Detection of Curved Road Edges in Radar Images Via Deformable Templates

*Bing Ma, Sridhar Lakshmanan, Alfred O. Hero**

1 Objective

In this paper, we deal with the problem of locating curved and parallel road edges in radar data that are acquired from an imaging platform mounted on a stationary automobile. The goal of road detection algorithms is to find the road edges without an existing model of road geometry, and do so in situations where there may be a great deal of clutter in the images due to cars on the road, backscatter from road edges, etc. Many prior detection algorithms that are applicable for structured edges such as road boundaries are edge-based and threshold the image gradient magnitude to detect edges. The performance of these edge detection algorithms is good when the images have uniform regions with good separation between the regions. However, in real road scenes it is difficult to select a threshold which eliminates noise edges without also eliminating many of the road points of interest. This problem is particularly severe in C band, L band or X band radar images (see Fig. ??). In order to overcome this problem, we make use of deformable template approaches which do not require thresholding the image gradient magnitudes. This allows weak edge points which are consistent with a prior geometric model of possible road boundary shapes to overrule strong edge points which are not consistent with the prior geometric model.

2 Detection Algorithms

Three methods of detecting road edges in radar images are presented in this paper. All of them are based on deformable template priors[?] and random field likelihoods. The first method employs an adaptive log-normal likelihood similar to [?]. The second method is a modification of the first, using a novel weighting scheme. The third method is based on a three-region indicator matrix which is used to impose the non-linear constraints implicit on road geometry via addition of a sum of quasi-quadratic matrix forms to the log-normal likelihood. This method also uses a recursive scheme designed to find the optimal indicator matrix.
In all the three methods, the road edges in the radar image are extracted by identifying "homogeneous" regions in the image. The road boundaries separate the image into three uniform regions which associate with the road surface, the left side of the road, and the right side of the road. The radar imaging likelihood is described using the conditional probability that the random field Z takes on a realization z (corresponding to the radar observation), given that the road edge information is known,

$$P(Z = z \mid road \;\; geometry) = \prod_{(x,y)} \frac{1}{z_{xy}\sqrt{2\pi\sigma_{xy}^2}} exp\{-\frac{1}{2\sigma_{xy}^2}(logz_{xy} - \mu_{xy})^2\} \qquad (1)$$

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

2.1 Method 1. Adaptive Log-normal Method

In this method, the road boundaries are parameterized as two parallel and hyperbolic curves.

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

The physical characteristics of the radar imaging process is described by a log-normal random field model which is represented by (1). The road edges detection problem is posed in a Bayesian framework where the deformable template plays the role of a prior and the log-normal pdf plays the one of a likelihood. The Maximum A Posterior(MAP) estimator is used to find the optimal deformation parameter values:

*Bing Ma, Alfred Hero are with the Dept. of Electrical Engineering and Computer Science, The University of Michigan–Ann Arbor, MI 48109. Sridhar Lakshmanan is with Dept. of Electrical and Computer Engineering, The University of Michigan–Dearborn, MI 48128

$$
\begin{aligned}
&(k^*, m^*, b_L^*, b_R^*) \\
&= \arg \max_{(k,m,b_L,b_R)} \ln P(k, m, b_L, b_R \mid Z = z) \\
&= \arg \max_{(k,m,b_L,b_R)} (-N^{rd} \ln \sigma^{rd} - N^{lt} \ln \sigma^{lt} - N^{rt} \ln \sigma^{rt})
\end{aligned} \tag{3}
$$

where N^{rd}, N^{lt} and N^{rt} denote the number of pixels in road, left-side and right-side regions, respectively. Since the objective function which we want to maximize is non-concave with many local maxima, we employ the Metropolis algorithm with a geometric annealing schedule[?] to perform this maximization(see [?] for a more detailed description). The unknown parameters (means and variances of three regions) of the likelihood are analytically determined from the data by a maximum likelihood method. The lognormal likelihood is modified by resubstituting these estimated parameters back in, thereby making the method adaptive.

2.2 Method 2. Weighted Log-normal Method.

In Method 1, the three regions are treated with the same weight, in terms of their contributions to the likelihood. However, in the radar images it is clear that the backscatter distribution of the road is virtually homogeneous while the backscatter distribution of the roadsides are much more complicated. In Fig. ??, we can see that the road edge detected from Method 1 is not perfect. Due to this attribute of the radar backscatters we propose a new method that gives the region of the road a different weight $w^{rd}(0 < w^{rd} < 1)$ from those of the roadside regions. The weighted log-normal method, when coupled with a penalty function $\alpha(\cdot)$, yields very good results in road edge detection(see Fig. ??).

$$
\begin{aligned}
&(k^*, m^*, b_L^*, b_R^*) \\
&= \arg \max_{(k,m,b_L,b_R)} (-w^{rd}\alpha(k, m, b_L, b_R) N^{rd} \ln \sigma^{rd} \\
&\qquad -N^{lt} \ln \sigma^{lt} - N^{rt} \ln \sigma^{rt})
\end{aligned} \tag{4}
$$

where

$$
\alpha(k, m, b_L, b_R) = \frac{2}{\pi} atan(d_{width} \times (b_R - b_L)) \tag{5}
$$

2.3 Method 3. Recursive Indicator Matrix Method

In both methods 1 and 2, the objective function being optimized, with respect to the deformation parameters, is non-concave and has many local maxima. To remedy this problem, a new 3-region indicator matrix based formulation is presented. The geometric constraints of the road edges imposed by the deformable template are rewritten in terms of constraints on the indicator matrix I_i(i-th iteration). I_i is a $mn \times 3$ matrix (the dimension of the radar image is $m \times n$) and its p-th row $[c_{p1}, c_{p2}, c_{p3}]$ ($0 \le p \le mn - 1$) corresponds to a pixel in the radar image. Let $j = 1, 2, 3$ denote the leftside, road and rightside region, respectively. If the pixel is in the j-th region, then

$$
c_{pk} = \begin{cases} 1 & \text{if k=j} \\ 0 & \text{otherwise} \end{cases} \tag{6}
$$

This reformation allows us to use a simple recursive method for optimization.

$$
I_i^* = \arg \max_{I_i} \parallel (I - I_i(I_{i-1}^T I_{i-1})^{-1} I_i^T) \log Z \parallel + P(I_i) \tag{7}
$$

where $P(I_i)$ is a quadratic penalty function, which is to guarantee the road edges are smooth and connected.

$$
P(I_i) = \parallel I_i - shift(I_i) \parallel^2 \tag{8}
$$

3 Results

Since neither of the three methods make use of the noise-sensitive gradient magnitude of the radar images, they overcome the shortcomings of the edge-based detection algorithms. The results (Fig. ??~Fig. ??) show that the methods we present in this paper promise to be better than the edge-based detection algorithms in many cases such as when there is a car on the road or the roadsides are relatively complicated.

References

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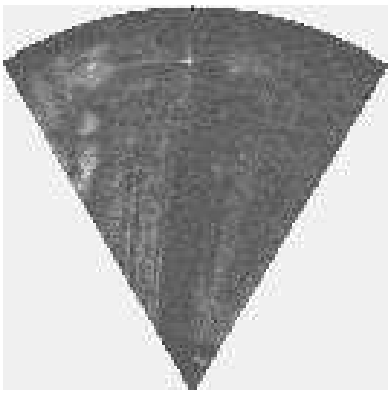

Figure 1: Original radar image(rdimg1)

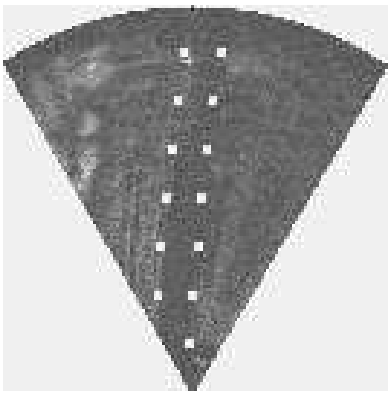

Figure 2: Result(of rdimg1) from Method 1

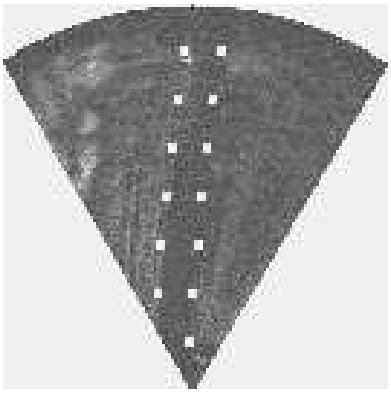

Figure 3: Result(of rdimg1) from Method 2

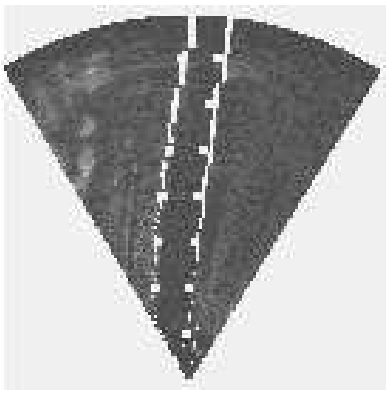

Figure 4: Result(of rdimg1) from Method 3

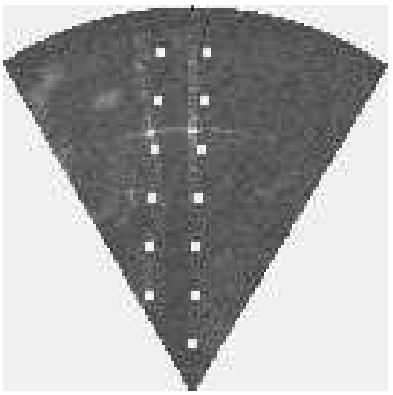

Figure 5: Result(of rdimg2) from Method 1

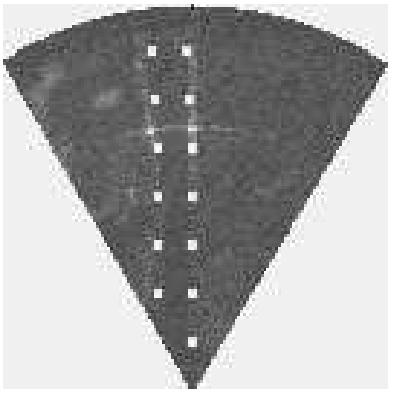

Figure 6: Result(of rdimg2) from Method 2