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Real Time Road Lane Detection with RANSAC and HSV Color Transformation

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Abstract

Autonomous driving vehicle research demands complex road and lane understanding such as lane departure warning, adaptive cruise control, lane keeping and centering, lane change and turn assist, and driving under complex road conditions. A fast and robust road lane detection subsystem is a basic but important building block for this type of research. In this paper, we propose a method that performs road lane detection from black box input. The proposed system applies Random Sample Consensus to find the best model of road lanes passing through divided regions of the input image under HSV color model. HSV color model is chosen since it explicitly separates chromaticity and luminosity and the narrower hue distribution greatly assists in later segmentation of the frames by limiting color saturation. The implemented method was successful in lane detection on real world on-board testing, exhibiting 86.21% accuracy with 4.3% standard deviation in real time.

Index Terms: Autonomous driving, Bezier spline, HSV, RANSAC, Road lane detection

I. INTRODUCTION

The lane detection problem, at least in its basic setting, has long been studied and is one of the basic building blocks of autonomous vehicle research. A relatively simple Hough transform-based algorithm, which does not employ any tracking or image-to-world reasoning, solves the problem in roughly 90% of the highway cases [1]. From the binary edge map, the classical Hough transform is then used to extract a set of lines as candidates for the lane markers. While this approach shows good results in general, the detected lanes are often skewed due to surface irregularities or navigational text markers on the road [2]. However, with high reliability demands, and large diversity in case conditions as well as real-time applicability, fast and robust lane detection is not as easy as one might imagine. Road and lane understanding includes detecting the boundaries of the road, the number and position of lanes, and merging, splitting and ending lanes and roads in urban, rural, and highway scenarios. Although much progress has been made in recent years, this level of understanding is beyond the reach of current perceptual systems. Thus, a great deal of recent research in autonomous driving requires complex road and lane understanding such as lane departure warning, adaptive cruise control, lane keeping and centering, lane change and turn assist, and driving under complex road conditions [3].

Vision-based lane detection methods can be divided into two categories: feature-based and model-based methods. The feature-based methods locate the road areas using segmentation methods whereas the model-based methods represent the lane boundaries by mathematical models.

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Lane marks can be detected based on either their shape or color. The least restrictive assumption about lane marks is that they have a different appearance compared with the road. Such an assumption leads to a whole family of gradient-based features and their variants. Simple gradients were computed in [4, 5], either from an original image or from a smoothed version of it. These systems give efficient path detection in both shadow and light. Later, a linear discriminant analysis (LDA)-based gradient-enhancing conversion was developed for an illumination-robust lane detection method that generates optimal RGB weights which maximize gradients at lane boundaries on the road to distinguish lanes from the road surface [6] while other research uses local gradients to improve robustness [7] or combines the Hough transform with gradient-based features for robust lane detection with shadow [8, 9].

However, most methods involve high computational complexity and it is difficult to meet real-time requirements. Thus, for urban streets and highways, the most commonly used methods are model-based methods.

In most cases, model parameter fitting has to cope with noisy boundary points extracted from the image in the form of missing data and a relatively large number of outliers. Random Sampling Consensus (RANSAC) [10] is commonly used for model fitting for all model types [2, 11] due to its ability to detect outliers and fit a model to the inliers only.

Recently, many model-based lane detection studies combine RANSAC with other algorithms to achieve fast, robust detection ability. One study combines input from multiple cameras and line models are formed from feature points using a RANSAC algorithm, although the method supports real-time operation only at low speeds [12]. Other studies construct a computational model of the ego-lane geometry by fitting candidate lane markings to the model parameters using RANSAC [13] or propose an improved RANSAC algorithm which is combined with least square analysis to calculate the lane model parameters with an edge detection algorithm [14] under different road condition assumptions.

In this paper, we propose a curved lane detection method based on RANSAC applied to a hue-saturation-value (HSV) color model for robustness. HSV color space explicitly separates chromaticity and luminosity and has been proven to set a mathematical formulation for shadow detection more easily than RGB. Also, the hue distribution in HSV is much narrower if a low exposure is used when capturing frames. The narrower hue distribution greatly assists in later segmentation of the frames by limiting color saturation [15]. Thus, we postulate that the proposed method can achieve acceptable performance in lane detection in real time.

II. PROPOSED METHOD

Lane detection is based on the localization of a specific pattern (the lane markings) in the acquired image and can be performed with the analysis of a single still image. The lane model is transformed from the image to real-world coordinates, typically using an inverse perspective transformation [3]. In this paper, our input image is obtained from the black box of the vehicle. The first step in our vision system is applying image warping for inverse perspective transformation based on [16].

Let W be the real-world 3D coordinates and I be the 2D image coordinate system. Then the original black box image (Fig. 1(a)) is converted to the bird's-eye view image that removes the perspective (Fig. 1(b)) by applying Eq. (1) to (3). The camera view is defined as C = {l, d, h}.

$$\begin{aligned} W &= (x, y, z) \in E^3 \\ I &= (u, v) \in E^2 \end{aligned}. \tag{1}$$

$$\begin{aligned} x(u,v) &= \frac{h}{\tan\left[(\bar{\theta}-\alpha)+u\dfrac{2\alpha}{n-1}\right]} \times \cos\left[(\bar{\gamma}-\alpha)+v\dfrac{2\alpha}{n-1}\right]+l \\ y(u,v) &= \frac{h}{\tan\left[(\bar{\theta}-\alpha)+u\dfrac{2\alpha}{n-1}\right]} \times \sin\left[(\bar{\gamma}-\alpha)+v\dfrac{2\alpha}{n-1}\right]+d \\ z(u,v) &= 0 \end{aligned}. \tag{2}$$

In the above equations, α, $\bar{\theta}$, and $\bar{\gamma}$ denote half of the aperture angle, and the horizontal and vertical angle of the optical axis of the camera, respectively.

$$\begin{aligned} u(x,y,0) &= \frac{\arctan\left\{h\sin\left[\arctan\left(\dfrac{y-d}{x-l}\right)\right]/(y-d)\right\}-(\bar{\theta}-\alpha)}{\dfrac{2\alpha}{n-1}} \\ \text{and } v(x,y,0) &= \frac{\arctan\left[\dfrac{y-d}{x-l}\right]-(\bar{\gamma}-\alpha)}{\dfrac{2\alpha}{n-1}} \end{aligned}. \tag{3}$$

Fig. 1 shows an example of such a transformation from the black box image.

(a) (b)

Fig. 1. The effect of image warping. (a) Input image and (b) bird's-eye view.

Then, we transfer the RGB space to the HSV color model. The HSV model is a common cylindrical- coordinate representation of the points in an RGB color model. HSV color space explicitly separates chromaticity and luminosity and easily allows one to set a mathematical formulation for shadow detection. Furthermore, using only the hue component makes the algorithm less sensitive (if not invariant) to lighting variations. The transformation process from RGB to HSV is as follows:

$$\begin{aligned} H &= \begin{cases} 0 & if\ B \le G \\ 360-\theta & if\ B \ge G \end{cases} \\ \theta &= \cos^{-1}\left\{ \frac{1/2 \times [(R-G)+[R-B)]}{[(R-G)^2+(R-B)(G-B)]} \right\}. \\ S &= 1-\frac{3}{(R+G+B)}[\min(R,G,B)] \\ V &= \frac{1}{3}(R+G+B) \end{aligned} \quad (4)$$

After the transformation, we apply a set of image processing algorithms such as Gaussian smoothing for noise removal, binarization, and expansion operations to enhance the intensity contrast.

From the image preprocessed with the above process, we apply RANSAC to obtain robust noise-immune lane detection.

RANSAC, first proposed by [10], is an iterative method to estimate the parameters of a mathematical model from a set of observed data that contains outliers, when outliers are to be accorded no influence on the values of the estimates. It is a non-deterministic algorithm in the sense that it produces a reasonable result only with a certain probability, with this probability increasing as more iterations are allowed. The RANSAC algorithm can adapt to the complex conditions of lane estimation based on the model parameters and it does not require the training process associated with the Hough transform and template matching method.

In this paper, we divide the image into several regions as shown in Fig. 2 to find the best models within the regions.

First, compute the number of iterations for each of the divided regions using Eq. (5).

$$N = \frac{\log(1-p)}{\log(1-u^m)} \quad . \quad (5)$$

In (5), u denotes the rate of inliers from the input, p is the probability that at least one effective data set will contain an inlier, and m is the number of effective objects extracted after one iteration.

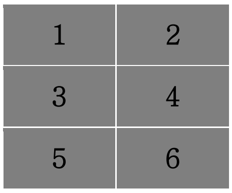

Fig. 2. Divided regions for RANSAC application.

Then, we compute the distance d between the point of intensity 255 and a point on the straight line represented by Eq. (6) with model parameters a and b.

$$y = ax + b \, . \quad (6)$$

$$d = \frac{|ax_0 + by_0 + c|}{\sqrt{a^2+b^2}} \, . \quad (7)$$

Then an outlier is defined as a point that has distance d greater than the predefined threshold t as shown in Eq. (8).

$$\begin{aligned} inlier &: t \ge d \\ outlier &: t < d \end{aligned} \, . \quad (8)$$

Thus, for each region, we find the best straight line model that has the largest inlier rate.

Note that feature points obtained from the best straight line of the regions 1, 3, and 5 of Fig. 2 are used to represent the left-side lane and those from regions 2, 4, and 6 represent the right-side lane.

Splines are smooth piecewise polynomial functions, and they are widely used in representing curves. Different spline models with different properties were used to model the lane boundaries/centerline. Then, we apply the Bezier spline [17] to reduce the error to represent the curved line using Eq. (9).

$$\begin{aligned} b_{i,n}(t) &= \binom{n}{i} t^i (1-t)^{n-1} \\ B(t) &= \sum_{i=0}^{n} p_i b_{i,n}(t) \end{aligned} \, . \quad (9)$$

In Eq. (9), p_i is the set of feature points with n feature points and t is the number of repetitions.

III. EXPERIMENT AND RESULTS

The proposed method is implemented with C# and OpenCV# under Microsoft Visual Studio 2015 on an IBM-compatible PC with Intel Core i7-4700 CPU @ 2.40 GHz and 8 GB RAM. Images from the video have a 1080×720 resolution.

Fig. 3. Snapshot of the implemented software.

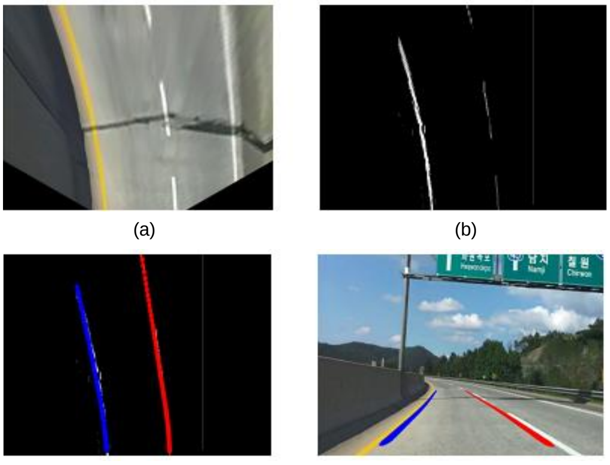

Fig. 4. Output for each process. (a) Warping, (b) candidate lane, (c) after RANSAC and Bezier spline, and (d) output.

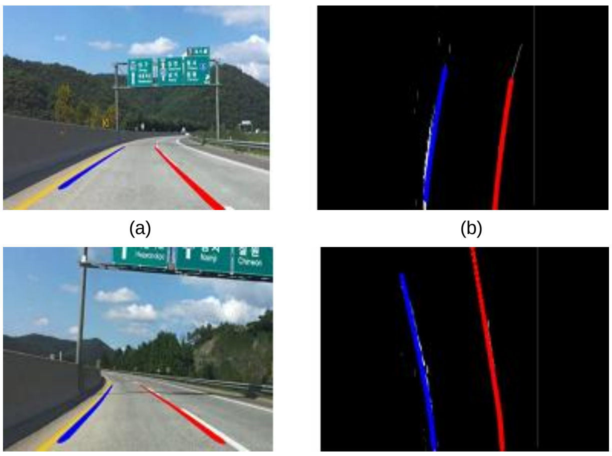

Fig. 5. Output for each turn in real world testing. (a) Right turn, (b) detection in process of right turn, (c) left turn, and (d) detection in process of left turn.

Table 1. Road lane detection rate

Input	Extraction rate (%)	Input	Extraction rate (%)
Video1	88.89	Video11	84.39
Video2	85.23	Video12	81.97
Video3	81.54	Video13	85.55
Video4	84.37	Video14	88.18
Video5	81.21	Video15	89.27
Video6	92.87	Video16	82.56
Video7	89.62	Video17	91,42
Video8	84.85	Video18	83.95
Video9	79.23	Video19	93.87
Video10	93.17	Video20	81.97

Table 2. Performance comparison (unit: %)

City view	Correct	Incorrect	Misses
Hough [1]	76.55	11.94	11.95
RANSAC-Kalman [2]	86.39	12.71	0.78
Proposed	86.21	13.79	0.00

Fig. 3 demonstrates an example output of the proposed software and Fig. 4 shows the intermediate outputs during the lane detection processes.

In real-world testing, the system gives outputs such as Fig. 5(a) and (c) with respect to the direction of the turns.

In our real-world experiment, we videotaped 20 different scenarios that contain at least one section of curved road for one minute each at 30 frames per second. Table 1 summarizes the experimental results for successful lane detection rate. The successful extraction rate is distributed between 79.23% and 93.87% with an average of 86.21% and standard deviation of 4.30%.

The lack of accessibility to other lane detection algorithms makes it extremely difficult to compare results with others, and different systems use different assumptions and road conditions. Thus, in this paper, we compare our results with Borka et al. [1, 2] for their "city view" experiment, which is most similar to our experimental conditions.

They used qualitative evaluation to detect lanes as follows [2];

i) A correct detection occurs when more than 50% of the lane marker estimate is overlaid on a lane marker in the scene.

ii) An incorrect detection occurs when the estimate is overlaid on something other than a lane marker.

iii) A missed detection occurs when no estimate is presented despite a relevant lane marker being visible.

The performance comparison of our proposed method with Hough-transform based [1] and RANSAC with a Kalman filter [2] is reported as shown in Table 2.

There was no "missed" detection in our case and the required time for lane detection is less than 0.5 seconds, which is faster than the 0.8 seconds detection time reported in [2], while the "correct detection" rate is very similar (statistically insignificant).

IV. CONCLUSIONS

For the road lane detection problem that is a basic component of autonomous vehicle research, vision-based approaches are the most natural and cost-effective paradigms. In this paper, we demonstrate our implementation of a fast and robust real-time road lane detection method using RANSAC and other image processing algorithms under the HSV color model.

In this area, many studies aim to provide solutions to complex situations and scenarios that are possible in autonomous driving. In these situations, other modalities, such as light detection and ranging (LIDAR), geographic information systems (GIS), GPS, and inertial measurement unit (IMU) may serve as richer information sources than visual imaging.

The basic understanding of fast and accurate identification of road lanes is still an important task. And, in this paper, we demonstrated that the accuracy of the proposed method (86.21% average accuracy) is acceptable in real-world experiments that use black box videos as input. However, tracking algorithms and other sources of information will be required to handle more complex driving scenarios.

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