sequences of images

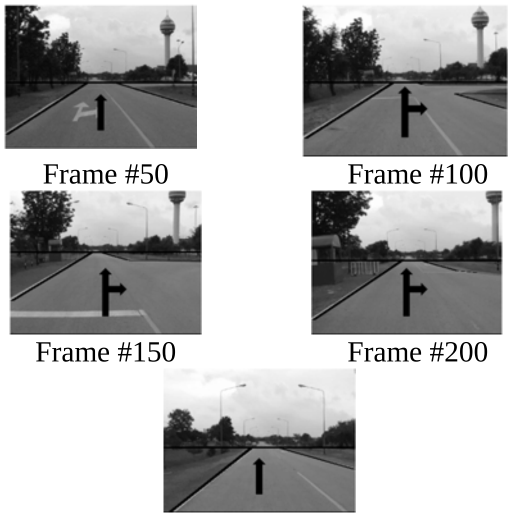
6 Conclusions

The paper presents the automatic lane detection and navigation system. The segmentation and classification of the lane are proposed. The parabola model is deployed for lane modeling and lane type classification with optimal parameters. The proposed system shows desirable performance for lane detection and classification. It is also less sensitive to unexpected conditions such as noise in the image, shadow, and obscured lane.



Frame #50 Frame #100
Frame #150 Frame #200
Frame #250

Figure 10 Lane detection from vehicle moving through straight lane and passing left T-junction



Frame #50 Frame #100
Frame #150 Frame #200
Frame #250

Figure 11 Lane detection from vehicle moving through straight lane and passing right T-junction

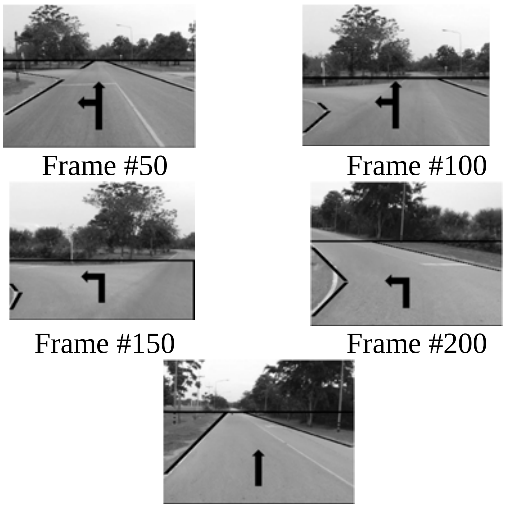


Figure 12 Lane detection from vehicle moving through straight lane and turning left

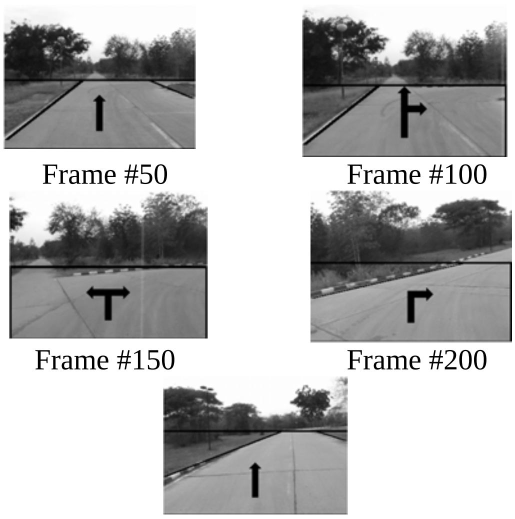


Figure 13 Lane detection from vehicle moving through straight lane and turning right

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