Lane Detection Using Catmull-Rom Spline

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Abstract--In this paper, 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. We have employed a multiresolution strategy to rapidly find an accurate solution. This coarse-to-fine matching offers an acceptable solution at an affordable computational cost and speeds up the detection. 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

Autonomous Guided Vehicles (AGV) have found many applications in many industries. Their utilization had been explored in areas such as hospitals for transportation of patients, automated warehouses and other hazardous related areas. In most applications, these AGVs have to navigate in unstructured environments. Path findings and navigational control under this situation are accomplished from the images feedback by camera mounted on the vehicles. These images are interpreted to extract meaningful information such as positions, road markings, road boundaries, and direction of vehicle's heading. Among many extraction methods, lane marking or road boundary detection from these images had received great interest. This is one of the most fundamental approach in detecting the curvature of the following the road. As the images received are usually corrupted by noises, lots of algorithms for boundary detection were developed to achieve robustness in rejection these noises.

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 boundaries 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. Analysis of the shortcomings of each detection technique are given. Section 3 presents a new lane model based on the Catmull-Rom spline. Relation between the control points of both sides lane model is shown. 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 Related Work

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

An approach embodied in the ARCADE system [1] uses robust estimation to determine road curvature and orientation from edge point positions and orientation without prior grouping of the edge points into lane edges. Once the road curvature and orientation have been found ARCADE uses them to reduce the problem of locating the lane edge offsets with respect to the vehicle to the problem of segmenting a one-dimensional signal. This signal is constructed by averaging together all images pixels with the same offset relative to the road center in order to smooth out variations due to shadows, texture, etc. The use of robust estimation allows ARCADE to work in cases where up to 50% of the input edge points are noise, but the algorithm fails if the fraction of noise edges rises above that point.

The approach in [2][3] based on morphological filtering has been used. This technique uses the morphological "watershed" transformation to locate the lane edges in the intensity gradient magnitude image. While this technique has the advantage of not requiring any thresholding of the gradient magnitudes, it has the disadvantage of not imposing any global constraints on the lane edge shapes.

A curve road model is proposed by [4][5], 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, such as a scene that a vehicle turns to a "T" turn. 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 [6][7][8][9], it can work nicely in well painted roads even under shadow condition, but for an unpainted road that must be detected by its boundaries, this detection algorithm will meet problems.

The approach by [10], working in the domain of locating pavement edges in millimeter wave radar imagery, used a deformable template approach to find the best fit of a straight road model with unknown width and orientation to the radar data. The likelihood function used to judge how well a given template shape matched the radar data combined geometric constraints with a model of the physics of the radar image formation. The Metropolis algorithm was used to identify the optimal set of template deformation parameters. This technique has a disadvantage of detection of straight road only.

An approach by combining the Hough transform and Line-Snake model is presented by [11], it divides an image into a few subregions 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 [12][13], an approach of lane boundary detection especially for country roads field by artificial vision is described. It uses statistical criteria such as energy, homogeneity, contrast etc. to distinguish between road and non-road-area. It combines random search with the chi-square fitting to obtain the best set of parameters of a deformable template. However, they used the same road model as [4][5].

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

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. Its initial use was in design of curves and surfaces, and has recently been used in several applications.

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. These splines don't posses the convex-hull property. The natural (interpolating) splines also interpolate points, but without the local control afforded by the Catmull-Rom splines.

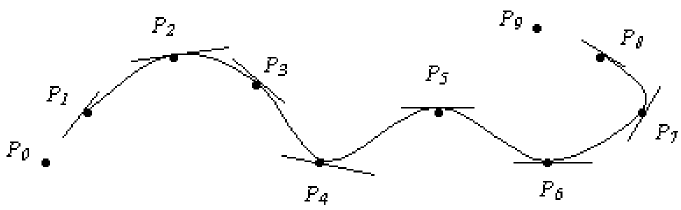


Figure 1 A Catmull-Rom spline. The points are interpolated by the spline, which passes through each point in a direction parallel to the line between the adjacent points. The straight line segments indicate these directions.

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}) and lane right(P_{R0}, P_{R1}, P_{R2})) can be formed a Catmull-Rom spline to approach the 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 interpolates all but the first and the last control point, it can be cheated by setting the first and the last two control points equal. The

Catmull-Rom spline implemented to real lane image is shown in Figure 2.

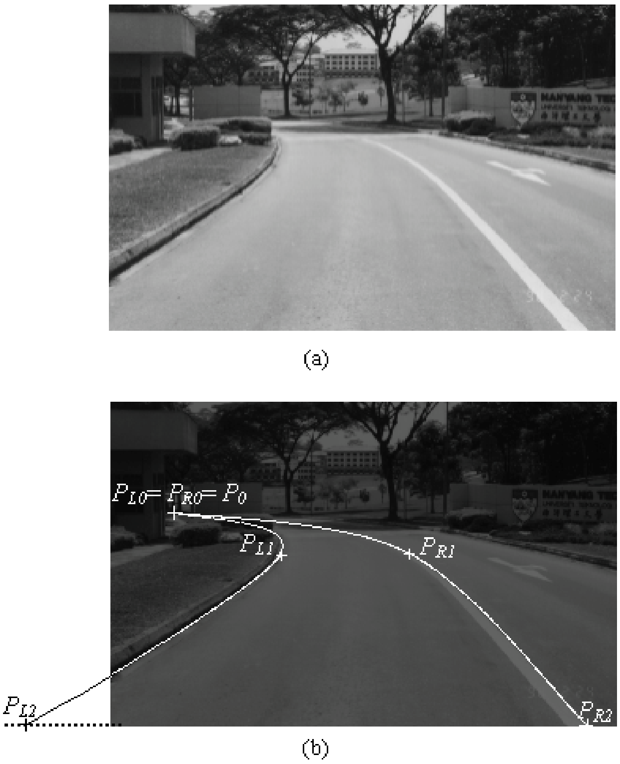


Figure 2 Estimation of Lane marking by Catmull-Rom spline. (a) Original Lane Image. (b) Present the lane marking by Catmull-Rom splines, (*P_{L0}, P_{L1}, P_{L2}*) and (*P_{R0}, P_{R1}, P_{R2}*) are the control points for left and right side of lane marking. *P_{L0}* and *P_{R0}* is the same control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

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

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

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.

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

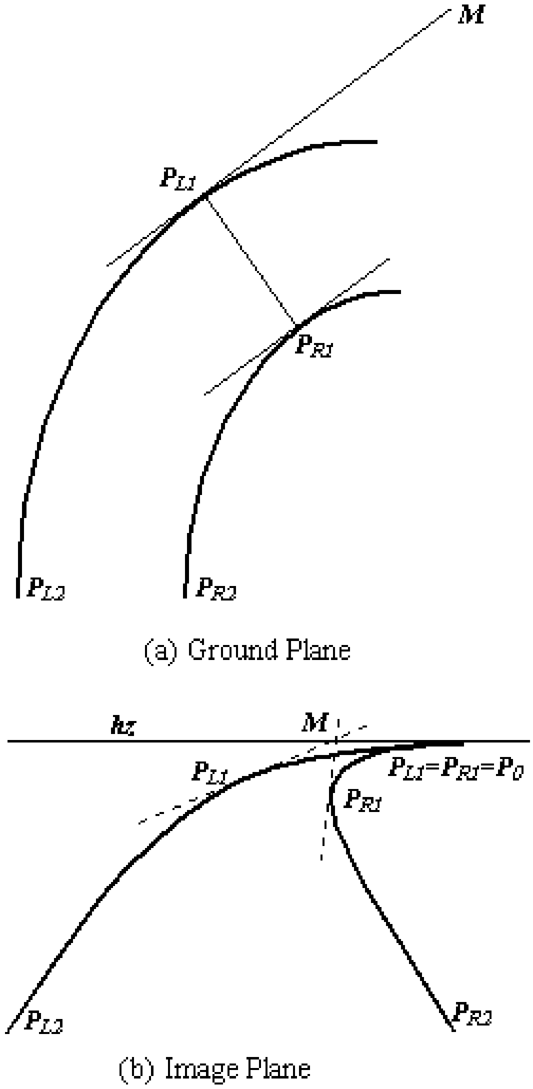


Figure 3 The lane in the ground plane and image plane.

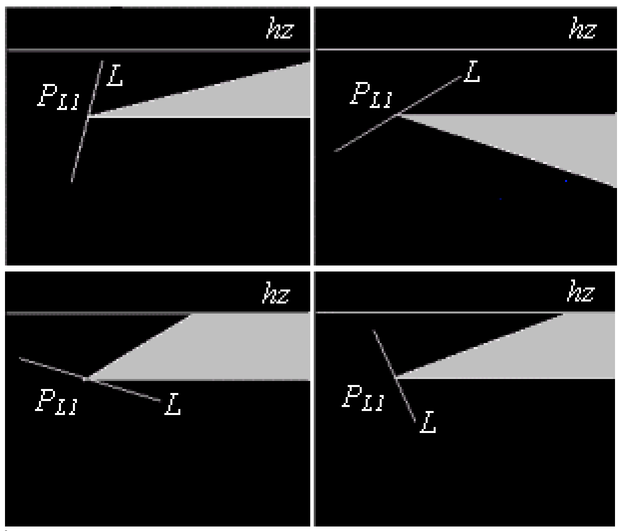


Figure 4 Possible locations of *P_{R1}. hz* is the horizon in the image plane, *L* is the tangent of *P_{L1}*.

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. Applying the Canny edge detector to a lane image, we can obtain two images that denote the edge pixels and the orientation of gradient. 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) Edge Image

(b) Gradient Orientation

Figure 5 Applying Canny Edge Detector to Figure 2(a).

4.2 Likelihood

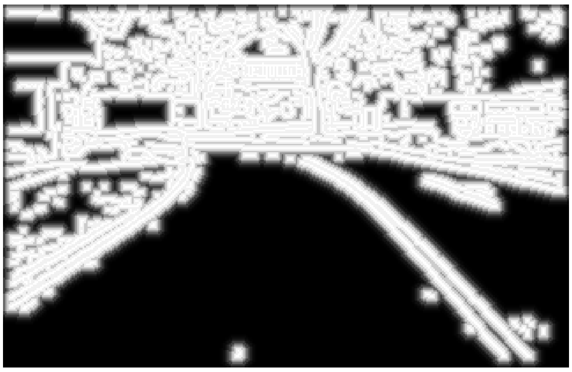
The likelihood specifies the probability of observing the input image, given a lane model at a specific position, orientation and scale. It is a measurement of the similarity between the lane model and the lane present in the image. The likelihood we propose here only uses the edge information in the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

4.2.1 Compute Potential Edge Field Image

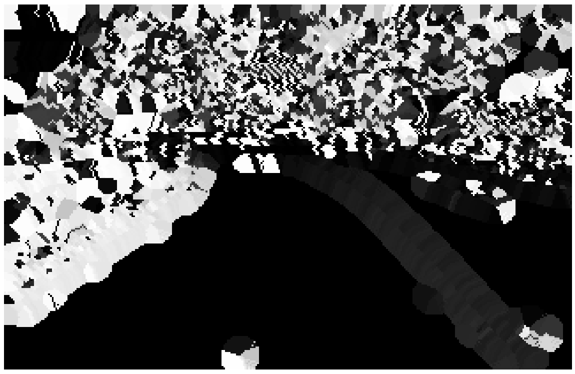
The lane model is aligned to the salient in the input image via a directional edge potential field. The positions and directions of the edges in the input image determine this field. For a pixel (c, r) in the input image its edge potential is defined as:

$$P(c,r) = exp\left(-\frac{\delta c^2 + \delta r^2}{2\sigma^2}\right) \qquad (2)$$

Where ($\delta c,\delta r$) is the displacement to the nearest edge point in the image, and σ control the smoothness of the potential field. Also the edge potential orientation is generated in the same time, it is simply equal to the nearest edge point's orientation if it is in this edge point's potential field. Currently we use σ=3 to do the calculation of potential edge and orientation field. Figure 6 shown the potential edge and orientation image when σ=3.



(a) Potential Edge Field



(b) Potential Orientation Field

Figure 6 Potential Edge and Orientation Field, σ=3.

4.2.2 Calculate Likelihood

We modify the edge potential by adding to it a directional component. This new edge potential induces an energy function that relates a lane model to the edge in the lane image.

The likelihood function is defined by:

$$L = \frac{1}{n_T}\sum \left(P(c,r)\cdot\left|cos(\beta(c,r))\right|\right) \qquad (3)$$

Where n_T is the number of pixels on the lane model, $\beta(c, r)$ is the angle between the tangent of the nearest edge and the tangential direction of the lane model at (c, r).

This definition requires that the lane model agrees with the image edges not only in position, but also in the tangential direction. This feature is particularly useful in the presence of noisy edges. The higher this likelihood the better the lane model matches the edges in the input image.

4.3 Search Control Points in Edge Image for Lane Model

In this method, 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. Firstly, we assume the ground is flat and 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 lies anywhere at row *hz* where the line is extended to the left and right beyond that shown in figure 7, with each distance equals to the width of the image.

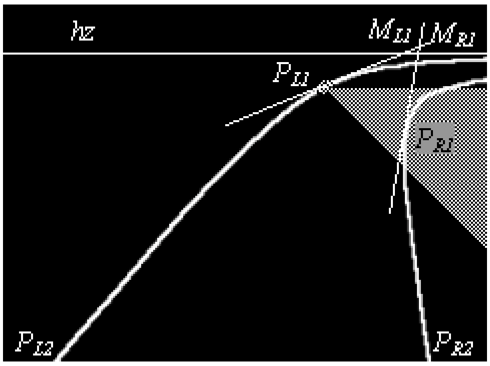


Figure 7 Search Area for P_{R1}

Beginning from row *hz*, we search downwards to obtain a edge point, P_{L1}. The left side of lane model can be constructed by using the position and orientation of P_{L1}. We can also get the end point P_{L2}, which is the intersection of the lane model with the bottom line of image. The tangent at P_{L1} intersects row *hz* at $M_{L1.}$ Then we need to calculate the likelihood L_L for left lane model. If L_L is more than a threshold, update record and then search for the next P_{R1}; otherwise restart the searching for P_{L1}.

Next, we can search for the edge point P_{R1}. The search area is determined by equation (3), and the tangent at P_{R1} intersects row *hz* at $M_{R1.}$ The horizontal distance between M_{L1} and M_{R1} should be less than a threshold M_{d1}. The likelihood L_R for right lane model is calculated. If L_R is more than a threshold, update record; otherwise restart searching for P_{R1}.

Thus, P_{L0} and P_{R1}, which have a maximum likelihood are able to construct the both sides of lane model.

4.4 Speed Up Control Points Searching by Multiresolution Strategy

We have employed a multiresolution strategy to rapidly find an accurate solution. At the coarse stage, for a $M \times N$ input image, we reduce it to $\frac{1}{2}M \times \frac{1}{2}N$ by laplacian pyramid [14]. In this low resolution of original image, we attempt to roughly locate the global optima efficiently without regard to accuracy. In the final stage, fine level matching is initialized using the good candidates screened from the coarse stage. A smaller search area and a finer step size are used to obtain better matches in the original image. This coarse-to-fine matching offers an acceptable solution at an affordable computational cost and speeds up the detection. Figure 8 shows the multiresolution approach.

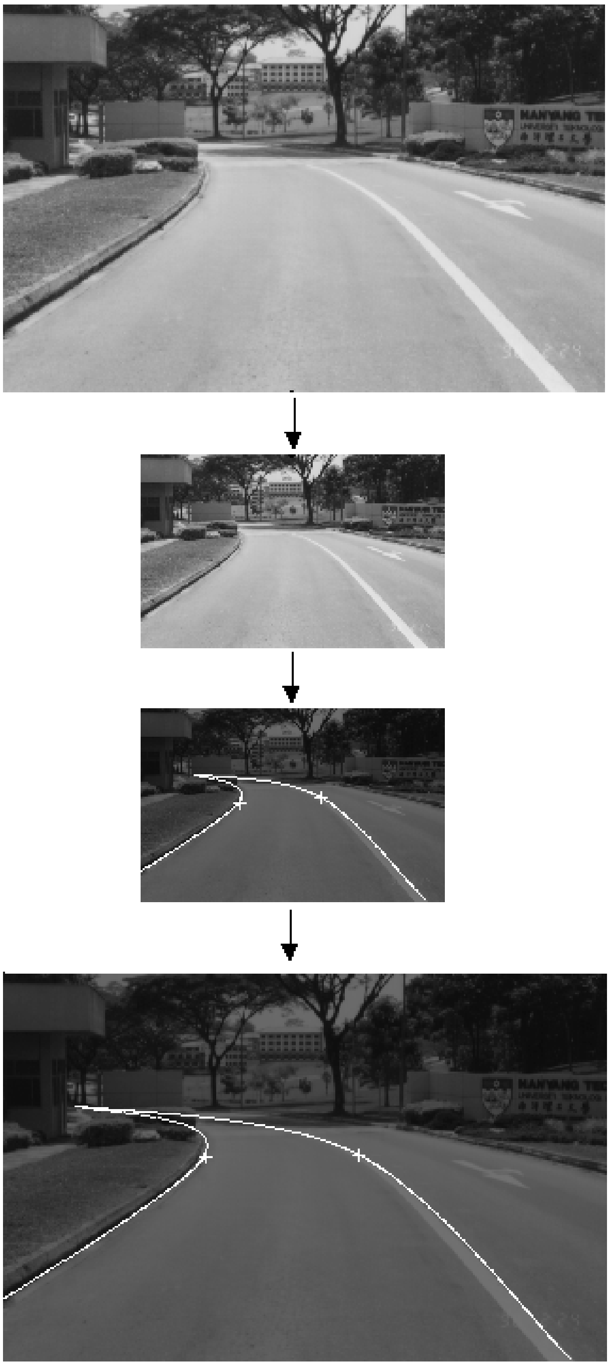


Figure 8 Multiresolution for Control Points Searching.

5 Results

The proposed algorithm has been simulated by C++ and tested on 20 images grabbed by an on-board camera at different locations and at different times. Figure 9 to Figure 11 show some of our experimental results of lane boundary detection where detected lane boundaries are superimposed onto the half gray of original images. The images on top are original images, below are the results. 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.

A fail case shows in Figure 12. Since it isn't a well-painted lane and has no clear boundary, so there is no enough edge information to build a lane model accurately.

Figure 9 Unpainted Road

Figure 10 Straight Road

Figure 11 Curve Road with Shadows

Figure 12 A fail case in lane detection

6 Conclusion

We have addressed the problem of lane 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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