

# Probabilistic Oriented Object Detection in Automotive Radar

Xu Dong<sup>\*</sup>

Pengluo Wang<sup>\*</sup>

Pengyue Zhang  
XSense.ai

Langechuan Liu<sup>Y</sup>

## Abstract

*Autonomous radar has been an integral part of advanced driver assistance systems due to its robustness to adverse weather and various lighting conditions. Conventional automotive radars use digital signal processing (DSP) algorithms to process raw data into sparse radar pins which do not provide information regarding the size and orientation of the objects. In this paper we propose a deep-learning based algorithm for radar object detection. The algorithm takes in radar data in its raw tensor representation and places probabilistic oriented bounding boxes (oriented bounding boxes with uncertainty estimate) around the detected objects in bird's-eye-view space. We created a new multimodal dataset with 102,544 frames of raw radar and synchronized LiDAR data. To reduce human annotation effort we developed a scalable pipeline to automatically annotate ground truth using LiDAR as reference. Based on this dataset we developed a vehicle detection pipeline using raw radar data as the only input. Our best performing radar detection model achieves 77.28% AP under oriented IoU of 0.3. To the best of our knowledge this is the first attempt to investigate object detection with raw radar data for conventional corner automotive radars.*

## 1. Introduction

Object detection holds the key for achieving autonomous driving. While camera and LiDAR have been the two major sensory modalities in autonomous driving field, they both have their own drawbacks. For example, 3D object detection from camera alone proves to be very challenging so far despite recent progress [45], and LiDAR is inherently not reliable in adversarial driving conditions [2, 22] and still too expensive for mass production. On the other hand, radar, as a widely-adopted sensor in traditional Advanced Driver Assistance Systems (ADAS), is very robust and reliable under different weather conditions. Using radar for object detection can be of great help for increasing both redundancy and robustness of perception in autonomous driving.

Figure 1: An sample scene from our dataset, with radar, camera, LiDAR, and radar-LiDAR overlaid data. The camera image is only used for visualization and is not consistently collected in our dataset. Radar is mounted at the front left corner at bumper height and LiDAR on the rooftop. The top left image is the radar data in data tensor representation; top right is the corresponding camera image; bottom left is the corresponding LiDAR data in bird's-eye-view (BEV) image; bottom right is the overlaid image from radar and LiDAR data, for better understanding of the semantics. Objects in the scene are marked with colored stars in the camera image, and colored boxes in the LiDAR image and overlaid image.

Data from radar can take on different representations. For conventional automotive radars, raw data are heavily processed by digital signal processing (DSP) algorithms and are reduced to sparse radar pins (normally only 10 to 50 points per frame). Under this representation, one object is generally denoted by only one radar pin, without any size and orientation information. One emerging revolution in the industry is *imaging radar*, which can produce semi-dense radar point cloud in a similar format to LiDAR point cloud [34]. Compared with sparse radar pins, point cloud representation requires fewer DSP modules and contains more low-level information. However, similar to LiDAR sensors, the *imaging radar* are more costly and not fully ready for deployment in mass production cars.

Another trend in autonomous driving is the use of corner radars for 360° surveillance. Compared with front radar, ob-

<sup>\*</sup> indicates equal contributions.

<sup>Y</sup> indicates corresponding author patri ckl@xsense.ai



















