2010 IEEE Intelligent Vehicles Symposium
University of California, San Diego, CA, USA
June 21-24, 2010

LIDAR-Based Road and Road-Edge Detection

Wende Zhang, *Member, IEEE*

Abstract—**In this paper, a LIDAR-based road and road-edge detection method is proposed to identify road regions and road-edges, which is an essential component of autonomous vehicles. LIDAR range data is decomposed into signals in elevation and signals projected on the ground plane. First, the elevation-based signals are processed by filtering techniques to identify the road candidate region, and by pattern recognition techniques to determine whether the candidate region is a road segment. Then, the line representation of the projected signals on the ground plane is identified and compared to a simple road model in the top-down view to determine whether the candidate region is a road segment with its road-edges. The proposed method provides fast processing speed and reliable detection performance of road and road-edge detection. The proposed framework has been verified through the DARPA Urban Challenge to show its robustness and efficiency on the winning entry Boss vehicle.**

I. INTRODUCTION

The purpose of this work is to develop a robust and real-time road and road-edge detection technique using LIDAR (LIght Detection And Ranging) for road modeling. The developed technique fulfills the objective of autonomous driving in an urban environment for the 2007 DARPA (the Defense Advanced Research Projects Agency) Urban Challenge [1], and has been validated on our General Motors-Carnegie Mellon University's entry Boss, the autonomous vehicle that won the challenge.

There has been great interest in developing sensing technologies and algorithms for autonomous driving, which includes road and stationary obstacle detection, world and relative pose estimation, moving object tracking, and sensor calibration [2]. Road and stationary obstacle detection creates terrain traversability cost maps. World and relative pose estimation addresses positioning of the vehicle (e.g., world pose and lane offsets) for route planning. Moving object tracking involves detection, tracking and prediction of other moving objects (e.g., vehicles) to avoid collision. Sensor calibration calibrates sensors' relative poses and intrinsic parameters.

The common approaches for road modeling (with various road boundary detection methods) use active sensors, such as LIDAR [3][4][5]. LIDAR transmits and receives shorter wavelengths of electromagnetic radiation in the ultraviolet, visible, and near infrared regions and measures the reflectivity of the environment. Prototype vehicles with active sensors have shown promising results for obstacle detection and road modeling in the autonomous vehicle competition, the 2007 DARPA Urban Challenge. LIDARs have been widely used to develop sensing algorithms, since it works well in various lighting conditions based on the range analysis. The main issue is the robustness and speed of the sensing algorithms in various scenarios.

In the proposed method, the road segment and road-edge points are first identified using the elevation information extracted from the range data. The identified 3D road-edge points are further projected and validated on the 2D ground plane. The two-stage approach not only improves the system robustness, but also reduces the computational complexity for real-time applications.

The paper is organized as follows. In the next section, the LIDAR-based road and road-edge detection method for road modeling is introduced. In Section 3, experiment results are discussed. Conclusion is given in Section 4.

W. Zhang is with Electrical and Controls Integration Lab, General Motors Corporation, R&D and Planning, 30500 Mound Rd, Warren, MI 48090, USA. (email: wende.zhang@gm.com).

II. ROAD AND ROAD EDGE DETECTION

A. Overview

A forward-looking LIDAR sensor is mounted on the front-top of the Boss vehicle as illustrated in Figure 2. The LMS-200 SICK sensor scans the scene with two-dimensional point array covering 90 degree field-of-view with half degree resolution at a 75 Hz scan rate as shown in Figure 3(a). The road-edge detection algorithm analyzes range data (e.g., the signal in the elevation direction z) as shown in Figure 3(b) to detect road-edge positions.

For an urban environment, it is assumed that the road is the lowest smooth surface and curbs are edges of the road. A cascade processing method is proposed for road and road-edge detection including the following 5 steps as shown in Figure 1: candidate selection, feature extraction, road segment classification, false alarm mitigation, and road curb detection. The road and road-edge points are first detected in elevation data, and then validated on the ground plane to improve system robustness and processing speed. An elevation-based road signal is extracted from the LIDAR range data. The signal is processed by a filter to select candidate regions for road-segment classification. In each candidate region, features are extracted and classified as road-segment or not. The positive results are passed through the false alarm mitigation module using a rule-based scheme (e.g., minimal road width requirement) to further reduce false alarms. The detected road edges are the left-most and right-most boundaries of the detected road-

978-1-4244-7868-2/10/$26.00 ©2010 IEEE

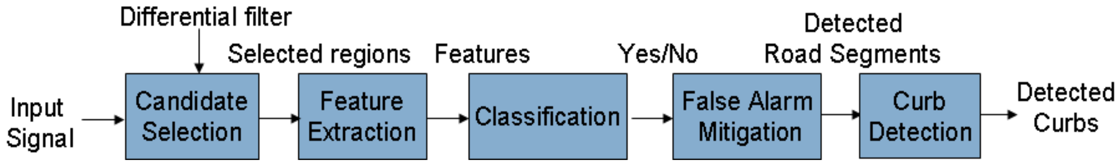

Figure 1. Flowchart of road/road-edge detection algorithm

Figure 2. SICK LIDAR sensor for road-curb detection

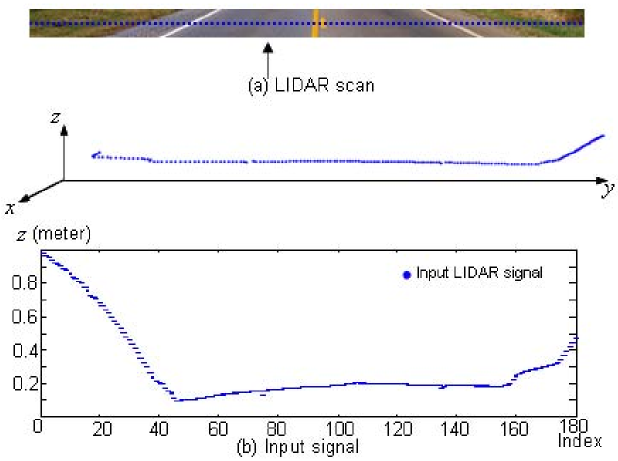

Figure 3. Input LIDAR signal

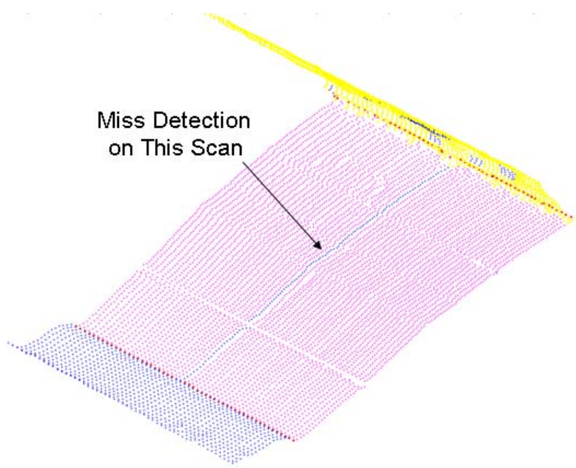

Figure 4. Detection results. The detected road points, road-edge points and curb lines are in magenta, red and yellow, respectively. The blue points are unclassified.

segments. The LIDAR range data is also projected onto the ground plane to identify curb lines using a road curb detection module. The line representation of the projected points is identified and compared to a simple road model in the top-down view to determine whether the candidate region is a road segment with its road-edges. Sample detection results are shown in Figure 4. The proposed algorithm runs up to 200 scans per second in our system [2]. Next, each step is discussed in detail.

B. Candidate Selection

The input signal is convolved with a local-extreme-signal detection filter (a Gaussian differential filter as shown in Figure 5) to identify the local extreme peaks of the filter response as the local maximal points and the local minimal points in the input signal. The peak response magnitudes are required to be larger than a fixed threshold to reduce noise. The regions between adjacent local minimal points (on the left) and local maximal points (on the right) are candidates to extract features for road-segment classification as shown in Figure 5.

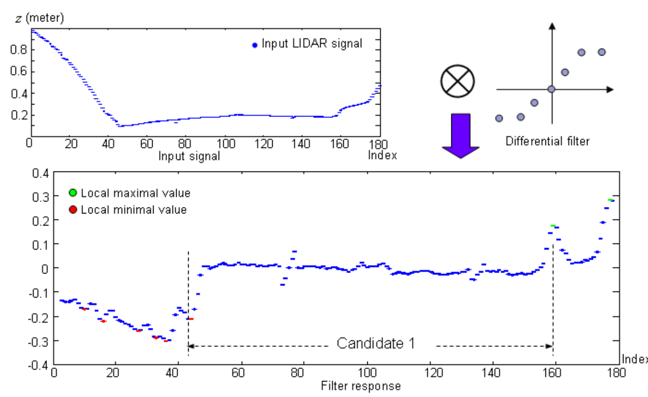

Figure 5. Candidate road-segment region selection

C. Feature Extraction

Ground is assumed to be a smooth surface. Therefore, the variance of ground elevation is used as a feature. The weighted standard deviation σ_z of elevation z is calculated in the candidate road-segment region. The statistic is biased towards the center region, since the weights are defined as follows (as illustrated in Figure 6):

$$\mathrm{w(i)} = \begin{cases} \mathrm{a(i)}, & \mathrm{a(i)} <= 1 \\ 1, & \text{otherwise} \end{cases}, \mathrm{a(i)} = 2 * \sin(\mathrm{i} * \pi/(N-1)),\ \mathrm{i} = 0,1,...,\mathrm{N}-1 \quad (1)$$

where N is the total number of points within the candidate region.

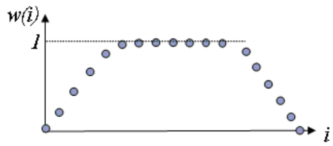

Figure 6. Weights for standard deviation calculation

D. Classification

A classifier is applied to determine whether the candidate region is a road-segment to strike the balance between the weighted standard deviation σ_z of road-segment elevation and the total number of points N within the candidate region.

$$f = \alpha^* \sigma_z + \gamma/N; \quad (2)$$

If the objective value f of the classifier is smaller than a fixed threshold, the candidate region is a potential road-segment region (magenta dots) as shown in Figure 7.

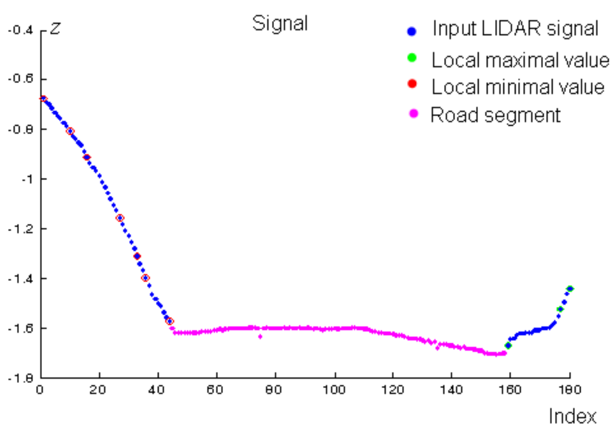

Figure 7. Region classification results

The classifier parameters (α and γ) can be trained by a linear Support-Vector-Machine classifier [6]. We use the following in our system.

$$\alpha = 2.0 \text{ and } \gamma = 2.0. \quad (3)$$

E. False Alarm Mitigation

Regions identified as potential road regions are validated with the false alarm mitigation module using the following minimal road width rule to reduce false alarms.

The width d of the road segment has to be greater than a threshold (4 meters in our system). The width d is defined as the distance between adjacent local minimal and maximal points.

F. Road Curb Detection

The road edges and curbs as shown in Figure 8 are the left-most and right-most boundaries of the detected road-segments in the input LIDAR signal as shown in Figure 3(b).

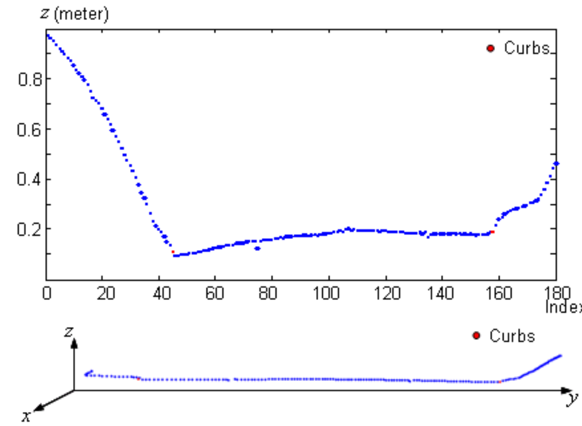

Figure 8. Sample curb point detection results

In addition, since the LIDAR sensor scans the scene surface with a small pitch-down angle to ensure a look-ahead distance, the road curb lines are perpendicular to the road surface on the projected ground plane. Therefore, road-edges and curbs of the road segment are further validated using curb detection in the top-down view by projecting the input data to the ground plane (with a simple 2D road model as illustrated in Figure 9). The line representation of the projected points is extracted using Hough transform [7]. The line-segments nearly perpendicular to the road segment (e.g., greater than 75 degree) are identified as additional curb segments in Figure 9. This approach also provides the curb orientations from Hough analysis in the top-down view.

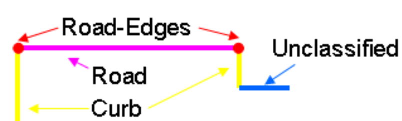

Figure 9. A simple Road model

III. EXPERIMENT

The proposed algorithm has been validated under various urban scenarios in preparation for the 2007 DARPA Urban Challenge. Single-scan detection results are shown in Figure 10 and Figure 11. The LIDAR scans the environment with a two-dimensional plane. As shown in Figure 11, it hits a road divider on the left, a side-walk curb on the right and a vehicle in the middle. The proposed algorithm detects the road divider and side-walk curb as the road curbs (yellow dots). The algorithm also correctly identifies the road segment (magenta dots) without confusing with any on-road objects (e.g., vehicles).

Sample results are also shown in Figure 12 in multiple scans with the host vehicle approaching an intersection. The detected road points, road-edge points and curb lines are in magenta, red and yellow, respectively. The algorithm detects most road points, road-curb points, and road-edge points correctly with a false alarm rate at 0.83% and a miss

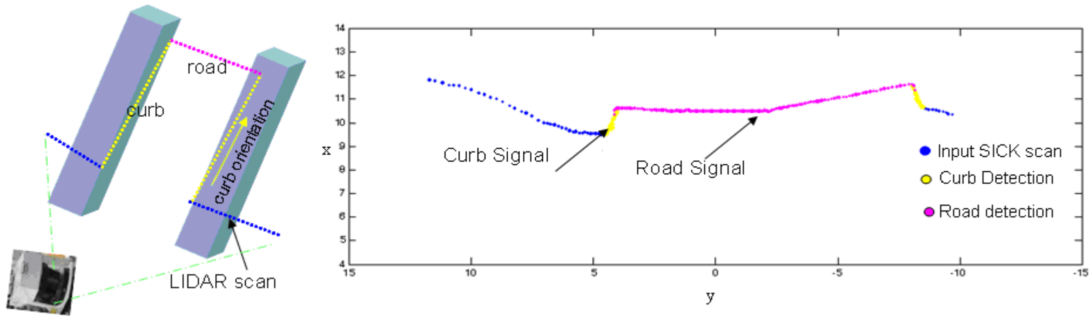

Figure 10. Curb detection in x-y space

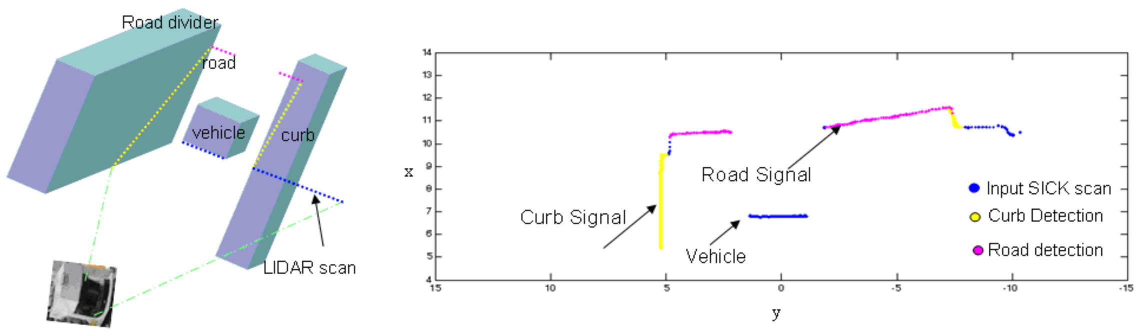

Figure 11. Detection result in a single scan

rate at 0.55% per scan on our dataset as shown in Figure 12. The detection results without temporal smoothing leave few road-edge points on the road surface in the middle, which are the false alarms of the single-scan-based road and road-edge detection algorithm. These errors can be further corrected by a temporal smoothing technique such as Kalman Filtering [8].

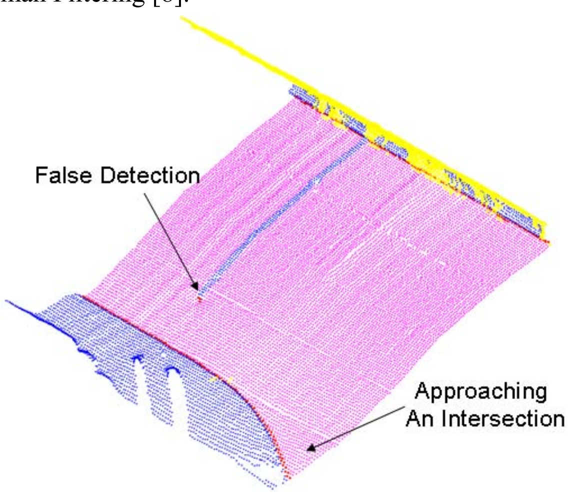

Figure 12. Sample detection results in multiple scans. The detected road points, road-edge points and curb lines are in magenta, red and yellow, respectively. The blue points are unclassified.

IV. Conclusion

A robust LIDAR-based road/road-edge detection algorithm has been developed. The proposed algorithm runs up to 200 scans per second in the system. And the system can detect road, road edges and curb lines with orientation in a single LIDAR scan. The robustness and efficiency of the algorithms has been demonstrated in various testing scenarios. As next steps, we look into combining a production front view camera with a production-intended LIDAR for road geometry identification.

References

[1] http://www.darpa.mil/GRANDCHALLENGE/

[2] C. Urmson, J. Anhalt, D. Bagnell, C. Baker, R. Bittner, M. N. Clark, J. Dolan, D. Duggins, D. Ferguson, T. Galatali, C. Geyer, M. Gittleman, S. Harbaugh, M. Hebert, T. M. Howard, A. Kelly, N. Miller, M. McNaughton, K. Peterson, M. Likhachev, R. Rajkumar, P. Rybski, B. Salesky, Y. Seo, S. Singh, J. Snider, A. Stentz, R. Whittaker, Z. Wolkowicki , J. Ziglar, H. Bae, T. Brown, D. Demitrish, B. Litkouhi, J. Nickolaou, V. Sadekar, W. Zhang, J. Struble, M. Taylor, and M. Darms, “Autonomous driving in urban environments: Boss and the Urban Challenge,” *Journal of Field Robotics Special Issue on the 2007 DARPA Urban Challenge, Part I*, Vol. 25, No. 8, pp. 425-466, 2008.

[3] J.C. Andersen, N.A. Andersen, and O. Ravn, "Vision assisted Laser scanner navigation for autonomous robots," *Experimental Robotics*, Vol.39, pp. 111-120, 2008.

[4] W.S. Wijesoma, K.R.S. Kodagoda, and A.P. Balasuriya, "Road-boundary detection and tracking using ladar sensing," *IEEE Transactions on Robotics and Automation*, Vol. 20, No.3, pp. 456-464, 2004.

[5] H. Cramer and G. Wanielik, “Road border detection and tracking in noncooperative areas with a laser radar system,” in *Proceedings of German Radar Symposium*, pp. 24-29, 2002.

[6] C.J.C. Burges, “A tutorial on Support Vector Machines for pattern recognition,” *Data Mining and Knowledge Discovery*, pp. 121-167, 1998.

[7] R.O. Duda and P.E. Hart, “Use of the Hough transformation to detect lines and curves in pictures,” *Communications of the ACM*, Vol. 15, pp. 11–15, 1972.

[8] R. E. Kalman, “A new approach to linear filtering and prediction problems,” *Transactions of the ASME-Journal of Basic Engineering*, Vol. 82, pp. 35-45, 1960.