Millimeter Wave Radar-Based Road Segmentation

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ABSTRACT

Research into autonomous vehicles has focused on purpose-built vehicles with Lidar, camera, and radar systems. Many vehicles on the road today have sensors built into them to provide advanced driver assistance systems. In this paper we assess the ability of low-end automotive radar coupled with lightweight algorithms to perform scene segmentation. Results from a variety of scenes demonstrate the viability of this approach that complement existing autonomous driving systems.

Keywords: millimeter wave, radar, ADS, road segmentation

1. INTRODUCTION

A 2015 study found that 94% of road accidents are caused by human error.[1] The largest error type was identified as recognition failure: certain aspect of the scene, being road path, presence or absence of an obstacle, lane markings, etc., was incorrectly perceived by the driver, resulting in the motor accident. In 2019 motor vehicle accidents resulted in over 36,000 deaths in the United States[2] alone. Two independent approaches have been developed to reduce human errors, advanced driver assistance systems (ADAS) and autonomous driving systems (ADS). ADAS augment the human driver with alerts based on the presence of detected objects and is widely implemented in industry using cost-effective camera, Lidar, radar, and ultrasonic sensors. ADS, on the other hand, is an emerging technology that relies on high quality camera, Lidar, and radar sensors to reduce or eliminate recognition errors. There are existing companies operating ADS taxi services[2] and more companies are nearing commercial operation of their own ADS taxis,[3] demonstrating ADS capabilities.

Though there has been significant progress towards developing ADS that can be mass deployed, there are still significant hurdles towards fully trusted ADS. The most common processing pipeline relies on high definition (HD) maps of the environment that the ADS will operate in. However, even the maps at a small city scale require more than a terabyte of storage for the maps, which also requires significant upkeep to maintain accuracy.[4,5] The sensing technology is another limiting factor. Of the sensing modalities used by ADS for localization in global map and local route planning, camera and Lidar are the most commonly-used sensors.[6] However, both sensing modalities suffer from severely degraded performance in inclement weather, illumination conditions[7] and transparent objects.[8] While Lidar systems can provide the most accurate sensing, they come at a hefty cost, where entry-level automotive grade Lidar can cost around $25,000 USD and high-end Lidar can cost as much as $100,000 USD.[9] On the other hand, commoditization of Lidar, increased production scale, and new designs are driving down the cost of automotive grade Lidar.

A complementary sensing modality for camera and Lidar-based ADS is frequency modulated continuous wave (FMCW) radar. FMCW radar is robust in the face of inclement weather and unaffected by illumination conditions,[10] but suffers from lower resolution compared to camera and Lidar sensors.[11] Imaging radars using several coupled radar chips offer fairly high azimuth resolution of less than 2 degrees and have been used to segment road surfaces[12] while single chip radar systems typically only provide 15 degree azimuthal resolution.

Single chip radar is common in the automotive industry with radar placed around the body of vehicles used for ADAS functions like adaptive cruise control, lane change assist, cross traffic warning, and blind spot detection.[13]

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In this work we propose a low computational complexity algorithm for segmenting roads using a single-chip automotive radar, providing ADS capability with an ADAS sensor. To the best of the authors knowledge, this is the first work targeting this class of radar for road segmentation and opens new research about the dual-use capability of existing automotive radar.

2. RELATED WORK

In this section we review related work in road segmentation and the application of radar to the ADS problem.

2.1 Road Segmentation

ADS increasingly relies on road segmentation to determine traffic lanes and road boundaries. Lidar and camera systems have been extensively studied both independently[14,15] and fused.[16] Early approaches made assumptions about road structure, such as what markings would be on the boundaries of roads and lane, but more recent approaches are able to operate in unstructured road environments.[17,18] However, the performance of both modalities is dependent on favorable weather.

The ability of FMCW radar systems to segment scenes has recently begun to be investigated with approaches using data from the range-angle heatmap[12,19,20] and others using range-doppler data.[21] A unique approach uses ground penetrating radar (GPR), instead of the traditional automotive radars, to segment the road.[22] Each of these approaches used custom designed or high-end imaging radar.

2.2 Radar ADS

Radar-based ADS are a less-developed field than its Lidar and camera-based counterparts. Three years after the Oxford Robotcar dataset[6] was published, a radar extension was published to encourage research in radar-based ADS.[23] Most radar ADS use mechanically actuated radars[10,12] which provide higher angular resolution than MIMO radar at the cost of lower frame rate and radial blur. More recent work has been using MIMO radar,[24] trading away the higher angular resolution of the mechanically actuated radar for the higher frame rate and lower complexity of the MIMO system.

3. BOUNDARY DETECTION AND SEGMENTATION ALGORITHMS

In this paper we investigate the ability of TI AWR1843, an FMCW radar representative of those installed on many vehicles, to segment individual scenes into drivable and non-drivable areas. Configuration and data collection were performed using TI DCA1000EVM data capture board which allowed a simple method for data to be transferred to Matlab for post-processing. The radar was programmed with the parameters given in Table 1.

Data was collected with the radar at a variety of heights low to the ground and representative of vehicle bumper heights. Scenes collected included pavement transitioning to curbs, grass, and snowbanks. We structure our approach to have low computational complexity in order to be applicable to the processors found in existing radar-equipped vehicles.

Parameter	Value
Virtual Antennas	8
Effective Bandwidth	2.56 GHz
Number of ADC Samples	256
Chirps per Frame	64

Table 1. Radar Configuration

Algorithm 1: Joint-Variance Towards Boundary Detection

```
for row r in i do
    r = r/max(r);
    v1 = variance(r);
end
for column c in i do
    c = c/max(c);
    v2 = variance(c);
end
V = elementwise multiply(v1, v2);
```

3.1 Proposed Algorithms

Once data has been collected and processed to a range-azimuth intensity heatmap **i**, we apply Algorithm 1 to calculate the joint variance **V** in range **v1** and azimuth **v2**. This approach minimizes the effect of large target sidelobes without the computational complexity of many constant false alarm rate (CFAR) algorithms. The joint variance is windowed in range and azimuth to exclude near- and far-field effects and compared against a threshold to identify surface transitions.

The output of Algorithm 1 is called the boundary map **M**. **M** is segmented by passing a window **w** over each ray **r** from the origin to the maximum range. If the window exceeds the threshold **t**, the section covered by the window is deemed to be non-drivable. The window is introduced as a low-complexity method of limiting the impact of radar noise in surface classification. Once the window passes the threshold, variable **b** is switched so any areas below the threshold after the non-drivable surface are deemed to be shadowed by the boundary and labelled as such. Labels are stored in the segmentation map **S**.

Algorithm 2: Segmentation

```
for ray r in M do
    if sum(w) >= t then
        S = boundary;
        b = true;
    end
    if sum(w) < t then
        if b then
            S = shadowed;
        else
            S = drivable
        end
    end
end
```

3.2 Comparable Algorithms

We compared our proposed boundary detection and segmentation algorithms against a variety of CFAR algorithms and the Sobel edge detection algorithm in an effort to validate the effectiveness of our approach in accuracy and execution speed. Cell-Averaging CFAR (CA-CFAR) and Greatest of Cell Averaging (GOCA-CFAR) were chosen as they are representative of the family of CFAR algorithms commonly applied to radar signals. CFAR operates by taking, for each cell-under-test (CUT) in the data, the average power of a number of surrounding cells and computing a threshold off that average. If the CUT power is greater than the threshold it is labelled as occupied, otherwise it is labelled as unoccupied.[25] Sobel edge detection is a classic image processing algorithm that calculates the gradient of each pixel of an image using a 3×3 kernel and compares the output to a threshold - gradients greater than the threshold are marked as edges.[26]

4. EXPERIMENTAL RESULTS

Figure 1 shows the capability of the proposed algorithms with a variety of surface transitions, with the easier surface transitions on the left and the harder transitions on the right. From left to right the system is looking at a curb, down a narrow alley, driveway flanked with snow, low (around 2cm) cement barrier between pavement and grass, and a direct pavement to grass transition. In all cases the third row - the boundary map output from Algorithm 1 - clearly shows the delineation between drivable and non-drivable surfaces. The fourth row - the segmentation map created by Algorithm 2 shows a strong agreement with ground truth for the easier transitions and decreasing performance with the harder surface transitions.

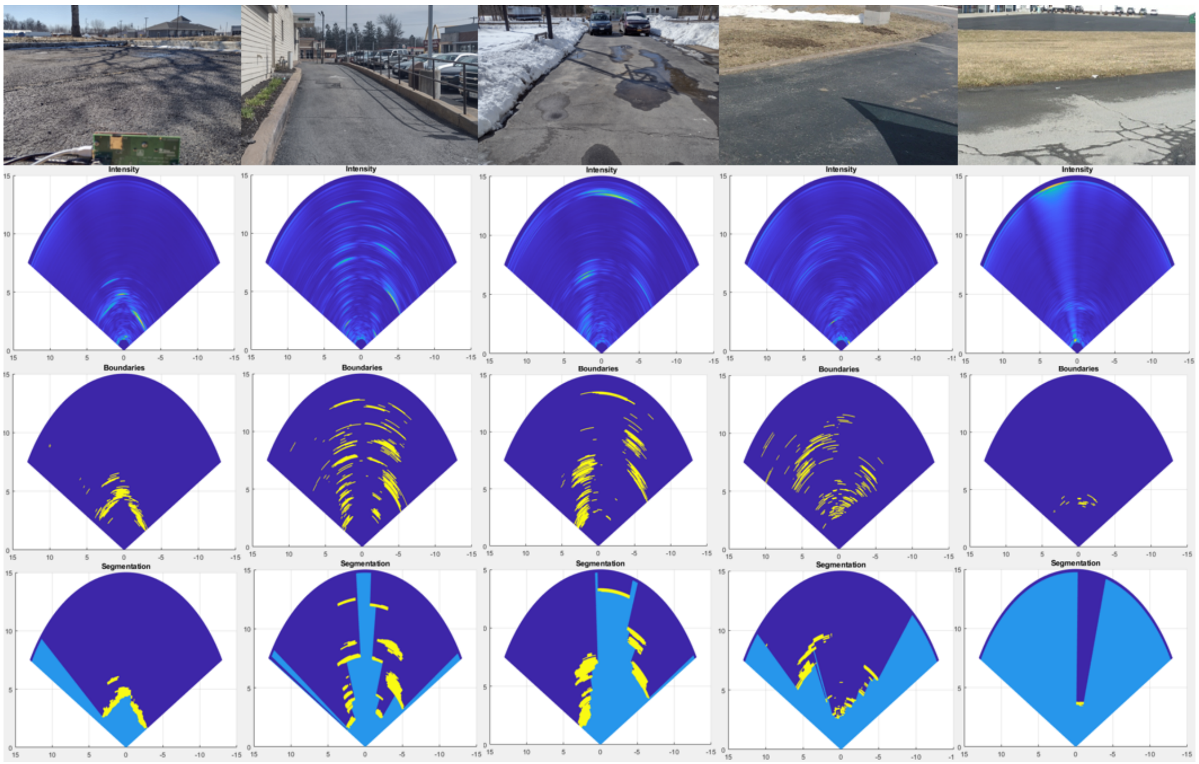

Figure 1. Top row: camera images of scenes, Second row: radar intensity heatmap, Third row: boundary detection, Bottom row: Scene segmentation where light blue is drivable, yellow is boundary, and dark blue is shadowed

Our algorithm was implemented in Matlab and compared against the built-in Matlab instances of the CFAR and Sobel functions. Figure 2 shows the superiority of the joint variance approach in repressing radial blur without sacrificing the actual data. The various CFAR and image processing algorithms clearly perform worse both in preserving the actual data and repressing radar artifacts. Furthermore, the joint variance method outperformed the CFAR methods by at least two orders of magnitude in execution speed as shown in Table 2. While Sobel edge detection outperforms the joint variance approach in execution speed, the detected edges are less accurate to ground truth than the joint variance method. Timing was taken by using Matlab's *timeit* function to provide an average execution time over several runs.

Method	Execution Time
Joint Variance (Our scheme)	.69 mS
Sobel	.25 mS
CA	87.0 mS
GOCA	114.5 mS

Table 2. Comparison of joint variance execution speed to CFAR and Sobel execution speeds

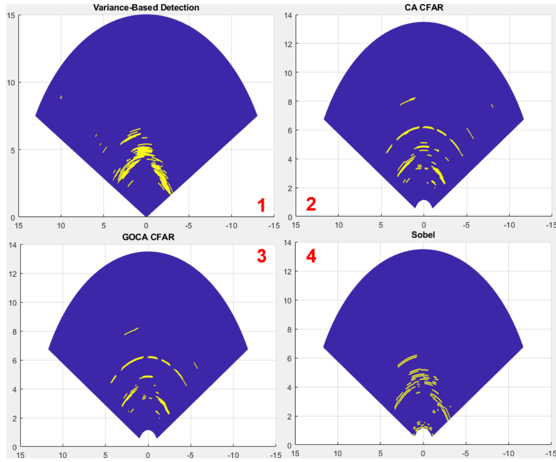

Figure 2. Comparison of (1) joint variance technique from this paper against (2) Cell-Averaging CFAR, (3) Greatest of Cell Averaging CFAR, and (4) Sobel edge detection

5. CONCLUSIONS

In this work we demonstrated the ability of a low-cost automotive radar to segment common surface transitions which outperforms common radar and image processing detection schemes. Our segmentation algorithm is computationally simple, designed to be suited for edge processors and real-time applications. Future work includes assessing these sensors with key point detection, map building for SLAM, and fusion with Lidar or camera sensors.

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