Oriented surface points for efficient and accurate radar odometry

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Abstract—This paper presents an efficient and accurate radar odometry pipeline for large-scale localization. We propose a radar filter that keeps only the strongest reflections per-azimuth that exceeds the expected noise level. The filtered radar data is used to incrementally estimate odometry by registering the current scan with a nearby keyframe. By modeling local surfaces, we were able to register scans by minimizing a point-to-line metric and accurately estimate odometry from sparse point sets, hence improving efficiency. Specifically, we found that a point-to-line metric yields significant improvements compared to a point-to-point metric when matching sparse sets of surface points. Preliminary results from an urban odometry benchmark show that our odometry pipeline is accurate and efficient compared to existing methods with an overall translation error of 2.05\%, down from 2.78\% from the previously best published method, running at 12.5 ms per frame without need of environmental specific training.

I. INTRODUCTION

Radar are promising sensors for robust perception in robotics and autonomous navigation. The sensor can operate in harsh environments and extreme weather due to its ability to penetrate snow, rain, fog and dust. However, radar data is notoriously hard to interpret due to sensing artifacts such as speckle noise, multi-path reflections and saturation. In order to overcome sensing artifacts for the task of estimating large-scale radar odometry, authors have proposed various techniques such as dense matching [2], [7], image feature extraction [7], landmark detection [4], learning to predict key points [1] or mask noise [2]. Sparse methods mitigate false detections during data association by finding the largest common subset [4], [7] or via dense search [1]. Existing learning methods requires an extensive amount of data [1], [2] and a ground truth positioning system to supervise the learning, despite this they provide limited generalization. Dense methods are inefficient and do not scale well with spatial resolution. Methods using landmarks or image features based have achieved limited accuracy, despite using robust data association algorithms to mitigate the effect of outliers and sensing artifacts [4], [7]. In this work we propose an efficient and accurate pipeline for radar odometry estimation. Radar data is filtered per azimuth keeping the strongest returns that exceed the expected noise level. The filtered data is used to compute a small number of oriented surface points that efficiently represent the local geometry of the environment. Sets of oriented surface points are registered by iteratively by associating pairs and minimizing a point-to-line metric. Preliminary results indicate that our method is both efficient and accurate compared to previous methods with the additional benefit of being learning-free and comfortably runs on a single CPU core without requiring training data.

II. METHOD

An overview of the method is depicted in Fig. 1.

a) Prepossessing: Our pipeline operates on a rotating 2d radar that provides data $Z_{m \times n}$ on polar form with $m$ azimtths and $n$ range bins per azimuth. For each azimuth (row), the $k = 12$ strongest reflections (columns), exceed- ing a minimum level $z_{min}$ are kept and converted to 2D Cartesian space. A cell grid with resolution $(r/2)$ is used to discretize space. Around each cell center with nearby points, we compute an oriented surface point (sample mean and normal $\{\mu_i, n_i\}$) from all points within a radius $r$. The normal is computed from the smallest eigenvector of the sample covariance of nearby points. All oriented surface points computed from sweep $t$ are added to $\mathcal{M'}$.

We compensate for motion distortion using the previous velocity estimate $v_{t-1}$, assuming acceleration is small.

b) Registration: Each oriented surface point $\{\mu_i, n_i\} \in \mathcal{M'}$ is assigned one correspondence by searching for neighbours within a radius $r$ in the nearest keyframe $\mathcal{M}^k$. The relative alignment $x$ between $\mathcal{M'}$ and recent keyframe $\mathcal{M}^k$ is then found by solving

$$\arg \min_x f(\mathcal{M}^k, \mathcal{M'}, x),$$

where $f$ computes the sum of point-to-line (P2L) distances for each pair of correspondences. The velocity $v_t$ is approximated from the last two pose estimates $v_t = \frac{1}{\Delta t} (x_t - x_{t-1})$. When the distance between current and keyframe position exceeds a threshold, a new key-frame is created at $x_t$.

III. EVALUATION

We evaluated our method using the Oxford Radar Robot-Car Dataset and follow the standard odometry benchmark proposed in [6] to compute odometry performance metrics.
TABLE I: Comparison of odometry methods by their translation error [%] and rotation error [deg/100m]. For our method we include the relative pose error as the last value per column. [1], [2] should be compared based on their Mean Spatial Cross Validation (SCV) error to make the evaluation fair.

| Method          | Evaluation resolution | Sequence 10-12-52 | 16-13-09 | 17-13-26 | 16-14-14 | 18-15-20 | 10-11-46 | 16-11-53 | 18-14-46 | Mean SCV |
|-----------------|-----------------------|-------------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Visual Odometry | [8]                   | N/A               | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      |
| SuMa (Lidar)    | [3]                   | 1.1/0.3           | 1.2/0.4  | 1.1/0.3  | 0.9/0.1  | 1.0/0.2  | 1.1/0.3  | 0.9/0.3  | 1.0/0.1  | 1.16/0.3 |
| Con [4]         | [2]                   | 0.175             | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | 3.72/0.95 |
| Robust Keypoints [1] | [2] | 0.146             | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | 2.05/0.67 |
| Barnes Dual Cart [2] | [2] | 0.143             | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | N/A      | 1.14/0.83 |
| Hong Odometry [7] | (ours) | 0.143             | 2.99/0.8 | 3.12/0.9 | 2.92/0.8 | 3.16/0.9 | 2.85/0.9 | 3.16/0.9 | 3.15/1.1 | 3.11/0.9 |
| Mean | [2] | 1.138/0.686/0.057 | 2.238/0.685/0.067 | 2.049/0.661/0.057 | 1.994/0.610/0.063 | 2.135/0.587/0.067 | 2.150/0.670/0.063 | 2.384/0.690/0.07 | 2.262/0.623/0.063 | 2.056/0.636/0.066 |

Fig. 2: odometry accuracy in the sequences 18-14-14 and 16-13-09. Each point is computed from odometry error averaged over 20 km. P2P and P2L are compared by their translation error and Relative Pose Error (RPE). A courser resolution increase the translation error and RPE, especially when matching P2P.

IV. DISCUSSION AND FUTURE WORK

Filtering originally noisy radar data to a small and clean set of points allows us to compute a sparse set of oriented surface points. Considering the normals in the registration cost function makes the method less sensitive to sparsity, and hence enables efficient and accurate matching. We believe that considering the local geometry is important when matching sparse set of points, especially via one-to-one correspondence (one neighbor per surface point). The difference between P2L and P2P seems to be lower for denser point clouds (lower resolution) as shown by the evaluation. This is intuitive as a denser point cloud inherently provides more information about the underlying geometry without explicitly modeling surfaces.

Surprisingly, a relative high odometry accuracy was achieved using a simple heuristic that filters radar data based on the k strongest returns exceeding the expected noise level \( z_{\text{min}} \). Limiting the maximum returns to e.g. \( k = 12 \) per azimuth can be too conservative for some applications and potentially filter important landmarks. However, the limitation also makes the filter largely insensitive to \( z_{\text{min}} \) and \( k \), and the noise level \( z_{\text{min}} \) can be chosen fairly low without introducing an excessive amount of false detections. For that reason, we hypothesize that the filter can generalize to new environments without needing to change the parameters, and hope that the presented odometry pipeline can serve as a basis to a versatile, flexible and highly robust localization system.

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