LANE DETECTION FOR AUTOMOTIVE SENSORS†

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ABSTRACT

This paper addresses the problem of detecting lane boundaries in color images of road scenes acquired from a car mounted visual sensor. It is shown that the lane boundaries in such images have to obey a set of global constraint equations. All images with such constrained lanes are modeled via deformable templates. The observed image is related to the underlying lane boundary features through a likelihood function which is based on the degree of match (in magnitude/direction) between the deformed template and the lane edges. The lane detection problem is formulhted in a Bayesian setting, and it is posed as an equivalent problem of maximizing a posterior pdf which sits over a low-dimensional deformation space. This pdf is multi-modal, hence a Metropolis algorithm is employed to obtain its maximum. Experimental results are shown to illustrate the performance of this algorithm.

1. INTRODUCTION

The ability to detect lane boundaries in color images of a road scene that is acquired from a ground-level visual sensor, is an enabling or enhancing technology with significant impact on the next generation of active vehicular sensors, and use in a number of driver's assistant applications. These applications have dual use in both commercial and military automotive systems such as intelligent cruise control, lane departure warning, virtual camber, autonomous driving, and navigation.

The goal that lane detection algorithms have to meet is -

> *Robustly detect lane boundaries without prior knowledge of the lane structure or road location in the image. Do so under a variety of road pavement types and lane structures, and under various weather conditions.*

To achieve this goal we have developed a new and novel solution to the lane detection problem. This solution inherits the best elements of both the edge map-based approaches and the variational template-based approaches that exist in current literature. This solution yields algorithms that find lane locations efficiently, and does so under a wide variety of lane, road and lighting conditions. The algorithm has the potential to work in real-time while being simultaneously robust - a highly desirable characteristic in both commercial and military applications.

More specifically, our approach to the lane detection problem is explained as follows:

1. Since lane boundaries are the only edges in the image that are of interest to us, we derive a parametric equation that each of the lane boundaries in the image have to satisfy. Using this equation, we form a template image of lane boundaries. This template has lane boundaries obtained by fixing the parameters of the lane equations at predetermined values. As these parameters change, the shape of the template lane boundaries deform with it. The template image and its deformations, constitutes a deformable template model of global shape (similar to those in [1]) for lane boundaries. Our objective is to deform the template (by changing the parameters of the lane equations) so that the corresponding lane boundaries "match" the ones in the observed image.

2. In order to determine the deformation that best "matches" the observed image, we derive a function that does a relative ranking among the different deformations. This constitutes our likelihood function, and it evaluates the degree to which the edge magnitude and direction in the observed image agrees with the one dictated by the deformed template.

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3. Using the deformable template model and the likelihood function, the lane detection problem is formulated in a Bayesian setting. The problem of locating the lane boundaries reduces to finding the parameters values which yield the globally maximal likelihood.

4. The likelihood function, however, is not convex with respect to the parameters of the lane equations - it has many local maxima. In order to escape these local maxima and find the deformation parameters of the template lane boundary image for which the likelihood function attains its global maximum, we employ a Metropolis algorithm.

5. We present experimental results that illustrate the performance of our lane detection (Metropolis) algorithm on a variety of images. We show a set of stills with the original image, and the detected lane boundaries in white dashes overlying on them - see Fig. 1. The lane detection algorithm seems to detect the desired boundaries accurately on a variety of images - those in which the lane markings are clearly marked, when the markings have gaps (dashed lanes), when there are no markings (bike path), and when the images suffer from degradations due to shadows, other markings, and poor lighting conditions.

The main distinction between this work and prior efforts in lane detection is that our algorithm does not require a symbolic segmentation of the image data. The systems for lane detection developed at Matsushita, Honda, U. Bristol, Munich, and U. Michigan, for instance, require a binary edge-map (see [2, 3] and the references therein). This map is obtained from the observed image by thresholding the underlying image gradient. Shadows, lighting conditions, and other environmental effects make selection of a suitable threshold difficult, and result in both missed and noisy edges. Our work makes use of the image gradient as well, but does so by asking what constitutes the most probable interpretation of the gradient field as a road scene without making local, pixel-by-pixel decisions regarding which points in the image correspond to edges.

We note that this paper focuses on the problem of *lane detection* - the determination of the location of the lane boundaries in a road scene without prior knowledge of the specific road structure. The results of our lane detection algorithm can be utilized to initialize a system which then performs *lane tracking* - the tracking of lane boundaries from frame to frame given a prior model of lane structure. Such systems include VaMoRs, VITA, YARF, SCARF, and VITS (again, see [2, 3] and the references therein).

2. LANE GEOMETRY MODEL

In this section we derive the deformable template model of global shape for the lane boundaries in a given road scene. Following [3], we assume that the lane markings and pavement boundaries defining the road and its lane structure can be approximated by circular arcs on a flat ground plane over the length of the road visible in a single image. A circular arc with curvature k can be further approximated a parabolic equation of the form

$$x = \frac{1}{2} k y^2 + m y + b. \tag{1}$$

Assuming that the camera is not tilted,[1] and assuming perspective projection, a pixel (r, c) in the observed image projects onto a point (x, y) in the ground plane according to the equations

$$\left.\begin{aligned} x &= c\, h_f\, y, \text{ and} \\ y &= \frac{H}{r\, w_f} \end{aligned}\right\}, \tag{2}$$

where H is the height of the camera above the ground plane, and h_f and w_f are the height and the width of an image pixel divided by the focal length, respectively. Substituting eq. (2) into eq. (1) and combining the camera calibration and road shape parameters together, we derive the following equation that each of the lane boundaries in the image have to satisfy:

$$c = \frac{\tilde{k}}{r} + \tilde{b}\, r + \tilde{v}_p, \tag{3}$$

where $r = 0$ denotes the row in the image plane corresponding to the horizon.

Note that the different parabolic lane boundaries eq. (1) in the ground plane are distinguished by different values of the corresponding offset parameter "b". All of them share the same curvature parameter "k" and tangent parameter "m". This relationship between the lane boundaries carries over to the image plane as well. The different lane boundaries in the image plane eq. (3) are distinguished by different values of the corresponding "$\tilde{b}$" parameter, whereas all of them share the same "$\tilde{k}$" and "$\tilde{v}_p$" parameters.

We form a template image of the lane boundaries by assuming that the observed image has two lanes of interest - we set the lane equation parameters to a predetermined set of values ($\tilde{k} = 0$, $\tilde{b} = \pm 1$, $\tilde{v}_p = \frac{1}{2} c_{max}$).

[1] In the case of tilted camera the derivation is very analogous - see [3].

The lanes in this template image (by its very construction) obeys the constraint equations. By changing the values of the lane equation parameters $\tilde{k}$, $\tilde{b}$, $\tilde{v}_p$ we deform the template lane boundaries, and obtain various other instances of it. The template image along with its deformations (obtained by changing the two lane equation parameter sets) constitutes an *a priori* deformable template model of global shape for the lane boundaries in the observed image.

3. LIKELIHOOD FUNCTION

In this section we construct a function that relates the observed image to the underlying lane boundary features. This function evaluates the relative likelihood of the various deformations of the template lane boundary image, and it is based on the degree of match (in magnitude/direction) between the deformed template and the underlying lane edges.

More specifically, let $\underline{\theta}_l = (\tilde{k},\ \tilde{b}_{left},\ \tilde{v}_p)$ and $\underline{\theta}_r$ = $(\tilde{k},\ \tilde{b}_{right},\ \tilde{v}_p)$ denote the two sets of lane equation parameters. The likelihood function is given by

$$\mathcal{L}(\underline{\theta}_l, \underline{\theta}_r) = \sum_{r,c} m_{r,c}\ f_a(\cos[d_{r,c} - t_{r,c}]) f_b(n_{r,c}) \quad (4)$$

Where,

$$f_\delta(x) = \frac{1}{1 + \delta\ x^2}, \quad (5)$$

denotes a spike function, $t_{r,c}$ denotes the tangent orientation at row r of the lane closest to column c, $m_{r,c}$ and $d_{r,c}$ denotes the magnitude and the direction of the image gradient at pixel (r, c),[2], and $n_{r,c}$ denotes the distance from (r, c) to the nearest lane edge.

The first term in eq. (4) weights each pixel by the magnitude of the gradient at that pixel. The second term weights each pixel by the extent to which the gradient at the pixel is perpedicular to the (deformed) template lane edge tangent. The third terms weights the pixel by its proximity to the (deformed) template lane edge. The value of the lane equation parameters $\underline{\theta}_l, \underline{\theta}_r$ that will maximize the likelihood function $\mathcal{L}(\underline{\theta}_l, \underline{\theta}_r)$ is the one for which image pixels that are closest to the corresponding lane edges have large local gradient magnitudes, while they simultaneously possess local gradient directions that are normal to the lane edges. A similar likelihood function is also employed in [5].

[2] The image gradient magnitude and direction are calculated by using a 3×3 Prewitt operator as in [4]

4. BAYESIAN LANE DETECTION

In this section, the lane detection problem is formulated in a Bayesian setting. This done by constructing an *a posteriori* pdf that is based on the deformable template model of section 2 and the likelihood function of section 3.

Let $(\underline{\theta}_l, \underline{\theta}_r)$ be the hidden (unobserved) variable, and $Y = y$ the given (observed) image. Then, the posterior pdf of $(\underline{\theta}_l, \underline{\theta}_r)$ given that $Y = y$ is

$$P(\underline{\theta}_l, \underline{\theta}_r \mid Y = y) = \begin{cases} K\ \exp\{\mathcal{L}(\underline{\theta}_l, \underline{\theta}_r)\}, & \text{if } (\underline{\theta}_l, \underline{\theta}_r) \in \Theta \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

where Θ is the space of all possible values that $(\underline{\theta}_l, \underline{\theta}_r)$ can take and K is a normalizing constant.

Given the image $Y = y$, the underlying lane boundaries are obtained by finding the value of the parameters $(\underline{\theta}_l, \underline{\theta}_r)$ that maximizes the posterior pdf in eq. (6). The posterior pdf, however, is non-concave and has many local maxima. In order to find the maximum of this function we employ a Metropolis with a geometric annealing schedule (see [6]).

The algorithm proceeds as follows:

1. Set $k = 0$, initialize $(\underline{\theta}_l^{(0)}, \underline{\theta}_r^{(0)})$, and evaluate $\mathcal{L}(\underline{\theta}_l^{(0)}, \underline{\theta}_r^{(0)})$
2. Pick $(\tilde{\underline{\theta}}_l, \tilde{\underline{\theta}}_r)$ at random among all the possible parameter values in the neighborhood of $(\underline{\theta}_l^{(k)}, \underline{\theta}_r^{(k)})$
3. Evaluate $\rho^{(k)} = \left[\frac{\mathcal{L}(\tilde{\underline{\theta}}_l, \tilde{\underline{\theta}}_r)}{\mathcal{L}(\underline{\theta}_l^{(k)}, \underline{\theta}_r^{(k)})}\right]^{T(k)}$, where $T(k) = T_0 \left(\frac{T_f}{T_0}\right)^{\frac{k}{k_{max}}}$
4. Update $(\underline{\theta}_l^{(k+1)}, \underline{\theta}_r^{(k+1)})$
$$= \begin{cases} (\tilde{\underline{\theta}}_l, \tilde{\underline{\theta}}_r) & \text{if } \rho^{(k)} \geq 1 \\ (\tilde{\underline{\theta}}_l, \tilde{\underline{\theta}}_r) & \text{w.p. } 1 - \rho^{(k)} \text{if } \rho^{(k)} < 1 \\ (\underline{\theta}_l^{(k)}, \underline{\theta}_r^{(k)}) & \text{otherwise} \end{cases}$$
5. Set $\mathcal{L}(\underline{\theta}_l^{(k)}, \underline{\theta}_r^{(k)}) = \mathcal{L}(\underline{\theta}_l^{(k+1)}, \underline{\theta}_r^{(k+1)})$ and $k = k + 1$
6. If $k \leq k_{max}$ go to step 2, else stop

5. CONCLUSIONS

A priori knowledge regarding the geometric structure of lane boundaries can be expressed via deformable template models. These models are obtained by deriving a set of global constraint equations that each of the lane boundaries in the image have to obey. The most important visual cue, namely, the spatial continuity of the lane edges in magnitude and in direction can be related to the lane boundary model by a likelihood function. This function can be locally computed and it is based on the degree of agreement between the deformed template boundary and the underlying lane edges. It is shown that the lane detection problem can be formulated in a Bayesian setting, and posed as a problem of maximizing a low-dimensional posterior pdf. This pdf is multi-modal, and to find its global maximum an Metropolis algorithm is employed. Experiments with this algorithm yields encouraging results on real road scene images.

6. REFERENCES

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7. EXPERIMENTAL RESULTS

In this section, we present experimental results that illustrate the performance of our (Metropolis) lane detection algorithm. Shown in Figs. 1 are stills of the observed image with the lane boundaries corresponding to the final results of the algorithm overlaid on top of them.

The top two images show the algorithm's performance on images in which the lanes are continuous and are clearly marked. The next two shows performance on images where the lane markings have gaps (dashed lanes), and when there are only pavements but no lane boundaries (bike paths). The middle pair show performance on images with shadows. The penultimate pair shows performance on images when there are other (non-lane) bright markings on the road, and the final pair shows performance on images that acquired under poor lighting conditions.

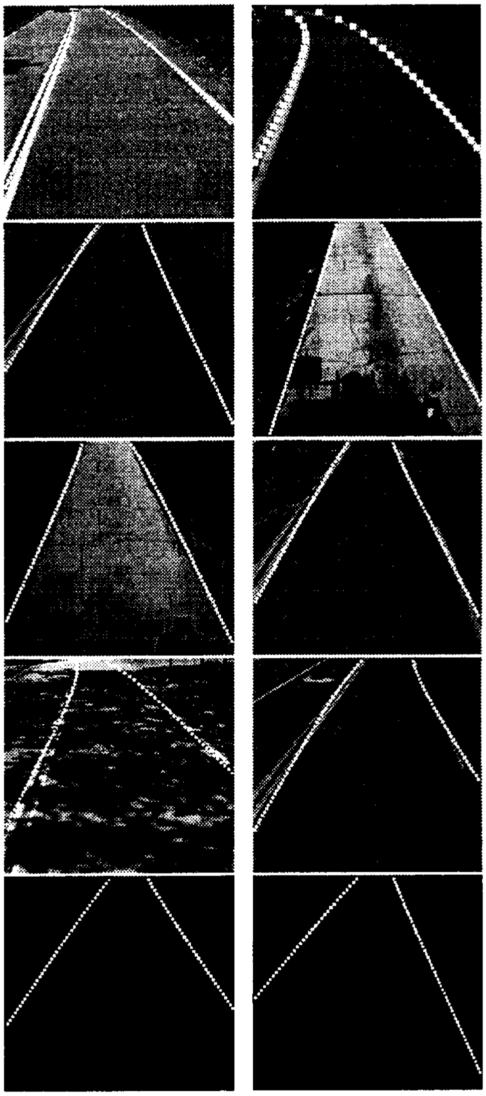

Figure 1: Stills of road scenes with the detected lane boundaries overlayed on top in dashed white lines.