Road and Lane Edge Detection with Multisensor Fusion Methods

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Abstract

This paper treats automated detection of road and lane boundaries by fusing information from forward-looking optical and active W-band radar imaging sensors mounted on a motor vehicle. A deformable template model is used to globally describe the boundary shapes. The optical and radar imaging processes are characterized with random field likelihoods. The multisensor fusion edge detection problem is posed in a Bayesian framework and a joint MAP estimate is employed to locate the road and lane boundaries. Three optimization approaches, multi-resolution pseudo-exhaustive search, Metropolis algorithm, and Metropolis algorithm with pre-tuned curvature, are proposed to implement the joint MAT estimate. Experimental results are shown to demonstrate that the joint MAP algorithm operates robustly and efficiently in a variety of road scenarios.

1 Introduction

Intelligent vehicle-highway systems(IVHS) promise to improve the safety, efficiency, and environmental friendliness of the transportation network through the application of emerging technology. Among the various IVHS technologies, a number of driver assisting applications, such as lane excursion warning, intelligent cruise control and ultimately autonomous driving, depend on reliable detection of road and lane boundaries without prior geometric information. In this paper we address the problem of automated detection of road and lane boundaries using forward-looking optical and radar imaging sensors mounted on a motor vehicle.

In early development of road and lane detection systems, edge-based detection algorithms dominate [1], [2], [3]. Since these algorithms require thresholding the image gradient magnitude to detect edges, they are not applicable to images containing extraneous edges or images with very low signal-to-noise ratio(SNR). Unfortunately, for the application studied here, the acquired radar images fall into the low SNR category while the corresponding optical images have edges other than the ones that we aim to locate.

In recent study of road and lane edge detection, some researchers sought to overcome the deficiency and limitation of edge-based algorithms by applying a global model of boundary shape, represented by a deformable template. In [4], Kluge and Lakshmanan proposed a vision-based algorithm for locating lane boundaries via deformable templates without thresholding the intensity gradient information. In [5], Ma, Lakshmanan and Hero investigated detection of road edges in radar images via deformable templates. In both cases, the globally deformable template models were shown to be suitable and robust for the edge detection application. Aware of these accomplishments, we take advantage of the deformable template approach in our edge detection problem.

In previous work, road edge detection in radar images [5] and lane edge detection in optical images [4] are studied separately. However, a single sensor, either optical or radar sensor, limits itself in the ability to sense and identify all the meaningful features in varying environments. In a well-illuminated environment, the optical sensor provides sufficient information to locate the lane boundaries. However, it is not able to operate in an ill-illuminated environment. On the other hand, although the radar sensor can successfully gather road boundary information both in well- and ill-illuminated environments, it fails to provide necessary information for distinguishing the lane markers on the road. In our image data acquiring setting, the optical and radar sensors are properly placed on an imaging platform so that they sense the same road scene if operated simultaneously. As we know, for a certain road, the road and lane boundaries are highly correlated, e.g., the boundaries are parallel, and the lanes are restricted inside the road region. Thus the optical and radar image pair provide complementary and correlated information about the road scene ahead of the vehicle. To take advantage of the strengths of both sensors, it is natural to think of combining the two different types of sensed data together to achieve better location of the road and lane boundaries.

In this paper the road and lane boundary detection problem is formulated in a Bayesian framework to im-

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plement the multisensor fusion method. The boundary shapes are represented by deformable templates, which define a set of deformation parameters. The deformation parameters, together with their statistical distribution, constitute the prior information for the Bayesian setting. The likelihood functions provide a relative measure of how well a given set of shape parameters match the data in a particular optical and radar image pair of a road scene. Then the fusion algorithm is implemented with a joint maximum *a posteriori*(MAP) estimator, which combines multisensor information efficiently and coherently.

2 Shape Model for Both Road and Lane boundaries

In most cases, we assume that road and lane boundaries can be approximated by parallel concentric arcs on a flat ground plane. Within a reasonable field of view, such arcs with small-to-moderate curvatures, are well approximated by parabolic curves in the ground plane,

$$x = \frac{1}{2}ky^2 + my + b \qquad (1)$$

The road and lane boundaries share the same parameters k and m, and they are distinguished by different offsets (b's).

The radar image is composed of reflections from the ground, so the shape model (Eqn.(1)) can be directly applied to the radar image. However, the optical image is a perspective projection of the ground plane, and a few more derivations are needed to represent the lane boundaries in the optical image [3]. Assuming a tilted pinhole camera perspective projection model, parabolic curves in the ground plane (Eqn. (1)) transform into hyperbolic curves in the image plane:

$$c = \frac{k'}{r - hz} + b'(r - hz) + vp' \qquad (2)$$

where

$$\begin{aligned} k' &= \eta_k \; k, \\ vp' &= \eta_m \; m + \eta_{m,k} \; k + \eta, \text{ and} \\ b' &= \eta_b \; b + \eta_{b,m} \; m + \eta_{b,k} \; k. \end{aligned} \qquad (3)$$

The constants $\eta_k, \eta_m, \eta_{m,k}, \eta, \eta_b, \eta_{b,m}$, and $\eta_{b,k}$ depend on the camera geometry (resolution, focal length, height of the camera from the ground plane, and camera tilt).

Let $\theta^o = \{k', vp', b'_L, b'_R\}$ and $\theta^r = \{k, m, b_L, b_R\}$ denote the unknown lane and road boundaries' parameters, respectively. Let $\theta = \{\theta^r, \theta^o\}$ and by changing the values of θ, various lane and road boundary shapes can be realized. Hence the problem of lane and road boundary detection becomes the problem of estimating θ. In this paper, the constraints and the *a priori* beliefs of θ are expressed by the so-called prior pdf:

$$\begin{aligned} P(\theta) = & \; I_{b'_L > b_L}(b'_L, b_L) \times I_{b'_R < b_R}(b'_R, b_R) \\ & \times \delta(k' - \eta_k \; k) \times \delta\left(vp' - [\eta_m \; m + \eta_{m,k} k + \eta]\right) \\ & \times \frac{2}{\pi}\text{atan}\left[\beta_{o,1} \times (b'_R - b'_L)\right] \times \frac{2}{\pi}\text{atan}\left[\frac{\beta_{o,2}}{b'_R - b'_L}\right] \\ & \times \frac{2}{\pi}\text{atan}\left[\beta_{r,1} \times (b_R - b_L)\right] \times \frac{2}{\pi}\text{atan}\left[\frac{\beta_{r,2}}{b_R - b_L}\right] \end{aligned} \qquad (4)$$

where $I_A(x,y)$ is an indicator function,

$$I_A(x,y) = \begin{cases} 1, & \text{if } (x,y) \text{ satisfies relation } A \\ 0, & \text{otherwise} \end{cases}$$

and $\delta(x)$ is the Kronecker delta function,

$$\delta(x) = \begin{cases} 1, & \text{if } x = 0 \\ 0, & \text{otherwise} \end{cases}$$

The terms on the first two lines of Eqn. (4)'s RHS correspond to the constraints that the elements of θ have to satisfy. The indicator terms impose the constraint that the lane markers be contained within the road region, while the Kronecker delta terms impose the constraint that the lane boundaries' curvature and tangential orientation be precisely related to the road boundaries' curvature and tangential orientation via Eqn. (3). The terms on the last two lines of Eqn. (4)'s RHS express the *a priori* beliefs that lanes and roads can be neither too narrow nor too wide.

3 Imaging Likelihoods

In the radar image, the road boundaries separate the image into three relatively homogeneous regions which are associated with the road surface, the left side of the road, and the right side of the road. For the radar image Z^r, the radar imaging likelihood is described using the conditional probability that the random field Z^r takes on a realization z^r (corresponding to the radar observation), given that the road edge information is known,

$$\begin{aligned} P(z^r \mid \theta^r) = & \prod_{(x,y)} \frac{1}{z^r_{xy}\sqrt{2\pi\sigma^2_{xy}(\theta^r)}} \\ & \exp\left\{-\frac{1}{2\sigma^2_{xy}(\theta^r)}(\log z^r_{xy} - \mu_{xy}(\theta^r))^2\right\} \end{aligned} \qquad (5)$$

where μ_{xy}, σ^2_{xy} denote the mean and variance of the region where the pixel (x,y) lies.

The optical imaging likelihood is based on an energy function, which encodes the knowledge that the edges of the lane should be near intensity gradients whose orientation is perpendicular to the lane edge. More specifically, given a hypothetical parameter set of underlying edges θ^o, the likelihood of observing the optical image Z^o is given by

$$P(z^o|\theta^o) = \gamma e^{-E(z^o, \theta^o)} \qquad (6)$$

Notations used to describe the energy function $E(z^o, \theta^o)$ are defined as

- The Cauchy density function $f(\alpha, x) \triangleq \frac{\alpha}{\pi} \frac{1}{1+\alpha^2 x^2}$.
- $gm(r, c) \triangleq$ the gradient magnitude at pixel (r, c), $gd(r, c) \triangleq$ the gradient direction at pixel (r, c).
- The edges of the lane in the image by the curves:

$$E_{L(R)}(r, c, \theta^o) = \frac{k'}{r - hz} + b'_{L(R)}(r - hz) + vp'$$

Then, the energy function of observing an image gradient field given a set of lane shape parameters θ^o is

$$\begin{aligned} E(z^o, \theta^o) &= E(gm, gd, \theta^o) \\ &= -\sum_{(r,c)} [gm(r, c) \times f(\alpha_m, c - E_L(r, c, \theta^o)) \\ &\quad \times f(\alpha_d, \cos(gd(r, c) - \text{atan}(\frac{d}{dr} E_L(r, c, \theta^o)))) \\ &\quad + gm(r, c) \times f(\alpha_m, c - E_R(r, c, \theta^o)) \\ &\quad \times f(\alpha_d, \cos(gd(r, c) - \text{atan}(\frac{d}{dr} E_R(r, c, \theta^o))))] \end{aligned}$$

4 Multisensor Fusion Method — Joint MAP Estimate

Since the prior distributions of the deformation parameters and the imaging likelihood functions are available, we shall pose the road and lane edge detection problem in a Bayesian framework. The optical and radar fusion detection problem can be solved by estimating the deformation parameters θ with the joint MAP estimate

$$\hat{\theta} = \arg\max_{\theta} P(\theta | z^r, z^o)$$

Utilizing the Bayes' rule and the fact that $P(z^r, z^o)$ is fixed by the observation, we have

$$\hat{\theta} = \arg\max_{\theta} P(z^r, z^o, \theta) \tag{7}$$

By the chain rule of conditional probability,

$$P(z^r, z^o, \theta) = P(\theta^r) P(z^r|\theta^r) P(\theta^o|\theta^r, z^r) P(z^o|\theta^o, z^r, \theta^r) \tag{8}$$

Since the radar and optical imaging processes are independent, the optical parameters θ^o are conditionally independent of the radar observation Z^r given the radar parameters θ^r, and the optical observation Z^o is conditionally independent of the radar observation Z^r and radar parameters θ^r given the optical parameters θ^o, that is,

$$\begin{aligned} P(\theta^o | \theta^r, z^r) &= P(\theta^o | \theta^r) \\ P(z^o | \theta^o, z^r, \theta^r) &= P(z^o | \theta^o) \end{aligned} \tag{9}$$

Combining Eqns.(8) and (9) yields

$$P(z^r, z^o, \theta) = P(\theta^r, \theta^o)\ P(z^r|\theta^r)\ P(z^o|\theta^o) \tag{10}$$

5 Optimization Approaches

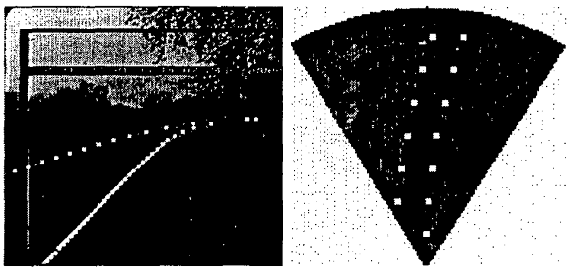
The optimal location of the road and lane boundaries is obtained by maximizing the joint density $P(z^r, z^o, \theta)$ as formulated in Eqn. (10). The edge detection problem is equivalent to finding the mode of a density surface. The surface is non-concave with many local maxima, hence we can not just apply the greedy search algorithms such as conjugate gradient methods. In this paper, we propose three maximization methods to search for the optimal, if possible, otherwise the close-to-optimal, deformation parameters.

5.1 Multi-resolution Pseudo-Exhaustive Search

Exhaustive search can find the optimal solutions at the cost of unacceptable computation resources in some optimization problems. For the problem addressed in this paper, exhaustive search is not feasible due to the large searching space. Instead, a multi-resolution pseudo-exhaustive search method is studied. The basic idea is as following:

1. Constrain the parameters in appropriate ranges.
2. Assign coarse step sizes for the parameters and do the pseudo-exhaustive search to find the maximum of the joint MAP objective function (Eqn. (10)).
3. Once this coarse maximum is found, take the corresponding estimated parameters as the center of a finer search procedure with finer step sizes of the parameters.
4. Repeat the last step for a couple of times and conclude the search procedure. The final estimated result is taken as the solution to the joint MAP estimate.

The detection results are satisfactory(see Figure 1).



(a) lane detection in the optical image (b) road detection in the radar image

Figure 1: Edge detection with multi-resolution pseudo-exhaustive search

5.2 Metropolis Algorithm with Geometric Annealing

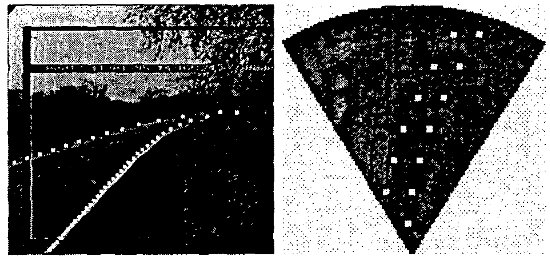
Although the multi-resolution pseudo-exhaustive search gives us relatively accurate solution, the search procedure is still time consuming. To accelerate the maximizing procedure, we employ a sub-optimal approach, the Metropolis algorithm [4] with a geometric annealing schedule [6], to perform this maximization,

1. Set $i = 0$, and initialize $\theta^{(0)}$.
2. Calculate $P(z^r, z^o, \theta^{(i)})$.
3. Pick $\tilde{\theta}$ at random among all the possible parameter values in the neighborhood of $\theta^{(i)}$.
4. Calculate $P(z^r, z^o, \tilde{\theta})$.
5. Calculate $\rho^{(i)} = \exp\left(\frac{\log P(z^r, z^o, \tilde{\theta}) - \log P(z^r, z^o, \theta^{(i)})}{T^{(i)}}\right)$, where $T^{(i)} = T_{init}\left(\frac{T_{final}}{T_{init}}\right)^{\frac{i+1}{max\_iter}}$
6. Update the deformation parameters
$$\theta^{(i+1)} = \begin{cases} \tilde{\theta} & \text{if } \rho^{(i)} \geq 1 \\ \tilde{\theta} & \text{w.p. } \rho^{(i)} \text{ if } \rho^{(i)} < 1 \\ \theta^{(i)} & \text{otherwise} \end{cases}$$
7. Set i = i+1 and go to step 2.

5.3 Metropolis Algorithm with Pre-tuned Curvature

Metropolis algorithm performs fairly well in estimating the deformation parameters at a much faster convergence rate to the fixed point than the pseudo-exhaustive search approach does, however, it fails sometimes to escape the local maximum of the searching surface and gives the wrong detection result. For example, the results shown in Figure 2 indicate that the curvature of the road boundaries has been overestimated. A potential reason for this failure is that the ranges of road scene in the optical and radar images are different. The optical image has a much larger range(over 1,000 meters) than the radar image does(128 meters). Since our deformable template model only applies to road and lane edges in a road scenario with a relatively short range, the curvature of the road edges might differs noticeably at the near range and the far range in the optical image. But with our template model we use the same curvature to represent the road edges in the entire optical image, which causes the Metropolis algorithm to converge to a local maximum and result in the wrong estimation of the curvature.

In the radar image, due to the relatively short range the deformable template model fits the road and lane boundaries very well and the Metropolis algorithm performs robustly in estimating the curvature of the road



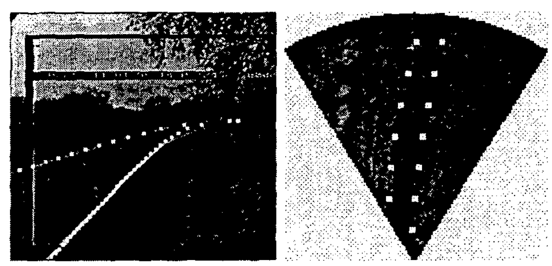
(a) Lane detection in the optical image (b) Road detection in the radar image

Figure 2: Wrong edge detection by Metropolis algorithm

edges [5]. To take advantage of such property, we propose the pre-tuned Metropolis algorithm. The estimation is implemented with two steps:

1. Estimate parameters θ^r in the radar image alone with the MAP method (details are referred to [5]). The curvature estimate $\hat{k}$ is kept for the joint estimation step.
2. Jointly estimate the parameters $\theta = \{\theta^r, \theta^r\}$. In this step, the curvature parameter k varies in a much smaller range with a smaller step-size around $\hat{k}$.

Significant improvement has been shown with this method(Figure 3) over the previous one. The overestimate of the curvature has been corrected and the estimated results match the sensed data reasonably.



(a) lane detection in the optical image (b) road detection in the radar image

Figure 3: Correct edge detection with the Metropolis algorithm with pre-tuned curvature

6 Experimental Results

We have applied the proposed multisensor fusion method to jointly detect the road and lane boundaries in registered radar and optical images. Since multiple (radar and optical) sensors provide more information and hence a more precise interpretation of the sensed environment, the performance of road and lane boundary detection is robust and accurate. For a particular road scene, the results obtained via independent optical and radar edge detection algorithms are illustrated in Figures 4(a) and (b), and the results with the fusion method are shown in Figures 4(c) and (d). We can see that the fusion method proposed in this paper outperforms the edge detection based on single sensors.

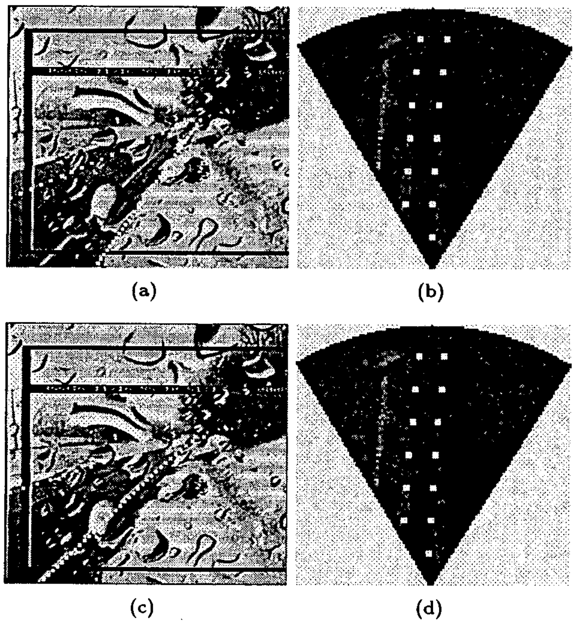
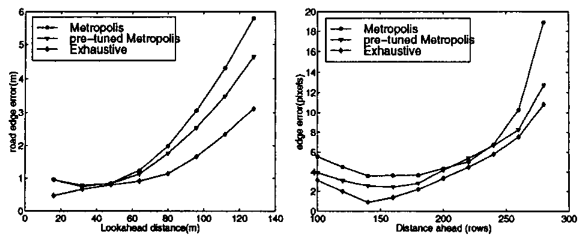


Figure 4: Comparison of the fusion method and sigle sensor based method

In order to compare the performance of the three optimization techniques, we plot the detection errors based on the hand-picked ground truth in Figure 5. The multi-resolution pseudo-exhaustive search method outperformed the other two methods in obtaining the optimal parameter set, but it has the largest computational complexity. The Metropolis algorithm with geometric annealing works fairly well in most cases, but occasionally it may get trapped into a local maximum and produce wrong results. The Metropolis algorithm with pre-tuned curvature has a good trade-off between the detection performance and computational complexity. Its detection performance is always very close to that of the pseudo-exhaustive search method but it converges at a much faster rate.

7 Conclusion Remarks

We employ a novel multisensor fusion technique to locate the road and lane edges in registered optical and radar images. The fusional edge detection problem is posed in a Bayesian framework, and a joint



(a) Errors for road edge detection

(b) Errors for lane edge detection

Figure 5: Performance comparison of the three optimization techniques

MAP estimate is employed to find the optimal deformation parameters, i.e., the optimal location of the boundaries. Three optimization techniques, multi-resolution pseudo-exhaustive search method, Metropolis algorithm with geometric annealing and Metropolis algorithm with pre-tuned curvature, are proposed and implemented to solve the joint MAP estimate. Experimental results have demonstrated that the three optimization techniques operate robustly in detecting the road and lane boundaries. The pseudo-exhaustive search outperforms the Metropolis algorithms, however, the pre-tuned Metropolis method has a good performance and complexity tradeoff.

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