Lane Detection using Color-Based Segmentation*

Kuo-Yu Chiu and Sheng-Fuu Lin**

Department of Electrical and Control Engineering, National Chiao-Tung University, Taiwan, ROC

E-mail: sflin@mail.nctu.edu.tw, TEL: 886-3-5712121 Ext. 54365

***Abstract*—Lane boundary detection is the problem of estimating the geometric structure of the lane boundaries of a road on the images captured by a camera. To be an intelligent vehicle, lane boundary is necessary information, so the system and the algorithm should be as simple and fast as possible. In this paper, we propose a new method based on color information and this method will be applicable in complex environment. In this system, we first choose a region of interest to find out a threshold using statistical method in a color image. The threshold then will be used to distinguish possible lane boundary from the road. We use color-based segmentation to find out the lane boundary and use a quadratic function to approach it. This system demands low computational power and memory requirements, and is robust in the presence of noise, shadows, pavement, and obstacles such like cars, motorcycles and pedestrians conditions. The result images can be used as pre-processed images for lane tracking, road following or obstacle detection.**

***Index Terms*— lane detection, color-based, statistical method, quadratic functions.**

I. Introduction

LANE detection is the problem of locating road lane boundaries without an a priori knowledge of the road geometry. It is important information for intelligent vehicle (IV) system. In this system, the tasks of automatically driven vehicles include road following and keeping within the correct lane, maintaining a safe distance between vehicles, regulating the speed of a vehicle according to traffic conditions and road characteristics, moving across lanes in order to overtake vehicles and avoid obstacles, searching for the correct and shortest route to a destination. Intelligent vehicle (IV) systems offer a simple, safe and efficient operation while using these intelligent vehicles. As one component of intelligent transportation systems (ITS), IV systems can understand the surrounding environment by several different sensors combined with an intelligent algorithm in order to either assist the driver in vehicle operations or fully control the vehicle (automation) [1]. For an IV system, the distance to the lane boundaries and obstacle is important. It makes sure that the vehicle is in a safe distance to avoid any possible collision. To get the information of the distance to the lane boundaries, we need to know the lane boundaries first. That is why lane detection is an important part of intelligent vehicle system.

The goal of lane detection is to locate the center line of each lane from a road image. To achieve this goal, lane markings may be used to differentiate the lanes from other features such as car, motorcycle, pedestrian or other vehicles. There are several major difficulties in detecting the lane markings correctly are that first, they are not always clearly visible due to their print quality and the changes in environmental conditions. Second, the geometry of the markings cannot be used as discriminating factor as there is no governing standard. Further, road splitting or merging and the interference from roadside objects or shadows could worsen the detection [2].

Lane detection is a well-researched area of computer vision with applications in autonomous vehicles and driver support system. This is in part because, despite the perceived simplicity of finding white markings on a dark road, it can be very difficult to determine lane markings on various types of road. These difficulties arise from shadows, occlusion by other vehicles, changes in the road surfaces itself, and differing types of lane markings. A lane detection system must be able to pick out all manner of markings from cluttered roadways [3]. Since erroneous findings will generate wrong steering commands which may jeopardize vehicle safety, a robust and reliable algorithm is a minimum requirement. However, the great variety of road environments necessitates the use of complex vision algorithms that not only requires expensive hardware to implement but also relies on many adjustable parameters that are typically determined from experience [4].

Many researchers have shown lane detectors based on a wide variety of techniques. The technique commonly be used is to detect the edges by various kind of filter and then use the Hough transform [5, 6] to fit lines to these edges. A B-Snake-based lane-detection and tracking algorithm is introduced in [7].The problems of detecting both sides of lane boundaries have been merged as the problem of detecting the midline of the lane by using the knowledge of the perspective parallel lines. Some lane detection methods [8, 9] rely on top-view images. Some do road boundary detection and tracking by ladar sensor [10] or laser sensor [11, 12]. It is an easy and convenient tool, but it can not be acceptable now for

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** correspondence author

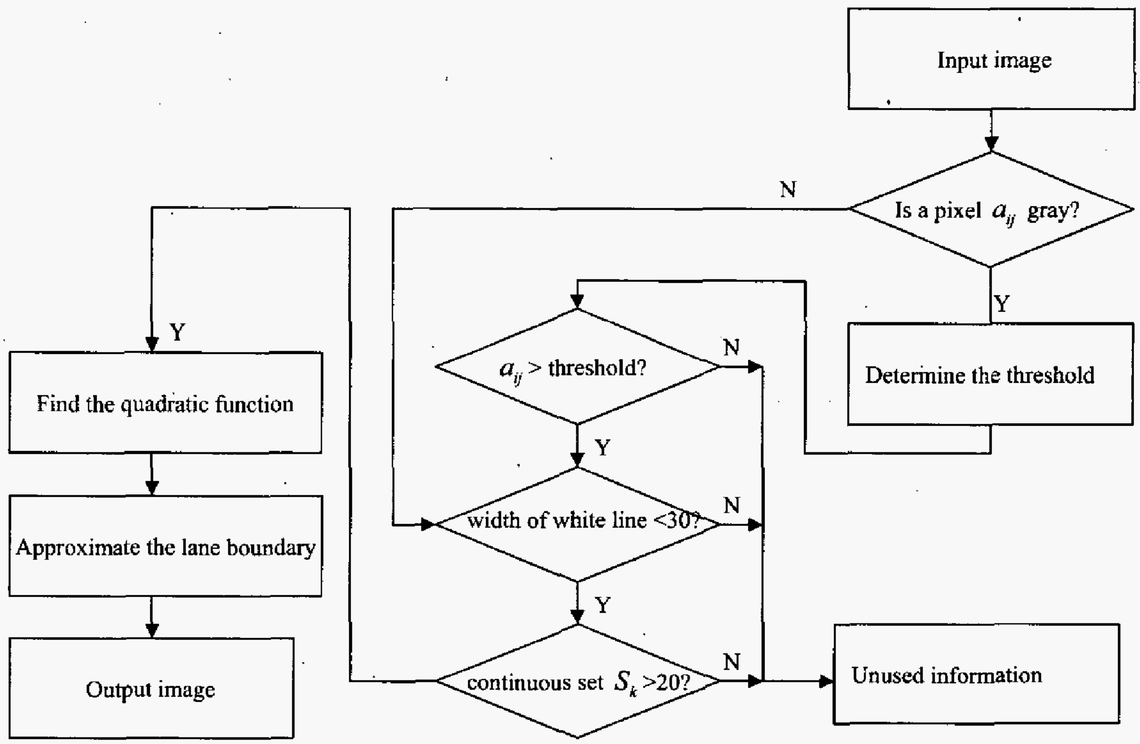


Figure1.Flow chart of the total system..

the price of these tools. Deformable road models are widely used for lane detection [13-15]. [16-18] use the histogram-based threshold selection, least median of squares estimation to determine the edge slope, while using a matched filter and a Kalman filter for lane detection is proposed in [19]. [20-22] transformed the perspective view image into a plan-view image. These techniques attempt to determine mathematical models for road boundaries [1, 3].

In this paper, we propose a color-based method to deal with the lane boundary problem. It will be organized as follow. In Sec. II, we will present a method based on color to determine the road and non-road object form a color image. We will then segment lane marking from road with histogram-based method in Sec. III. In Sec. IV, the possible lane marking set is used to get a parabola to approach the real lane marking using least-square method. The results will be discussed in Sec. V and the conclusion will be made in Sec VI.

II. Road Model

In this section, the properties of road and lane marking will be introduced here. Most of the models only focus on the lane boundaries without using the information of road. Because it is known that the lane boundary is drawn onto the road, searching the lane boundary will be easier if we have the information about where the road is. So, we will try to point out the road in a color image first according to its properties.

A. *Road property*

Lane marking indicates all the markings which are drawn onto the lane, and the lane boundary is one kind of lane marking. Since the lane marking is one the road, we can find the lane marking directly from the road instead of searching the whole image. Here we will give a short description about the road. Most of the road is near the color of dark gray. Although it is not exactly gray, it is still in certain range. For RGB color model, a pixel is said to be gray is with the property:

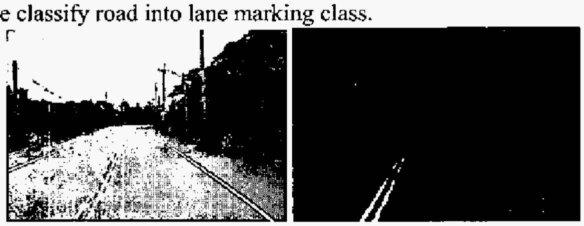
$$v_R = v_G = v_B \qquad (1)$$

And, it is nearly white when v approaches 255 and is nearly black when v approaches 0. In the real road, it is not exactly the color of gray when it is repaired, besmirched, cleaned, or with some other color component due to the reflection of light. However, most of them are still in a range during our experiments. For general road, the gray level value of road is 100-130, and the difference between *RGB* is less than 25. Special case, such like sunny day or rainy day, the parameter will change lightly. In the sunny day, the gray value of road is 80-130 with shadow and 130-170 with sunlight. The value of *R* will be 20-40 higher with sunlight and the value of *B* will be also 20-40 higher with shadow. In the rainy day, the gray value of the road is 70-120 and the difference between *RGB* is still less than 25. For this reason, we can assume that it may be a pixel of road if it has the property:

$$\begin{cases} |v_R - v_G| < th \\ |v_G - v_B| < th \\ |v_B - v_R| < th \end{cases} \tag{2}$$

The value of *th* is found out during experiments. The major reason that the road is not exactly gray is the sun light. For example, the color of road will be obviously different in the morning, afternoon, and evening. Backlight or headlight will also affect the results.

Lane marking, on the other hand, should be a contrast to the road in color. Although we cannot make sure if the color of the lane marking in every country are all the same, it should be a brighter color in contrast to the dark gray color of road, like white and orange red in Taiwan. However, the road will get redder due to the reflecting of the sun light. According to our experiments, the road is redder and the value of *th* is still suitable if it is set to be *40*. With this value, the road will be distinguished from orange red lane marking even it is redder than usual due to the sun light. Although this will absolutely over-detect the road, it is not matter for misclassification unless we classify road into lane marking class.



(a) (b)

Figure2. (a) Original image. (b) After processing: the color near gray is set to be black.

B. White lane marking

After distinguishing the none-road object (ex. lane marking) from the road, there is still a kind of lane marking that will be set to be road – the white lane marking, for white is still a kind color of gray. For this reason, we need a threshold to distinguish not only white lane marking but also darker lane marking which is far from us from the road. Due to the different sun light and the shadow, prefixed threshold is unsatisfied. Here we propose a method. First, we choose a window of interest that is in the front middle of the captured image. In a 352×242 color image, for example, the window of interest is set to be from the 25^{th} pixel to the 125^{th} pixel in vertical and from the 50^{th} pixel to the 300^{th} pixel in horizontal. After using equation (2) to find out the near-gray pixels, each pixel can be viewed with a gray level value. Suppose the number of each gray level value is *n(t)*, we need to find a threshold to classify the gray level value into two class: road and the lane marking. Set $n(i_{\max})$ to be the gray value with the most pixels, and th_{head} and th_{tail} are defined the right boundary and left boundary of these two classes respectively. The right boundary of road class is roughly defined as the first value such that the number of pixels is lower than *20* after $i_{\max}$, while the left boundary of lane marking class is roughly defined as the last value such that the number of pixels is more than *20*.

$$\begin{cases} th_{head} = \min\limits_{i_1 = i_{\max} \dots 255} i_1, n(i_1) > 20 \text{ and } n(i_1 + 1) \le 20 \\ th_{tail} = \max\limits_{i_2 = 255 \dots i_{\max}} i_2, n(i_2) > 20 \text{ and } n(i_2 - 1) \le 20 \end{cases} \tag{3}$$

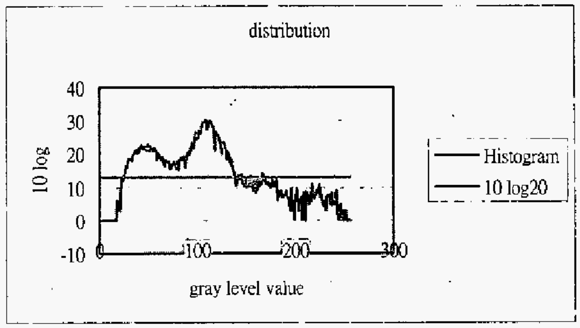


Figure3. It shows the distribution of gray level value. Crossover point indicates the boundary of the two classes.

In Figure2, we can see that the horizontal line ($10 \times \log 20$) intersect the histogram of gray level with several points. The most left crossover point is defined as th_{head}, while the most right crossover point is defined as th_{tail}. By the distribution of gray level value, we can see that th_{head} and th_{tail} are almost the boundary of the two classes. So, we can make a value among the value of th_{head} and th_{tail} to be the threshold. We defined the threshold value *th* as:

$$th = \sqrt{\frac{th_{head}^2 + th_{tail}^2}{2}} \tag{4}$$

With this threshold value, we can classify the gray level value into road class and lane marking class. Each pixel is set to be 0 if it may be road and set to be 255 if it may not be road.

$$\begin{cases} a'_{ij} = 255, & \text{if} \quad a_{ij} > th \\ a'_{ij} = 0, & \text{if} \quad a_{ij} \le th \end{cases} \tag{5}$$

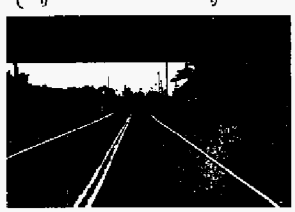


Figure4. Image after eq. (5): the color which is brighter is set to be white while the color is darker is set to be black.

III. Lane Boundary

After getting the possible lane marking pixels, which are defined as non-road, we should classify these pixels into two parts, lane boundary and others. According this, we need more information to distinguish lane boundaries from the other objects, such as car, motorcycle, pedestrians, other vehicles, or traffic signs drawn on the road. The lane boundary has some properties, and we can use two major properties to find the lane boundary:

1. The width of a lane boundary is in a range in horizontal.
2. The lane boundary is continuous in vertical.

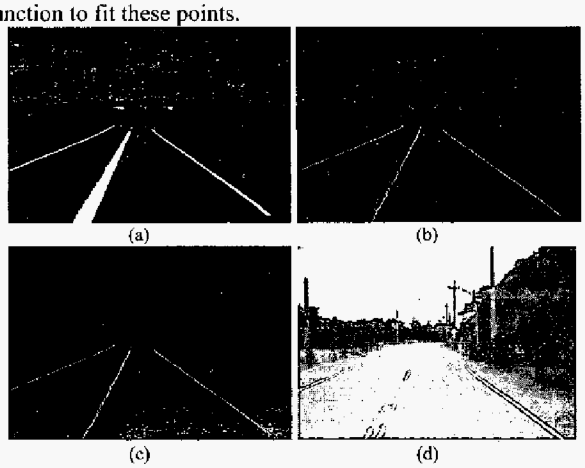
The lane boundary is a continuous line in vertical and is a short line with less than 30 pixels in horizontal. Due to this reason, we scan each row first. If a line is thinner than 30 pixels in horizontal, it may be a lane boundary. Then, we use the middle point to represent each possible lane boundary which is thinner than 30 pixels in horizontal. A point $a_{i\bar{j}}$ is said to be a possible lane marking if the adjacent pixels are possible lane marking and the width is no more than 30 pixels.

$$\begin{cases} a''_{i\bar{j}}=1, & \text{if } a'_{ij}=1, j=j_1\ldots j_n, j_n-j_1<30, \bar{j}=\dfrac{j_1+j_n}{2} \\ a''_{i\bar{j}}=0, & \text{otherwise} \end{cases} \quad (6)$$

After that, we can use Hough transform to find the quadratic function to approach the lane boundaries or use road geometry model to approximate the lane boundaries with likelihood function. Here, we do one more step to gather these points up in to several classes. For each starting point $a_{k(i,j)}$, we try to find out a continuous set S_k from the bottom up. A new point $a_{k(i+m,j+n)}$ is said to be in the continuous set S_k if the distance between two points *(m, n)* is in a certain range in both x-axis and y-axis.

$$S_k=\left\{a_{k(i+m,j+n)} \middle| a_{k(i+m,j+n)}=1,\ m,n<20, a_{k(i,j)}\in S_k\right\} \quad (7)$$

Two or three continuous sets with the most possible lane boundary points will be used to determine the lane boundaries. These kinds of continuous set S_k will be taken into consider. We will use the least square method to find out a quadratic function to fit these points.



(a) (b) (c) (d)

Figure5. (a)Image after eq.7: white lines whose width is less than 30 pixels are reserved. (b)Image after eq.8: only middle point is reserved. (c) Three continuous sets with the most number of points are shown. (d) The original image.

IV. LEAST-SUQARE METHOD

In the real world, lane marking is extensional vertically. We can use a quadratic function to approach the lane marking if it is a kind of parabolic. The quadratic function should be in the form:

$$f_k : a_k y^2 + b_k y + c_k = x. \quad (8)$$

For a continuous set S_k, each point (x_i, y_i) should satisfy the equation (9). We will then try to find an optimal solution of (a,b,c) to minimize the square error. For a continuous set S_k, we can obtain:

$$\begin{bmatrix} y_{k_1}^2 & y_{k_1} & 1 \\ y_{k_2}^2 & y_{k_2} & 1 \\ \vdots & \vdots & \vdots \\ y_{k_n}^2 & y_{k_n} & 1 \end{bmatrix} \begin{bmatrix} a_k \\ b_k \\ c_k \end{bmatrix} = \begin{bmatrix} x_{k_1} \\ x_{k_2} \\ \vdots \\ x_{k_n} \end{bmatrix} \quad (9)$$

Then set:

$$\begin{aligned} v_1 &= [1 \quad 1 \quad \cdots \quad 1]^T \\ v_2 &= [y_{k_1} \quad y_{k_2} \quad \cdots \quad y_{k_n}]^T \\ v_3 &= [y_{k_1}^2 \quad y_{k_2}^2 \quad \cdots \quad y_{k_2}^2]^T \\ u_k &= [x_{k_1} \quad x_{k_2} \quad \cdots \quad x_{k_n}]^T \end{aligned} \quad (10)$$

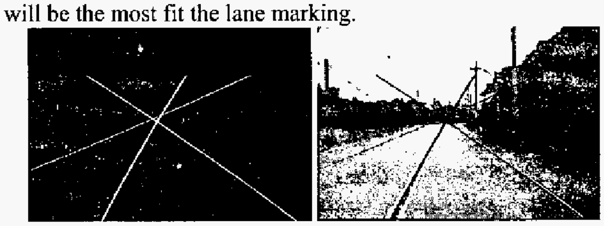
Use Gram-Schmidt method to find orthogonal vector set (ϕ_1, ϕ_2, ϕ_3) by setting:

$$\begin{aligned} \phi_1 &= v_1 \\ \phi_2 &= v_2 - \frac{(v_2 \bullet \phi_1)}{|\phi_1|^2}\phi_1 \\ \phi_3 &= v_3 - \frac{(v_3 \bullet \phi_1)}{|\phi_1|^2}\phi_1 - \frac{(v_3 \bullet \phi_2)}{|\phi_2|^2}\phi_2 \end{aligned} \quad (11)$$

The value of (a,b,c) will be obtained by:

$$\begin{aligned} a_k &= \frac{(u_k \bullet \phi_3)}{|\phi_3|^2}\phi_3 \\ b_k &= \frac{(u_k \bullet \phi_2)}{|\phi_2|^2}\phi_2 \\ c_k &= \frac{(u_k \bullet \phi_1)}{|\phi_1|^2}\phi_1 \end{aligned} \quad (12)$$

Thus, the quadratic function $f_k : a_k y^2 + b_k y + c_k = x$ will be the most fit the lane marking.



(a) (b)

Figure6. (a) The quadratic function generated from the three continuous point sets. (b) Comparing with the original image.

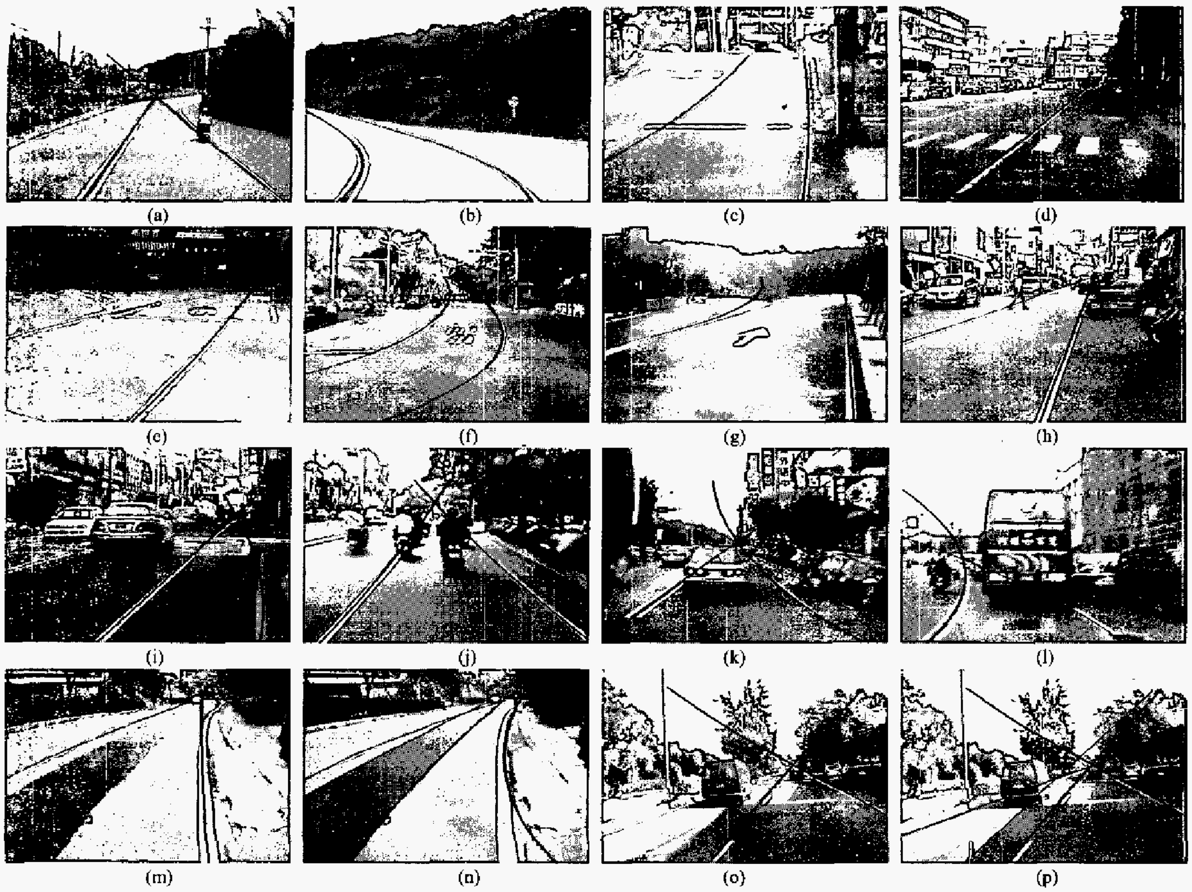


Figure7. (a)-(l) Experimental results of different road scenes. (m)-(p) Comparison with general Sobel or gradient method.
(m),(o) Images processed by Color-Based Segmentation. (n),(p) Images processed by general Sobel or gradient method.

V. RESULTS

This section presents the performance of the proposed method in the real road scenes. We can extract the middle and right lane boundaries, and left lane boundaries can also be extracted if it can be seen in the image. The proposed algorithm is tested on some images from video grabbed by an onboard camera. All experimental images are 24-bit color images of size 352×242. Figure 7 shows some of our experimental images of lane-boundary detection, and the detected lane-boundaries are superimposed onto the original images. These images represent various real roads in city, which is much more complicated than road in highway. These images include: (a) a straight lane with three lane boundaries and the right lane marking is partly occupied by a motorcycle, (b) a non-straight lane with higher curvature, (c) road which is uphill, (d) road with zebra-stripe crossing, (e) two straight lane with shadow, (f) curved lane marking with blank and other traffic signs on the road: speed no more than 50, (g) road with serious sun light reflection, (h) city road with various object: parking cars, walking pedestrians, and motorcycles, (i) city road with a car obstacle on the lane boundary and the road has another kind lane marking, (j) city road with several motorcycles on the lane boundary, (k) a car ahead is in the middle of the road , (l) a bus is in front of us and much closer so that, there is only a few lane marking information, (m) road with long pavement, (n) the long pavement is regarded to be a lane boundary for the edge of the pavement is obvious and vertically continuous to the gradient method, (o) road with sunlight and shadow, (p) the border of the sunlight and the shadow is regarded to be a lane boundary for the border is vertically continuous to the gradient method. These experiments show that this method can deal with solid or broken line, straight or curved line, obstacle on lane marking, other traffic signs drawn on the road, shadow, and sun light reflection. Hence, the lane boundary information can be obtained by using a quadratic function curve to approximate the lane marking and we can see that it indeed has good performance.

VI. CONCLUSION

In this paper, we proposed a new lane detection algorithm. Unlike the gradient method, the color-based segmentation method can easily get rid of the influence due to the sunlight, shadow, pavement, and obstacles, like vehicles and pedestrians. Using the possible lane marking sets also save us a lot of time so that we can use least-square method to approach the lane boundary with high accuracy without prior information, while using Hough transform or other road model are much more complicated. As shown in Sec. V, this algorithm can deal with solid or broken line, straight or curved line, obstacle on lane marking, other traffic signs drawn on the road, road pavement, shadow, and sun light reflection. However, imperfect lane detection can still be found occasionally while dealing with traffic signs drawn on the road and illumination problem due to the reflection. When the headlight or brakelight of a car is reflected by the road in rainy day or at night, the road color model will change. We then need to use the general gradient method to find out the lane boundary. And the traffic signs drawn on the road will also cause imperfect lane detection for they have some properties as the lane boundaries do. It is a task to classify the lane markings into two parts, lane boundary and traffic signs. Though it is now a defect to our lane boundary detection system to overcome, it is an interesting topic in the future work to do recognition to each traffic signs and this information will be useful to an intelligent vehicle.

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