Radar Dataset for Robust Localization and Mapping in Urban Environment

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Abstract—Recent development and application of radar sensors to the urban environment has attracted much attention in autonomous research due to their robustness against challenging environments compared to light detection and ranging (LiDAR)s and cameras. However, the radar is not universalized for simultaneous localization and mapping (SLAM) research and has different characteristics from general ranging sensors. This paper presents a radar dataset for localization and mapping research in the urban environment. This dataset provides the baseline trajectory of a vehicle for evaluation together with a 3D point cloud as prior information for multimodal radar-LiDAR research. Unlike existing radar datasets, the provided radar data support both raw-level and image format data, including 360° cumulated 1D intensity arrays with time stamps and 360° polar images. In doing so, we provide flexibility between raw data and image data depending on the purpose of the research.

I. INTRODUCTION

This paper describes a radar dataset for navigation and mapping aggregated on a mobile platform. As SLAM has progressively become important in autonomous navigation systems, various SLAM studies using real data have been conducted. Sensors largely used in SLAM include vision sensors (cameras) and range sensors (LiDAR, radar, and sonar). Compared to research on LiDAR and cameras, radar-based SLAM has been relatively less reported. For example, conventional approaches in radar sensors are mainly used for imaging radar on a large scale [1]. On a mobile platform, radar has been used for dynamic object detection as an auxiliary sensor and has not been studied much in SLAM research [2,3]. The major challenge of using radar arises from the sparse and noisy sensor characteristics compared with LiDAR, despite their robustness and long-range capturing capability.

Nevertheless, recently the focus has been moved to the robustness of radar sensors in extreme environments [4]. Radar has a lower frequency of signals than LiDAR, which has the advantage of long-range sensing instead of decreasing straightness. Also, because the object can be limitedly penetrated, the context on a wide map can be confirmed [5]. The existing research on the radar as a ranging sensor includes the following: [Cen and Newman] proposed radar odometry using feature extraction and shape matching methods [6]. [Lundgren et al.] performed radar map estimation using the variational Bayesian expectation maximization (VBEM) framework [7]. [Rapp et al.] performed ego-motion estimation with spatial registration of consecutive scans using normal distribution transform (NDT)-based optimization and likelihood model for Doppler velocity [8].

As the need to use radar sensors for general range sensing as well as dynamic object detection has increased, several high-performance radar sensors have been developed; however, the price and size are relatively large compared to conventional ranging sensors, and the radar is difficult to use due to the noisy and sparse data of the sensor. In existing datasets, [Peynot et al.] provided only 2D cartesian
TABLE I
SENSORS USED IN THE SENSOR SYSTEM (CH: CHANNEL).

<table>
<thead>
<tr>
<th>Type</th>
<th>Manufacturer</th>
<th>Model</th>
<th>Description</th>
<th>No. Hz</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>2D radar</td>
<td>NAVTECH</td>
<td>CIR204-H</td>
<td>FMCW radar scanner (360° FOV)</td>
<td>1</td>
<td>3360 (range bin), 400 (angle bin), 0.06 m (range resolution)</td>
</tr>
<tr>
<td>3D LiDAR</td>
<td>Velodyne</td>
<td>VLP-16</td>
<td>16 CH LiDAR (360° FOV)</td>
<td>2</td>
<td>100</td>
</tr>
<tr>
<td>2D LiDAR</td>
<td>SICK</td>
<td>LMS-511</td>
<td>1 CH LiDAR (190° FOV)</td>
<td>2</td>
<td>100</td>
</tr>
</tbody>
</table>

radar images at each sweep. The radar image data is convenient to use because the existing vision algorithm can be applied directly. However, the radar sensor has a relatively slow sensing speed compared with LiDAR due to the characteristics of using a low-frequency signal. As a result, the image data without time stamps in measurement at each angle bin have relatively large data distortion due to vehicle movement. Also, signal processing considering the physical properties of radar such as constant false alarm rate (CFAR) and target presence probability (TPP) include algorithms and equations using 1D intensity data. In the proposed radar dataset, both data type and convenience are considered for users.

II. OVERVIEW

This dataset provides sparse long-range intensity data using radar for robust localization and mapping. Sample radar sensor data are shown in Figure 2. To support multimodal research with short-range sensors such as LiDAR, a prior map and a 3D point cloud map are also provided. The sensor specifications used to create this dataset are shown in Table I. The data output from each sensor can also be compared with the actual map in Figure 3.

A. Radar data

We provide two types of radar data. One is 1D intensity arrays (raw data) at each angle. In this dataset, data are accumulated by 1 sweep (400 angle bins), and timestamps are added to reduce the communication load. Another is 360° polar images. All of the radar data are sent using robot operating system (ROS) messages.

B. Baseline trajectory using SLAM

The baseline is one of the key attributes when using the dataset to evaluate the performance of the algorithm. In complex urban areas in which Global Positioning System (GPS) data are very sporadic, it is difficult to get the exact baseline position of the vehicle. Typical GPS and high-precision virtual reference station (VRS)-GPS cannot estimate the exact global location due to the environmental complexity of these environments. In this paper, partially measured VRS-GPS data, fiber optic gyro (FOG) data, and graph SLAM were used to estimate the baseline of the vehicle position. If a loop occurs in the vehicle path, the relative poses are calculated by an iterated closest point (ICP) algorithm using a local point cloud and the poses are used as a constraint in the graph SLAM. The baseline of the vehicle location in 6-DOF is provided to 100 Hz.

C. 3D pointcloud

The 3D point cloud map was constructed using the estimated baseline and LiDAR measurements. The point cloud generation and sensor specifications for baseline trajectory used in this dataset can be found in detail at 10.

D. Data format

For radar data, this dataset provides ROS bag files, in which the array and image are output at 4 Hz. The dense point cloud is provided in the LASer (LAS) format file, and the baseline trajectory is provided in the CSV file. The LAS format is a public file format for 3D point clouds. The LAS data of the reconstructed 3D point clouds for all datasets are provided in this dataset. The provided LAS data can be used as prior information for research such as localization and place recognition. The LAS data contain 3D information in the Universal Transverse Mercator (UTM) coordinate system and the intensity values of the point cloud.

E. Calibration

Extrinsic calibration between pointcloud coordinate and the radar sensor is also provided by using 11.

F. Environment

In total, four sequences are presented. Two sequences were obtained in a campus environment, and the other two sequences were collected from a town-size urban environment. Detailed baseline trajectories are shown in Figure 4. Sequence 01, 02, and 04 include abundant structural features due to the buildings near the path. On the other hand, sequence 03 captures fewer features because there are relatively few buildings near the path.

III. CONCLUSION

In this paper, we introduce a radar dataset to support radar-based robotics research. The provided dataset contains both image-like and raw-level datasets together with a pose baseline and reconstructed point cloud suitable for multimodal research.

REFERENCES


Fig. 3. Sample 3D point cloud and related radar image in each part of maps. The dataset aims to provide entire sensor data with synchronized timestamps. Red lines in the real maps present approximately sensed road in the radar image. Post-processing is performed for visualizing radar image.

Fig. 4. Baseline trajectory with dimension overlaid. The blue line means the baseline trajectory.


