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A Novel Lane Model for Lane Boundary Detection

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Abstract

This paper addresses the problem of the navigation of a mobile vehicle in outdoor environment. A Catmull-Rom Spline based lane model which described the perspective effect of parallel lines was proposed for generic lane boundary. As Catmull-Rom Spline can form arbitrary shapes by control points, it can describe a wider range of lane structures than other lane models such as straight and parabolic model. It formulates the lane detection problem in the form of determining the set of lane model control points. The proposed algorithm uses a Maximum likelihood approach to the lane detection problem. In contrast to other approaches like Edge-Link and Snake, the proposed algorithm can increase the accuracy of estimation which approximates to global optimum. The proposed method is robust to the noise present in the road image with shadows, variations in illumination, marked and unmarked road.

Index Terms-- Lane detection, Catmull-Rom Spline, lane model, machine vision, maximum likelihood.

1. INTRODUCTION

The detection of lane marking or boundary in images of road scenes, obtained from a camera mounted on the vehicle, is an important ability for auto-vehicle in outdoor environment.

The main properties that must be possessed by a solution of the lane marking or boundary detection are:

- The detection should not be affected under shadow condition. These shadows can be cast by trees, buildings, etc.
- It should be capable of processing painted or unpainted roads. It has to detect painted lines and road boundary for painted and unpainted road respectively.
- It should handle curved road rather than assuming straight road.
- It should use the parallel constraint as a way to improve the detection of both sides of lane markings or boundaries in the face of noise in the images.
- It should produce an explicit measure of the reliability of the result it has produced.

In Section 2, reviews on existing lane detection techniques are presented. Section 3 presents a new lane model based on the Catmull-Rom spline. In Section 4, a proposed algorithm which uses the new lane model and the maximum likelihood method for lane detection is developed. Section 5 shows representative results of applying this proposed lane model and algorithm to various road types and environments. Conclusions are given in Section 6.

2. RELATION WORK

At present many different vision-base lane detection algorithms have been developed. They depend on different road models (2D or 3D, straight or curve) and approach techniques (Hough, template matching, neural networks, etc.).

A curve road model is proposed by [1][2][3], it supposes that the lane boundaries can be presented by a parabolic curve on a flat ground. Although it can approximate normal road structures, it still can not describe some cases. A deformable template method was proposed by optimizing a likelihood function based on this model. However, this algorithm can not guarantee a global optimum and accuracy without requiring huge computational resources.

An edge-based road detection algorithm is presented by [4][5][6][7], it can work nicely in well painted roads even under shadow condition, but for an unpainted road that must be detected by boundaries, this detection will meet problems.

The approach by [8], worked in the domain of locating pavement edges in millimeter wave radar imagery, used a deformable template approach to finding the best fit of a straight road model with unknown width and orientation to the radar data. This technique has disadvantage of detection of straight road only.

An approach by combining the Hough transform and Line-Snake model is presented by [9], it divides an image into a few sub-regions along the vertical direction. The Hough transform is then performed for each sub-region to obtain an initial position estimation of the lane boundaries on the road. Then line snake improves the initial approximation to an accurate configuration of the lane boundaries. This approach suffers from two problems. First, in the case of a broken lane marking, it may not extend all the way to the bottom of the image. Second, the contrast of one or both of the lane edges may not be high enough to detect near the bottom of the image.

In [10][11], using statistical criteria and Chi-Square fitting to do lane boundary detection. However, they used the same road model as [1][2][3].

Here we present a road model based on Catmull-Rom spline, and matching measurement between model and real edge image by a maximum likelihood function.

3. ROAD MODEL

3.1 Catmull-Rom Spline

The Catmull-Rom spline, also called Overhauster spline, is a local interpolating spline developed for computer graphics purpose.

Very often, we have a series of positions and want a curve smoothly to interpolate (pass through) them, for this situation, the Catmull-Rom spline is able to interpolate the points P_1 to P_{m-1} from the sequence of points P_0 to P_m. In addition, the tangent vector at point P_i is parallel to the line connecting points P_{i-1} and P_{i+1}, as shown in Figure 1.

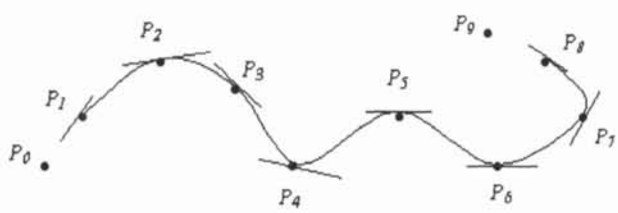


Figure 1 A Catmull-Rom spline. The points are interpolated by the spline, which passes through each point in a direction parallel to the line between the adjacent points. The straight line segments indicate these directions.

The formula of Catmull-Rom spline for one segment is:

$$P(t)=\frac{1}{2}\begin{bmatrix} t^3 & t^2 & t & 1 \end{bmatrix}\begin{bmatrix} -1 & 3 & 3 & 1 \\ 2 & -5 & 4 & -1 \\ -1 & 0 & 1 & 0 \\ 0 & 2 & 0 & 0 \end{bmatrix}\begin{bmatrix} P_{i-3} \\ P_{i-2} \\ P_{i-1} \\ P_i \end{bmatrix}$$

Where $(P_0, P_1, ..., P_n)$ is the control points which require Catmull-Rom spline to pass through, $t \in$ [0 to 1].

3.2 Use Catmull-Rom Spline to Describe Lane Marking or Boundary

In the general situation (straight, turn left and turn right lane), two sets of three control points (lane left: (P_{L0}, P_{L1}, P_{L2}). Lane right: (P_{R0}, P_{R1}, P_{R2}) can be formed a Catmull-Rom spline to approach left and right side lane boundary or marking, this two splines joint point is vanishing point, which is located on the horizon in the image. Although the Catmull-Rom spline interpolate all but the first and the last control point, it can be cheated by setting the first two control points equal and the last two control points equal. The Catmull-Rom spline implemented to real lane image is shown in Figure 2.

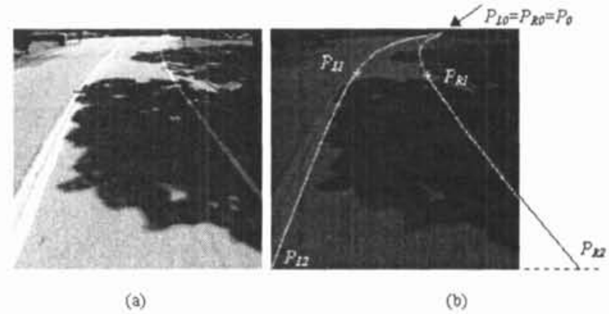


Figure 2 Estimation of lane marking by Catmull-Rom spline. (a) Original Lane Image. (b) Present the lane marking by Catmull-Rom splines, (P_{L0}, P_{L1}, P_{L2}) and (P_{R0}, P_{R1}, P_{R2}) are the control points for left and right side of lane marking. P_{L0} and P_{R0} is the same control point, which suppose to be vanishing point.

3.3 Control Point Search Area

Figure 3 shows the road shape in the image plane and ground plane, after estimating left side of lane model by (P_{L0}, P_{L1}, P_{L2}), it is possible to reduce the searching area for right side lane model corresponding control point P_{R1} by parallel line property in ground plane.

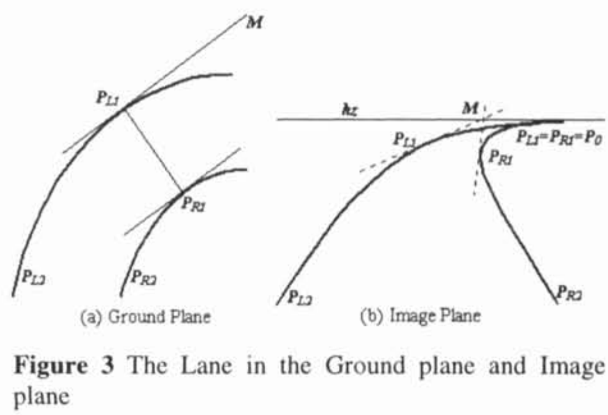


Figure 3 The Lane in the Ground plane and Image plane

The derivation of the slope of line $P_{L1}P_{R1}$ in the image plane is more complicated, it has the form:

$$k_{l1r1}=\frac{(r_{l1}-hz)(r_{l1}k_{l1}-r_{l1}+hz)}{c_{l1}{}^2k_{l1}+k_{l1}(\lambda^2+hz^2)-c_{l1}(r_{l1}-hz)} \quad (1)$$

Where (r_{l1}, c_{l1}) is coordinate of point P_{L1} in image plane. k_{l1} is the slope of tangent of point P_{L1}. λ is the focal length. hz is the horizon in the image plane.

Equation (1) determines the possible location of point P_{R1} in the image plane.

Figure 4 Gray areas show the possible location of P_{R1} in terms of P_{L1} and its slope of tangent.

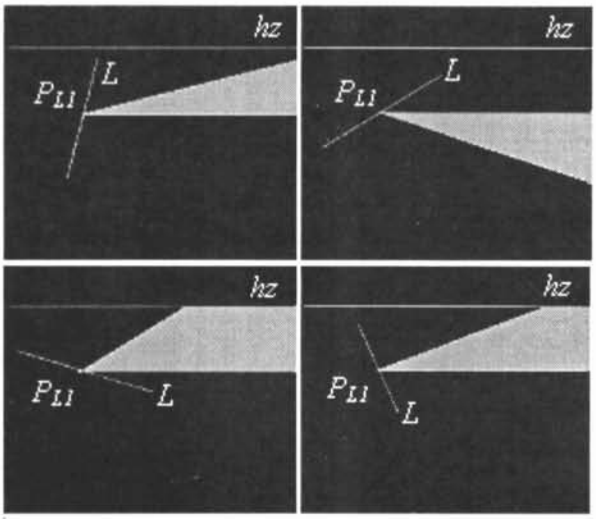
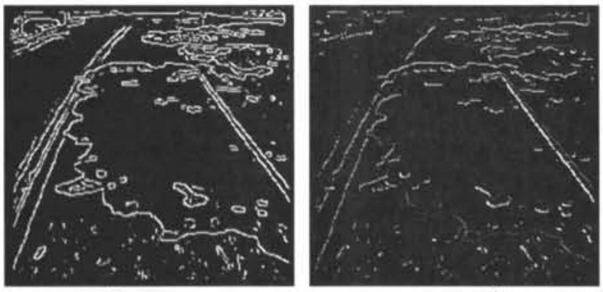


Figure 4 Possible location of P_{R1}, hz is the horizon in the image plane, L is the tangent slope of P_{L1}, assume we do not know the focal length λ, we suppose $\lambda \in (0, +\infty)$.

4. Maximum Likelihood Approach to Lane Detection

4.1 Edge Detection

Currently we use Canny Edge detector to locate the position of pixels where significant edges exist. It was shown in Figure 5. Figure 5 We choose σ=1 and a 9×1 mask is used for Gaussian convolution in both X and Y directions, the high and low gradient threshold for edge detector is set to 90% and 40% of the maximum.



(a) (b)

Figure 5 Apply Canny Edge Detector to Figure 2(a): (a) Edge detection (b) Orientation of gradients

4.2 Likelihood

The likelihood specifies the probability of observing the input image, given a lane model at a specific position, orientation and scale. It is a measurement of the similarity between the lane model and the lane present in the image. The likelihood we propose here only uses the edge information in the input image.

4.2.1 Calculate Likelihood

The likelihood function was defined by:

$$L = \frac{1}{n_T} \sum \left(\exp\left(-\frac{\delta_c^{\,2} + \delta_r^{\,2}}{2\sigma^2} \right) \cdot \left| \cos(\beta(c, r)) \right| \right) \quad (2)$$

Where n_T is the number of pixels on the lane model, $\beta(c, r)$ is the angle between the tangent of the edge and the tangent direction of the lane mode at (c, r). Currently we set $\sigma = 3$.

4.2.2 Search Control Points in Edge Image for Lane Model

Since we need two sets of three control points (P_{L0}, P_{L1}, P_{L2}) and (P_{R0}, P_{R1}, P_{R2}) to build the lane model by Catmull-Rom spline. First we assume the ground is flat and we know the horizon is at row=hz in image plane. In order to reduce search area, we define P_{L0} and P_{R0} as the same points at hz, namely the vanishing point. We assume the vanishing point can be any position at hz. Then the rows of the edge image are processed selectively at increased steps between proceed rows from hz to search the edge point as P_{L1}. The left side of lane model can be constructed by P_{L1} position and its orientation, so we have a few sets of vanishing point P_{L0} and end point P_{L2}. Next we can search for the edge point as P_{R1}, the search area is determined by equation (1), the right side of lane model can be constructed by P_{L0} and P_{R1}.

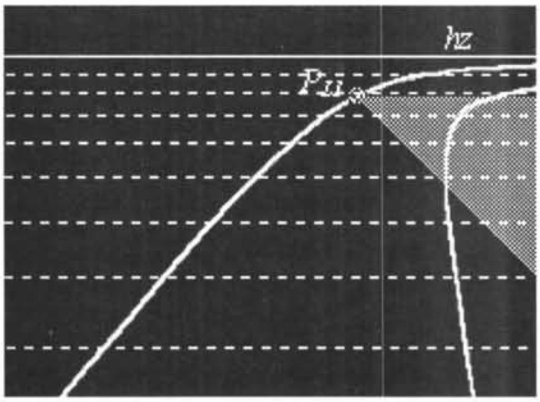


Figure 6 Search Area for P_{R1}. The dash lines are the rows searched for control points. The gray area is the search area for P_{R1}.

5. Results

The proposed algorithm has been tested on 20 images grabbed by an on-board camera at different locations and at different times. Figure 7 to Figure 9 show some of our experimental result of lane boundary detection where detected lane boundaries are superimposed onto the half gray of original images. These images contain both paved and unpaved roads and lanes which are either marked or unmarked. The proposed method is robust in terms of the noise present in the input image in the form of shadows, variations in illumination and road conditions.

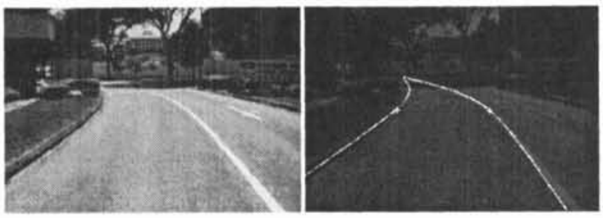


Figure 7 NTU Main Entrance, Well Painted Road

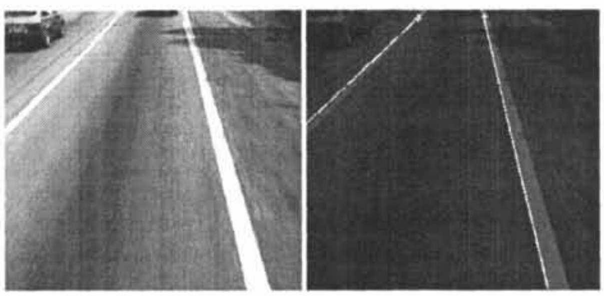


Figure 8 Straight Painted Lane

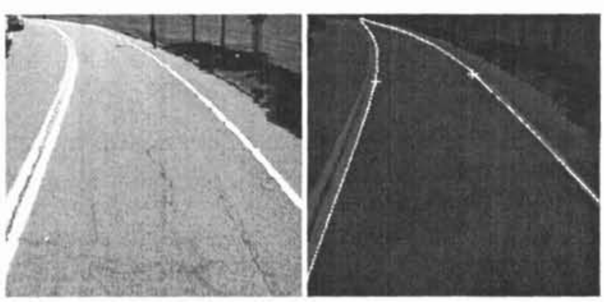


Figure 9 Left Turn Lane

6. CONCLUSION

We have addressed the problem of lane marking detection. A new Catmull-Rom spline based lane model which describes the perspective effect of parallel lines is constructed for generic lane boundary or marking, it is able to describe a wider range of lane structures than other lane models such as straight and parabolic models. The lane detection problem is formulated by determining the set of lane model control points. Using a maximum likelihood method that measures the matching between the model and the real edge image. The results obtained are good and accurate under shadow conditions.

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