# An Improved Approach for Vision-Based Lane Marking Detection and Tracking

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**Abstract.** Lane marking detection plays an important role within intelligent vehicles research. The proposed kernel based lane marking detection method, decreases time consuming and improves the detection performance in heavy traffic scenarios. To this end, a horizontal filter is applied to binarize IPM-view images, a cell based blob algorithm is used to eliminate outliers. Starting points of current lane markings in a camera image are estimated as an initialized stage of lane detection. A multi-density kernel based method is introduced to fit quadratic parabolic marking lines. In the end, the detection results are evaluated. Obtained results show that this method is capable of robustly and accurately detecting lane markings in different road and urban traffic scenarios.

## I. Introduction

On-vehicle lane detection plays a significant role in Advanced Driver Assistance Systems (ADAS) and autonomous vehicles. This subject has been deeply studied for more than twenty years, where studies such as [1–3] can be considered as representative works. The main objective here is to determine the position of the lane markings, which represents key information of the environment structure for road geometry estimation and context recognition (e.g. highway, urban) [4]. Such results are usually exploited within more complex systems, for instance vehicle lateral control, automatic cruise control, autonomous driving [5], driver assistance [6], and vehicle localization systems [7].

Most of existing lane detection approaches follow a common strategy composed of different stages: perception modality, feature extraction, and model fitting.

The perception modalities employed in this state-of-the-art include monocular vision (projective and fisheye cameras), stereovision systems [8], range finder sensors and multi-sensor systems. Laser-based approaches are quite effective since such a sensor provides a clear signature (i.e. reflectiveness) of the lanes, however they are rarely adopted because of their high integration cost. Vision-based systems constitute a polyvalent and affordable solution. Thus, our study is then focused on vision-based approaches.

Feature extraction methods enclose different techniques employed to detect potential lane markers. Such features can be defined as low-level descriptors [9], however they are sensitive to lighting changes. More complex feature extraction approaches [10] provide robust results exploiting more discriminant criteria (e.g. contours, color gradients and marking ridges).

Lane marking models and fitting methods are strongly related. Different image road models have been studied in the aim of determining a trade-off between complexity and precision. Straight lines are often fitted by the means of Hough transform. This approach constitutes relatively simplistic structures which is restricted to straight road areas only. Splines[11] deal with more complex lane marking shapes, but they are time consuming. Parabolic curves [12] and polylines [13] are regarded as mediums between complexity and precision.

Taking into account the latter considerations, our study focus on a kernel based lane marking detection method using a monocular vision system. The image pre-processing stage of the proposed approach is presented in Section II. Then Section III presents lane marking fitting estimation approaches. Section IV addresses the experimental tests and illustrates the obtained results. Finally, conclusions are provided in Section V. The outline of the proposed method is illustrated in Fig. 1.

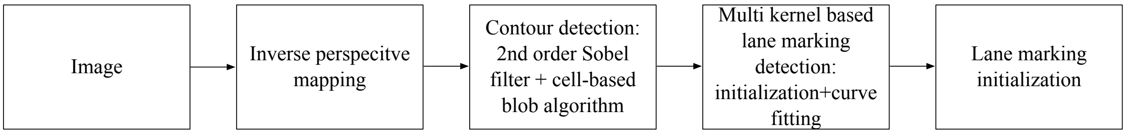


Fig. 1. Algorithm outline

## II. Image processing

**Inverse Perspective Mapping.** Monocular vision is adopted to gather road situations, since its prime cost is acceptable, and certain complex situations (e.g. intensity affects) can be alleviated by image processing and prior knowledge. A facing-forward camera on board a vehicle is considered. This camera is modeled using a pinhole projective model assuming no distortion and zero skew. Images are processed through Inverse Perspective Mapping (IPM) to obtain a bird-eye's view of video frames. This transformation provides vertical and paralleled lane markings which greatly facilitates lane detection strategies. In addition, IPM images are stabilized in case of distortion caused by slopes, according to pitch and yaw angles provided by inertial measurement unit.

**Contour detection.** An image in which a pair of lane marking is nearly vertical and parallel is obtained by the means of IPM. Therefore, a Second order Sobel filter following horizontal direction, is applied. This filter is expressed as Eq. 1. Normal differential-based extraction methods, like Canny filter and Histograms of Oriented Gradients (HOG), emphasis on the pixels where there are important gray scale gradients, which means that normal methods localize lane marking edges rather than the marking bodies. When Sobel filter computes a gradient approximation of the gray scale image intensity, lane marking edge pixels perform high norms because of high frequency variations. When Sobel filter convolves the image intensity again, marking body pixels in the middle of left and right edges, performs higher norms, because of the high norms from first order Sobel operator. Hence, thanks to Second order Sobel filter, lane marking pixels represent differentiable values. In addition, the time consuming of this method is much less than complex extraction methods.

$$A_{xx} = G_x * G_x * A. \tag{1}$$

where, $A_{xx}$ is the IPM input image, $A$ is the filtered image, and $G_x$ is x-axis Sobel mask. Here, * denotes the convolution operator.

After Second order Sobel filter, a binary image is produced, including outliers (e.g. road branches, arrow markings, guard bars). To eliminate these outliers, a cell-based blob algorithm, inspired from [14], is introduced. The main idea of this method is to remove the outlier blobs with respect to the image direction, the cell direction and the blob size. At first, the binary image is divided into 4×4 cells. Then all the blobs are searched in all the cells, and classified into 9 bins (20$^\circ$ per bin) according to the blob direction. After that, among all the blobs in a cell, a main direction (bin) is voted in a single cell. Then, the main direction of whole image is voted from all the main directions in all cells. In the end, outlier blobs are excluded according to three conditions: the main direction of the image, the template direction in each cell, and the size of current blob.

## III. Lane marking fitting

A quadratic parabola: $x=a\cdot y^2+b\cdot y+c$ is chosen as the model of lane marking shape [12]. On one side, spline-like lane markers almost disappear from a bird's eyes view with limited range on the road. On the other side, a straight line model, which is the most common shape in real situation, is a subset of quadratic parabola model.

**Initialization.** The first step to fit the lane markings is to initialize the intersections of the parabola and x-coordinate, which provides the parameter denoted c in the model. These intersections can be also regarded as a prior guess of the two current lane markings. To obtain this prior, a Region of Interest (ROI) is selected. The range of ROI should be set in which curves can be regarded as straight lines, and in which the discontinuous markings are included also. Then, Hough transform is employed to identify all the feasible straight lines *($x_i = k_i \cdot y_i + b_i$, $i=1,2...$)*, representing potential lane markers. After that, a weighted multi-cue probability of each Hough line is implemented to estimate two starting points of the current lane, according to Eq. 2.

$$m_i = k_1 \cdot m_{i,1} + k_2 \cdot m_{i,2} + k_3 \cdot m_{i,3} + k_4 \cdot m_{i,4}. \tag{2}$$

where $m_{i,1} \in (0, 1)$ represents the likelihood of each Hough line as a lane marking according to empirical experiences. $m_{i,2} \in \{0, 1\}$ is the direction constraint of each Hough line. $m_{i,3} \in (0, 1)$ and $m_{i,4} \in (0, 1)$ depict the variety constraints of each line compared to historical data, $k_1$ to $k_4$ are weights of each item.

**Multi kernel based lane marking detection.** A multi kernel density based method is introduced to decide the curve parameters [15]. The basic characteristic of this algorithm is the similarity between a random pixel on the image and the model:

$$G_{pi}(d, e) = \int_{-\infty}^{+\infty} K_x^{'} K_y K_\theta^{'} dy, \tag{3}$$

where

$$K_x^{'} = \frac{1}{\sigma_{xi}} \phi(\frac{x_m - x_i}{\sigma_{xi}}), \quad K_\theta^{'} = \frac{1}{\sigma_{\theta i}} \phi(\frac{\theta_m - \theta_i}{\sigma_{\theta i}}), \quad K_y = \frac{1}{\sigma_{yi}} \phi(\frac{y_m - y_i}{\sigma_{yi}}).$$

Here, Gauss-Hermite quadrature method is employed to calculate the integration.

Therefore, the probability of a specified model *p(d,e)* is obtained as:

$$p(d, e) = \frac{1}{N} \sum_{i=1}^{N} G_{pi}(c, d, e). \tag{4}$$

In addition, a two-line model is introduced instead of one-line model. The two line model is based on the initialization referred before. The two lines are not strictly parallel, but follow the relationship in Eq. 6 and Eq. 7.

$$(d_{1m}, e_{1m}, d_{2m}, e_{2m}) = \max_{i_1, j_1, i_2, j_2} [p_{left}(c_1, d_{i_1}, e_{j_1}) + p_{right}(c_2, d_{i_2}, e_{j_2})], \tag{5}$$

$$i_2 \in (i_1 - i_\triangle, i_1 + i_\triangle), \tag{6}$$

$$j_2 \in (j_1 - j_\triangle, j_1 + j_\triangle). \tag{7}$$

Finally, the curve parameters $d_{1m}$, $e_{1m}$, $d_{2m}$ and $e_{2m}$ are chosen according to Eq. 5.

## IV. Results

This algorithm is programmed in C++ on a laptop with INTEL Core i5 (2.5GHz) for evaluation and analysis purpose. To validate our method, we considered dataset coming from the KITTI database [16]. Fig. 2 shows the detected lane markings on camera images with various outside conditions: discontinuous lane markings in Fig. 2(a), road curves in Fig. 2(b), heavy traffics and shadows in Fig. 2(c), mixture of multi conditions (curves, traffics, and shadows) in Fig. 2(d). The image processing area is marked within a trapezoid-like box. The trapezoid-like shape is decided by IPM, a nonlinear mapping from camera view to bird's eyes view. The detected lane markings are depicted as dark thick curves in the image processing area. In these four example results, the detections are not affected by common difficulties such as irregular markings, heavy traffics or shadows. Therefore, the results demonstrate that the proposed method provides robust lane markings in highway and road scenes.

Fig. 3 is the road map of one of database scenarios, depicting the comparison between map-based road markings and detected road markings. Map-based lane markings are derived from OpenStreetMap, according to the road properties (coordinate, number of lanes, type of road) from map. Meanwhile, detected lane markings are located on the map according to adjusted GPS position. The average absolute error of marking pixels between detection and map is 15 cm. This comparison between detection and map demonstrates the result accuracy in a long-term and continuous driving procedure.

This algorithm has been tested on 12 different challenging scenarios in the database, including more than 1900 frames. The average processing time per frame is 68.18 ms, which represents an average frequency of 14.7 Hz. Compared to the frequency of database frames (10Hz), the proposed method is adequate to process the frame streams in real-time.

Consequently, the results show that this algorithm provide robust, accurate, and real-time lane marking detection.

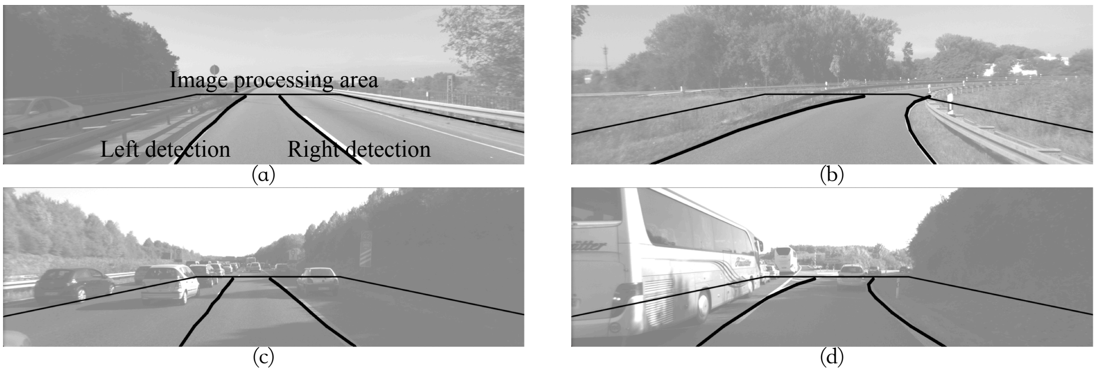


Fig. 2. Lane detection results in different road scenes.

## V. Conclusion

This paper demonstrates a multi kernel estimation based lane marking detection method. Quadratic parabola model works on real-world road conditions, and fits the road marking shape accurately. Compared to the state-of-the-art in this field, this method has threefold advantages. Firstly, in binary images, lane markings are clear with few disturb pixels, thanks to Second order Sobel filter and improved blob algorithm. Secondly, the initialization stage of curve fitting increases model estimation accuracy, and decreases time-consuming of model fitting as well. Thirdly, a near-parallel parabola model, considering both left and right lane markings together, increases marking detection robustness, especially in challenging scenes (e.g. heavy traffic).

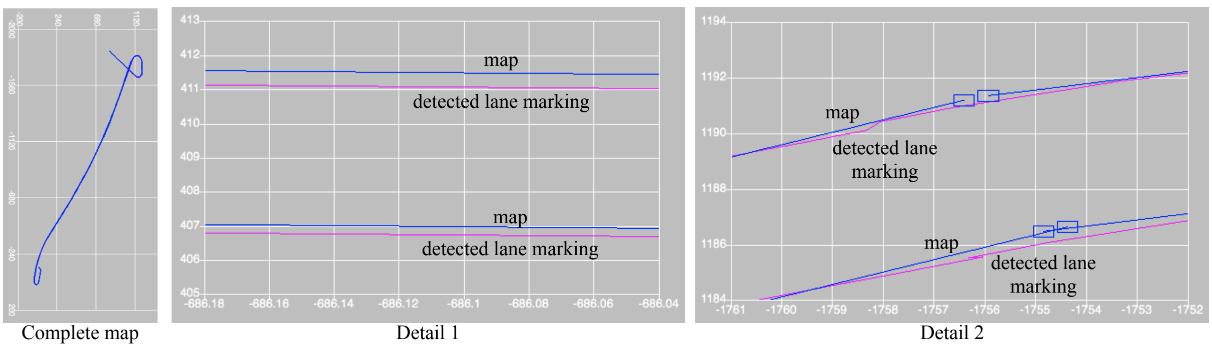


Fig. 3. Detected lane markings on OpenStreetMap. Darker curves are map-based lane markings, and lighter ones are detected markings using the demonstrated method.

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