

Lane Boundary Detection Using A Multiresolution Hough Transform

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Abstract

Lane boundary detection is the problem of estimating the geometric structure of the lane boundaries of a road based on the images grabbed by a camera on board a vehicle. We use Hough transform to detect lane boundaries with a parabolic model under a variety of road pavement types, lane structures and weather conditions. In the three-dimensional Hough space, a parabolic curve is represented as a straight line. To simplify the computation, the parametric space can be divided into (i) a two-dimensional space measured by the parameters which are shared by all the lane edges, and (ii) a one-dimensional space of the parameter which makes a distinction among different edges in an image. A multiresolution strategy is used to improve both the speed and accuracy of the Hough transform. Experimental results show that the proposed method is relatively less prone to the image noise and is computationally tractable.

1 Introduction

Lane detection is the problem of locating road lane boundaries without an *a priori* knowledge of the road geometry. Together with lane tracking techniques, a vision-based lane boundary location system can assist in a number of "driver assistant" applications, including intelligent vehicles, highway maintenance with intelligent cruise control, cambered power steering and automatic navigation. An automatic lane detector should be able to handle both straight and curved lane boundaries and the full range of lane boundary markings (either single or double and solid or broken) and pavement edges. At the same time, it should take advantage of global scene constraints to improve its robustness in the presence of noise in the images. Figures 1(a) shows an input image containing lane boundaries.

A number of systems for lane boundary detection have been reported in the literature [1, 2]. Several of them make the assumption that the lane boundaries are straight lines and detect them by using the Hough transform [3]. Kluge [4] proposed a parabolic

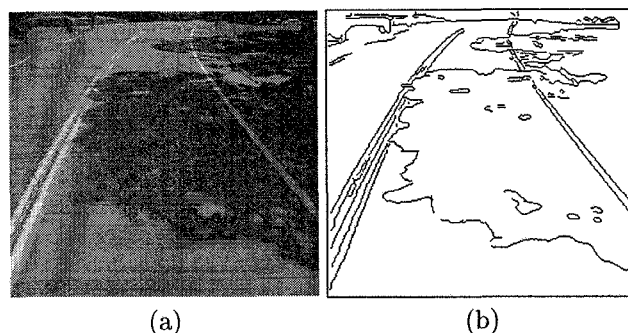


Figure 1: An example: (a) input image; (b) edge detection.

model for generic lane boundaries. A deformable template method was proposed by optimizing a likelihood function based on this model [5]. However, this algorithm cannot guarantee a global optimum without requiring huge computational resources. Using Kluge's model and an edge detector, we estimate the parameters which characterize a lane structure in the Hough space. In order to reduce the computational complexity and increase the accuracy of the estimation, the Hough space is separated into two subspaces in which parameters are separately estimated using a multiresolution strategy [6] with a modified Hough voting algorithm. Experimental results show that our method works well on lane images in various situations, including different lane marking conditions and road environments. Further, our method has a higher accuracy in the presence of noise because Hough transform can utilize all the lane edges, which share two of three parameters of the lane structure in an image instead of only two edges used in the deformable template method.

2 Model of Lane Boundaries

According to Kluge [4], the markings and pavement boundaries defining the road and its lane structure can be approximated by circular arcs on a flat ground (x, y) plane over the length of the road visible in a single frame of image. Furthermore, a circular arc of cur-

vature k can be approximated by a parabolic equation of the form $x = \frac{ky^2}{2} + my + b$, where m and b are tangent and offset parameters, respectively. In the case where the camera is not tilted, the derivation of the shape of individual lane boundaries in the image plane is straightforward. Assuming perspective projection, a pixel $f(c, r)$ in the image plane projects onto a point (x, y) on the ground plane according to the equations $x = cw y$ and $y = \frac{H}{r h}$, where H is the height of the focal point above the ground plane and h and w are the height and the width of an image pixel divided by the focal length, respectively. Combining the camera calibration and road shape parameters together, the parabola on the ground plane projects into the image plane as a curve of the form

$$c = \frac{\kappa}{r} + \beta r + v, \quad (1)$$

where $\kappa = \frac{kH}{2wh}$, $\beta = \frac{hb}{wH}$, and $v = \frac{m}{w}$. Note that $r = 0$ is the row representing the horizon in the image plane.

In the case where the camera is tilted downward [4], the lane structure has the same form as Eq. (1), but the parameters are defined as

$$\kappa = \frac{kH^2(1 + r_0^2 h^2)^2}{2whH\sqrt{1 + r_0^2 h^2}},$$

$$\beta = h^2(b - mHr_0h + \frac{1}{2}kH^2r_0^2h^2),$$

and $v = Hh(1 + r_0^2 h^2)(m - kHr_0h)$, where r_0 is the row corresponding to the center of the field of view of the camera.

If we assume that all parabolic lane boundaries in the ground plane have approximately the same curvature k and have parallel tangents at their x intercepts, then all lane boundaries in the image plane share the same parameters κ and v and are distinguished by the parameter β . The problem of detecting lane boundaries is then converted into estimating the parameters κ , v and β_l and β_r for the left and the right lane boundaries in an image.

3 Edge Detection

We use Canny edge detector [7] to locate the position of pixels where significant edges exist. The key idea of Canny edge detector is to use Gaussian directional operator. Let $g(c, r) = e^{-\frac{c^2 + r^2}{2\sigma^2}}$ be a two-dimensional Gaussian function. Its directional operator is

$$g_n(c, r) = \frac{\partial g(c, r)}{\partial \mathbf{n}} = \mathbf{n} \cdot \nabla g(c, r),$$

where \mathbf{n} is the directional vector oriented normal to the direction of an edge to be detected and can be

estimated as

$$\mathbf{n} = \frac{\nabla g(c, r) * f(c, r)}{|\nabla g(c, r) * f(c, r)|},$$

An edge point is defined to be a local maximum of the operator g_n applied to the image $f(c, r)$. That is $\frac{\partial}{\partial \mathbf{n}}[g_n(c, r) * f(c, r)] = 0$ or $\frac{\partial^2}{\partial \mathbf{n}^2}[g(c, r) * f(c, r)] = 0$.

Figure 1(b) shows edges extracted by the Canny edge detector from the image shown in Fig. 1(a). A Canny edge map is obtained by thinning the binary image output from the edge detector where an edge consists of the pixels with a gradient value higher than 50% of the maximum and at least one 8-connected pixel with gradient value higher than 90% of the maximum. In our experiments, we choose $\sigma = 1$ and a 9×1 mask is used for Gaussian convolution in both X and Y directions.

4 Multiresolution Hough Transform

Applying the Canny edge detector to a $N_c \times N_r$ lane image $f(c, r)$, we can obtain two images: a binary image $f_e(c, r)$ denoting edge pixels and an image $f_g(c, r) = \frac{\nabla_r f(c, r)}{\nabla_c f(c, r)}$, denoting the ratio of vertical and horizontal gradients. We can also take a derivative of Eq. (1) with respect to the variable r as

$$\frac{dc}{dr} = -\frac{\kappa}{r^2} + \beta, \quad (2)$$

where $\frac{dc}{dr} = -f_g(c, r)$.

There are three parameters in Eqs (1) and (2) from which three parametric equations representing a straight line in the three-dimensional parametric space (β, κ, v) can be derived as

$$\begin{cases} \beta(t) = t, \\ \kappa(t) = (t - \frac{dc}{dr})r^2, \\ v(t) = c + (\frac{dc}{dr} - 2t)r. \end{cases} \quad (3)$$

The Hough transform as such was first introduced by Hough in 1962 [8]. Yu and Jain presented a multiresolution Hough transform to reduce the computational cost in document skew detection [6]. This method can be used in the lane detection application. The idea is to implement Hough transform multiple times, say twice, for the same data. The bin size in the Hough space changes from a low resolution to the desired resolution and, meanwhile, the detection range changes from the desired range to a smaller one centered at the preceding estimate.

Assume that the bin size in a 3D Hough space is $(\Delta\beta, \Delta\kappa, \Delta v)$. In each implementation of the Hough transform, we accumulate the integral value instead of the number of occurrences of the curve in the Hough

space to increase the accuracy. Therefore, we define the Hough accumulator array as

$$\mathcal{V}(\beta, \kappa, \nu) = \sum_{c,r} f_e(c, r) \int_{\Delta t(\beta, \kappa, \nu)} \sqrt{\dot{\beta}(t)^2 + \dot{\kappa}(t)^2 + \dot{\nu}(t)^2} dt, \quad (4)$$

where, $\Delta t(\beta, \kappa, \nu)$ is the interval of integration and is defined as $\Delta t(\beta, \kappa, \nu) = \Delta t_\beta(\beta) \cap \Delta t_\kappa(\kappa) \cap \Delta t_\nu(\nu)$. The three intervals in individual dimensions are respectively defined as

$$\begin{cases} \Delta t_\beta(\beta) = [t_\beta(\beta), t_\beta(\beta + \Delta\beta)], \\ \Delta t_\kappa(\kappa) = [t_\kappa(\kappa), t_\kappa(\kappa + \Delta\kappa)], \\ \Delta t_\nu(\nu) = [t_\nu(\nu), t_\nu(\nu + \Delta\nu)], \end{cases}$$

where

$$\begin{cases} t_\beta(\beta) = \beta, \\ t_\kappa(\kappa) = \frac{\kappa}{r^2} + \frac{dc}{dr}, \\ t_\nu(\nu) = 0.5\left(\frac{dc}{dr} - \frac{\nu-c}{r}\right). \end{cases}$$

Substitute the integrated term in Eq. (4) with Eq. (3), we have

$$\mathcal{V}(\beta, \kappa, \nu) = \sum_{c,r} f_e(c, r) \sqrt{r^4 + 4r^2 + 1} |\Delta t(\beta, \kappa, \nu)|,$$

where, the term $|\Delta t(\beta, \kappa, \nu)|$ denotes the length of the integration interval, $\Delta t(\beta, \kappa, \nu)$. In spite of the fact that we only need the geometric parameters for the left and the right lane boundaries, actually, there are a number of individual lane edges extracted by the edge detector (see Fig. 1(b)) because a lane marking has two edges and several lane markings and other objects in the image such as shoulders and lane fences have edges that share the same lane structure. Among the three lane structure parameters, these edges approximately share the two parameters, κ and ν . The difference among them is the value of the parameter β . This property allows us to divide the 3D Hough space into a 2D and an 1D space shown in Fig. 2. We can estimate parameters κ and ν as $(\hat{\kappa}, \hat{\nu}) = \arg \max_{\kappa, \nu} \mathcal{V}(\kappa, \nu)$, where

$$\mathcal{V}(\kappa, \nu) = \sum_{c,r} f_e(c, r) \sqrt{r^4 + 4r^2 + 1} |\Delta t(\kappa, \nu)|.$$

The integration interval is $\Delta t(\kappa, \nu) = \Delta t_\kappa(\kappa) \cap \Delta t_\nu(\nu)$. The parameter β can be estimated by $\hat{\beta} = \arg \max_\beta \mathcal{V}(\beta)$, where

$$\mathcal{V}(\beta) = \sum_{c,r} f_e(c, r) \sqrt{r^4 + 4r^2 + 1} |\Delta t(\beta, \hat{\kappa}, \hat{\nu})|.$$

We choose two maximum values with different signs as estimates of the left and right lane boundaries.

In implementation, we execute Hough transform at two resolutions for estimating the parameters (κ, ν) . The bin sizes are chosen such that the number of total iterations is minimized and given as follows.

$$\begin{cases} \Delta\kappa^{(1)} = 800, \\ \Delta\nu^{(1)} = 20, \end{cases}$$

and

$$\begin{cases} \Delta\kappa^{(2)} = 100, \\ \Delta\nu^{(2)} = 4. \end{cases}$$

The bin size in Hough transform for estimating the parameter β is $\Delta\beta = 1$.

5 Experimental Results

This system has been tested on 34 images grabbed by an on-board camera at different locations and at different times. Figure 3 shows some of our experimental results of lane boundary detection where detected lane boundaries are superimposed onto the 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. Our program runs on a Sun UltraSPARC-I workstation and takes approximate 0.5 seconds for Canny edge detection and 0.2 seconds for parameter estimation. All experimental images are 8-bit gray scale images of size 256×240 . Theoretically, the proposed method can utilize many edge detection algorithms with less computational complexity than Canny operator which can reduce the cost of the whole system.

6 Conclusion

We have addressed the problem of lane boundary detection. A multiresolution Hough transform is employed to solve this problem to reduce the high computational cost associated with the traditional Hough

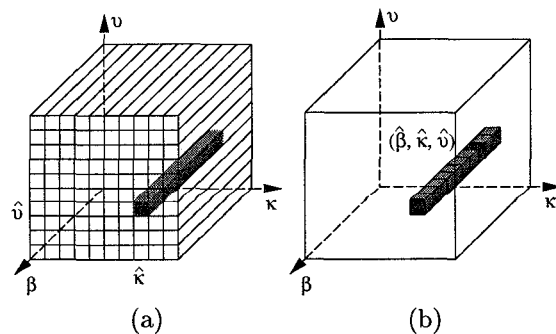


Figure 2: Hough space separation: (a) $\kappa - \nu$ space; (b) β space.

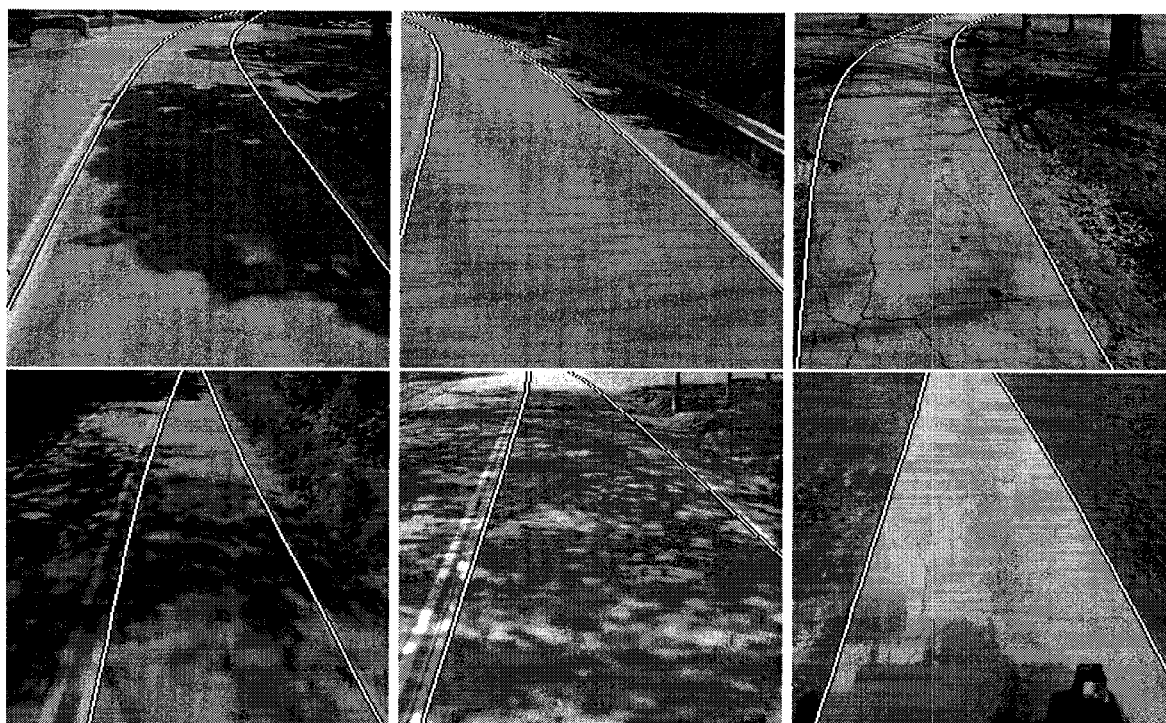


Figure 3: Experimental results of lane boundary detection. The detected lane boundaries are overlaid on the input gray scale image.

transform and at the same time to preserve its advantages of high accuracy, especially for the noisy images. To simplify the problem, the 3D Hough space is divided into a 2D and a 1D space. The Hough transform extracts as much useful information as possible from the input data which gives the system the capability of handling images with different qualities including those with paved and unpaved roads, marked and unmarked roads, shadows, and poor illuminations. Another advantage of using Hough transform for this problem is that instead of one single output given by most other methods, our system can provide more plausible candidates which can be fed to a post-processing module.

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