

# Fast Lane Detection Based on the B-Spline Fitting

Jiayong Deng, Junghu Kim, HyunChul Sin, Youngjoon Han

**Abstract**—Lane detection is a key problem in driving assistance system. In this paper, a novel real time lane detection method is proposed to detect the lane marking lines based on generating a top view of the road, the region of interest (ROI), filtering using selective oriented Gaussian High pass filter, using Hough transformation and Kalman filter to a new and fast algorithm for fitting Bezier Splines. Our experimental results and accuracy evaluation show that our algorithm has good precision and our detecting method is suitable for various conditions.

**Keywords**—lane detection; top view; Gaussian filters; Hough transformation; Bezier Spline.

## I. INTRODUCTION

Lane detection plays a significant role in driver assistance systems. Typically, lane detection is used for localizing lane boundaries in the given road images, and can help to estimate the geometry of the road ahead, as well as the lateral position of the ego-vehicle on the road. Lane detection is used in intelligent cruise control systems, for lane departure warning, road modeling, and so on. [11]. Automating driving system may help reduce this huge number of human fatalities. The road detection algorithm is one of the key technologies of the system [6].

Lane detection also can be used to infer the position and orientation of the vehicle within a lane and can provide a reference system for locating other vehicles or obstacles in the path of that vehicle which can be applied to further development of the Obstacle Avoiding System [10].

Throughout the last two decades, a significant amount of research has been carried out in the area of road/lane analysis. This topic can be separated into two essential building blocks: lane detection and tracking [12]. There are several useful technology of lane detection which has achieve good results for application requirements, such as, open uniform B-spline curve model [6], Multiple hyperbola road model [8], a K-means cluster algorithm [16]. Furthermore, the essential tracking technologies, like Kalman Filter and particle filter, are utilized frequently.

However, most of these algorithms were focused on lane detection on highway roads or the condition that few vehicles and obstacles ahead or the road was clear, which is an easier task compared to lane detection in general streets.

This paper presents a robust and effective approach to extract

the road markings. It is based on taking a top view of the image in ROI or called the Inverse Perspective Mapping (IPM) [17]. This image is then filtered by Gaussian spatial filters in vertical orientation, and then thresholded by keeping only the highest values. In order to eliminate edges around vehicles ahead and shadows of other objects, an effective template is utilized and get satisfied result, which is followed by Hough transformation and classification for Hough lines. Our line-classifier can separate entire detected line into several line-groups and calculate the central line from every group, which provides the initial boundary of lane marking the following step. Actually, the boundary based on Hough transformation is a shrunken and separated ROI, and then, a novel 3 degree Bezier Spline fitting algorithm is performed to refine the detected straight lines and correctly detect curved lanes.

## II. APPROACHS

### A. Inverse Perspective Mapping (IPM)

In the Euclidean space, define two kinds of description of traffic scene, i.e. the world coordinate system  $W$  and the image coordinate system  $I$ . The coordinate transformation relationship from  $I$  to  $W$  can be shown in Fig. 1.

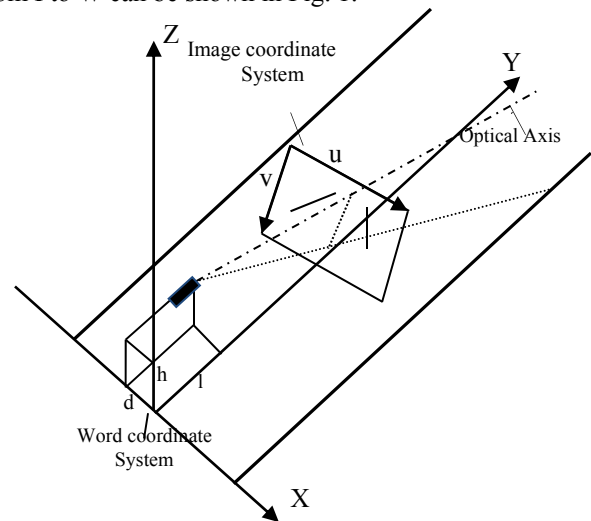


Fig. 1 Schematic diagram of IPM

Assuming that the coordinates of mounting position of the camera in the world coordinate system is  $(d, l, h)$ , the calibrated parameters of camera are as follows;  $\gamma$  represents the angle between the projection line of optical axis at  $z=0$  plane and  $y$ -axis;  $\theta$  represents the deviation angle of optical axis to  $x=0$  plane;  $2\alpha_u$  and  $2\alpha_v$  represents field of view of the camera in

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horizontal and vertical direction respectively; Width and Height represent the horizontal and vertical resolution of traffic image.

Through coordinate transformation, the inverse perspective transform model from I to W is shown in equation (1) and (2).

$$x(u, v) = h \times \cot\left(\frac{2\alpha_v}{R_v - 1} \times v - \alpha_v + \theta\right) \times \sin\left(\frac{2\alpha_u}{R_u - 1} \times u - \alpha_u + \gamma\right) + d. \quad (1)$$

$$y(u, v) = h \times \cot\left(\frac{2\alpha_v}{R_v - 1} \times v - \alpha_v + \theta\right) \times \cos\left(\frac{2\alpha_u}{R_u - 1} \times u - \alpha_u + \gamma\right) + l. \quad (2)$$

However, in practical systems, the direct utilization of (1) and (2) will bring about blank pixels in the resultant image, because this equation is nonlinear and such transformation is not bidirectional one-to-one mapping, but unidirectional to one mapping [18]. Therefore, we only using equation (1) and (2) to get the range of x and y, and then adopt a reverse IPM transform model as shown in equation (3) and (4).

$$v = \frac{(R_v - 1) \times (\arctan \frac{h}{\sqrt{(x-d)^2 + (y-l)^2}} + \alpha_v - \theta)}{2\alpha_v} \quad (3)$$

$$u = \frac{(R_u - 1) \times (\arctan \frac{(x-d)}{(y-l)} + \alpha_u - \gamma)}{2\alpha_u} \quad (4)$$

In such way, we can ensure that each pixel in resultant image will find its correspondence in original image and accordingly remove blank points effectively, the IPM image shows in Fig. 2-b.



Fig. 2 Result of IPM algorithm. (a) Original image (b) Result image of IPM transformation

### B. Gaussian Filter and Binaryzation

The transformed IPM image is filtered by a two dimensional Gaussian kernel. The vertical direction is a Gaussian High Pass Filter, whose  $\rho_y$  is adjusted according to the specific requirements of lane segment (set to the equivalent of 10) to be detected, and the convolution function is:

$$f_v(y) = \exp\left(-\frac{2 \times \rho_y^2}{y^2}\right) \quad (5)$$

The horizontal direction is a Gaussian Low Pass Filter, whose  $\rho_x$  is adjusted according to the specific requirements of lane segment (set to the equivalent of 5) to be detected, and the convolution function is:

$$f_u(x) = \exp\left(-\frac{x^2}{2 \times \rho_x^2}\right) \quad (6)$$

The filter is tuned specifically for vertical bright lines on dark background of specific width, which is our assumption of

lanes in the IPM image, but can also handle quasi-vertical lines which produce considerable output after the thresholding process.

Using this separable kernel allows for efficient implementation, and is much faster than using a non-separable kernel [2]. The filtered image shows in Fig. 3-a. As can be seen from the filtered image, it has high response to lane markers, and so we only retain the highest values. We keep the actual pixel values of the thresholded image, which is the input to the following steps. In this step, we use the assumption that the vehicle is parallel/near parallel to the lanes. Fig. 3-b shows the result image after thresholding.

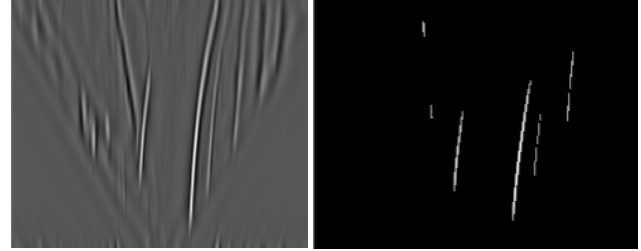


Fig. 3 Filtering and thresholding (a) The image after filtering. (b) The image after thresholding

### C. Denoising Template

This paper proposes a novel template denoising algorithm. The template is designed according to follow rule set, such as specific pixel value, wide, edges' orientation of lane marking and gray distribution of two sides of lane.

Given a filtered and thresholded image, and template efficiently calculates eigenvalues of the partial images whose central pixel is bright of the input image. The partial image which is most correspond to the rule set is detected from the input image, and these location should be on one or several vertical lines. However, these bright pixels which is not fit the rule set will be changed to dark.

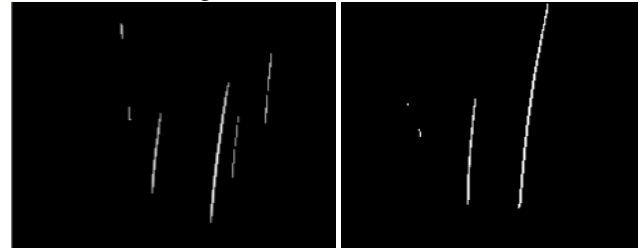


Fig. 4 (a) Input binary image (b) Result image after filtered by denoising template

The proposed algorithm is effective especially when there are a lot of edges of the vehicles ahead or shadows of objects, like trees, telegraph poles, traffic signs etc. It is shown theoretically and experimentally that the computational cost of our algorithm is much smaller than the existing methods. Fig. 4-b shows the resulting denoising image.

### D. Lane Boundary Detection and Tracking

This stage is concerned with detecting lines in the denoising image. We use two techniques: Hough Transform to estimate the location of lane marking where Hough lines distribute

together, and followed by a line-classifier.

The Hough transform just detect straight lines in vertical orientation approximately. Moreover, the nearby lines are grouped together to eliminate multiple responses to the same line, so, the all of detected lines are classified into several line-groups which grouped together to a specific lane marking respectively by line-classifier. Fig. 5-b shows the result image after Hough transform.

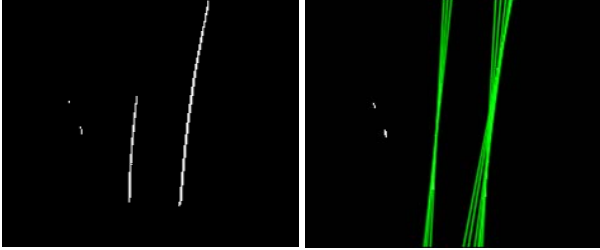


Fig. 5 (a) Input denoising image (b) Result image of Hough transform

For every line-group, line-classifier can also calculate its central line and extract the corresponding boundary, which as shown in Fig. 6-a and Fig. 6-b.

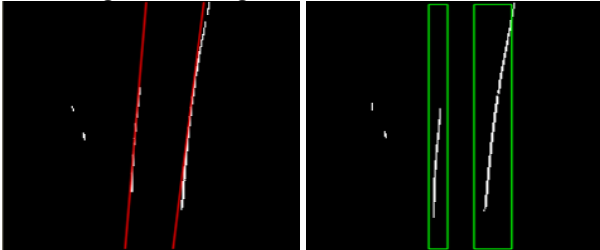


Fig. 6 (a) the result image drawing calculated central line (b) the result image drawing boundary

It is significant to track the lane marking boundary for our driver assistance. Kalman filtering provides a way to incorporate a linearized version of the system dynamics to generate optimal estimates under the assumption of Gaussian noise. Boundary tracking can provide improved results in noisy situations and generate useful metrics for lane detection next frame. Kalman filtering also provides estimates of state variables that are not directly observable, but may be useful for the system.

In my experiment, the Kalman filter state variables are updated using the coordinate of lane marking boundary and the translation vector of the lane marking position in u-axis between two consecutive frames with a common lane. These measurements are then used to update the discrete-time Kalman filter for the road and vehicle state. When a valid lane marking cannot be found using a Hough transform, thus, the estimation by Kalman filter can acts as the measuring value.

Actually, the lane boundary detection provide with a critical initialization of candidate range for the following spline fitting algorithm.

#### E. Optimized B-Spline Fitting

The previous step gives us candidate range in the image, which are then used by this step. For each such boundary, we will run the spline fitting algorithm.

The spline used in my experiment is a third degree Bezier

spline which has the useful property that the control points form a bounding polygon around the spline itself. The third degree Bezier spline is defined by:

$$p(t) = \frac{1}{6} [1 \ t \ t^2 \ t^3] \begin{bmatrix} 1 & 0 & 0 & 0 \\ -3 & 3 & 0 & 0 \\ 3 & -6 & 3 & 0 \\ -1 & 0 & -3 & 1 \end{bmatrix} \begin{bmatrix} P_0 \\ P_1 \\ P_2 \\ P_3 \end{bmatrix}, t \in [0,1] \quad (7)$$

Where  $t \in [0, 1]$ ,  $p(0) = P_0$  and  $p(1) = P_3$  and the points  $P_0$  and  $P_3$  control the shape of the B-spline (Fig. 7).

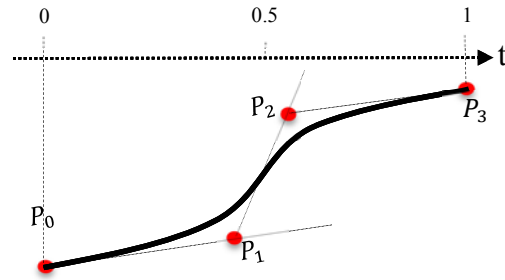


Fig. 7 Schematic diagram of Bezier Spline

As we know, getting point sample in general spline fitting algorithm is in random absolutely, namely, there has not candidate region for each sample point selection. However, in my optimized spline fitting algorithm, because of entire candidate point are distribute around a vertical line in a specific lane marking boundary, so, I segment all of the candidate points into 4 sub-regions, and then, every sample point must be selected from a sub-region separately, thus, the run time of optimized spline fitting algorithm reduce to 30% of general spline fitting algorithm for a common precision.

### III. EXPERIMENT AND ACCURACY EVALUATION

We ran the algorithm to detect only two lanes of current frame, detection results of two video clips shows in Fig. 8.



Fig. 8 The interface of sample point collection

We collected a number of clips on different types of urban streets, with shadows, vehicles ahead and on straight and curved streets. Unlike previous papers that would just mention

rough percentages of detection rates, and in order to get an accurate quantitative assessment of the algorithm, we hand-mark all visible lanes in two different test video, totaling 1746 sample points which are shown in Tab I.

Table I Datasets of precision evaluation

Test video	frames	lanes	Sample points
Video_1	159	285	854
Video_2	174	296	892

Our evaluation system was written using in C++/MFC based on the open source library of OpenCV.

For our sample precision evaluation, we load the sample point file and computer the distance from every sample point to corresponding fitted B-spline, if the distance is less than our threshold which is defined according to specific pixel wide of lane marking in you test video, for instance, the threshold is 3 pixels if the wide of lane marking equal to 6 pixels, and then the corresponding point on spline is correct.

Finally, make a statistics for the correct point number and accuracy equal to the number of correct point divided by total sample point number, the accuracy of our experiment is shown as Tab II.

Table II Accuracy of for test video

Test video	Sample points	Correct point	Accuracy rate
Video_1	854	793	92.857%
Video_2	892	838	93.946%

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#### V. CONCLUSION

In this paper, we proposed an efficient, real time, and robust algorithm for detecting lanes on urban roads. The algorithm is based on taking a top view of the road image, filtering with Gaussian High Pass kernels and a robust denoising template, then using Hough Transform, line-classifier, Kalman filter and an optimized 3 degree Bezier spline fitting technique to detect lanes on the road.

We compared our results and precision to other algorithms which is just can run in high way or few vehicles along with shadows, our algorithm can detect lanes in various conditions and has good accuracy.

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