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EPFL

COM-304 - Communications Project
Project proposal

SLAM with Radar

Introduction and Problem Statement

The development of the autonomous vehicle is one of the big challenges of the following decades. At the moment, much of the automotive navigation is performed using visible (with cameras) or near-visible light (LiDAR). While there are strong reasons for this, such as the high resolution, both LiDAR and cameras struggle to operate in poor weather conditions, such as rain, fog, or heavy snow. In order to maximize the safety of cars, we want to introduce some redundancy, and therefore a system that combines camera, radar, and LiDAR could be an improvement.

While radar excels in some areas, its low resolution makes it difficult to use as the primary method for gathering data for navigation. Our goal with this project is to use radar to reconstruct some surrounding environment by performing SLAM (Simultaneous Localization And Mapping). While resolution from a single radar scan might be poor, we hope to reconstruct a higher-resolution environment through the use of some kind of structure from motion techniques, reducing noise through probabilistic filtering or deep learning, and performing feature matching and tracking through point cloud optimization.

Project Plan

Our plan involves a step-by-step process to improve radar data fidelity for SLAM. This includes the initial data gathering, noise reduction via filtering, object tracking, and localization. The implementation of these stages will be done sequentially, with interim goals set for the progress report.

The resulting system is one where the radar can create a basic point cloud of obstacles while understanding its position as we move around indoors or outdoors. Here there are a few papers for reference:

1. https://arxiv.org/pdf/2104.05347.pdf
2. https://ras.papercept.net/images/temp/IROS/files/1795.pdf
3. https://www.uni-das.de/images/pdf/veroeffentlichungen/2017/01.pdf

Test the radar and get some data on its performance (2 weeks)

First, we want to get comfortable and understand the limitations and strengths of our hardware platform. We will do as many exercises as needed to completely understand the algorithms behind 3D imaging.
Then, we will start collecting data to see the performance of the hardware in a real scenario: resolution, noise level, systematic errors, etc.

Data cleaning through the use of filtering (1 week)

We expect one of the main challenges to be the noise in the raw data, so we will try to reduce this noise through the use of several techniques, possibly including but not limited to:

- Kalman filter
- Gaussian filter
- Particle filters
- Hidden Markov models

Implement environment tracking (2 weeks)

Using the raw data we need to be able to estimate how the radar is moving to map the environment as accurately as possible. This means we need to be able to take snapshots while the radar is moving and matching one snapshot to the next. The two most popular choices for tracking and understanding moments are:

a) Landmark estimation and tracking, basically to extract objects from the background and use them to track our position through the environment
b) Using global map matching, we perform direct matching with the raw data (the cloud of points)

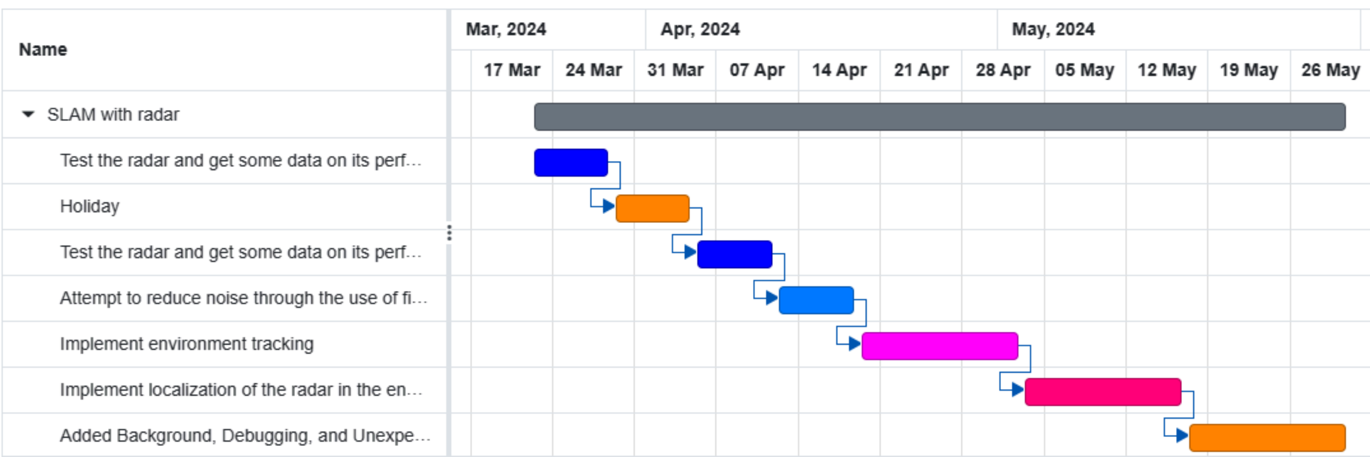
We will also attempt to perform some rejection of outliers between different frames (e.g. using RANSAC) to further filter out noise.

Implement localization of the radar in the environment (2 weeks)

We are going to take inspiration from the established methods in the field of Visual SLAM, which uses camera imagery (RGB-D), and techniques used in LiDAR systems, and find a suitable way of implementing the localization aspect without immediate ground truth odometry data. Camera calibration and bundle adjustment in “Structure From Motion” pipelines can serve as inspiration, keeping in mind we are dealing not just with Radar but with mmWave Radar that has a beam of roughly 80 degrees FoV, so we will need to make big adjustments to these workflows. This should allow us to develop a functioning pose estimation without the need for extra data, e.g. an Inertial Measurement Unit (IMU).

Report, presentation, debugging, and unexpected problems with hardware (2 weeks)

Throughout the project, we need to account for unexpected setbacks as we are attempting to complete this project as a team with very different backgrounds and skills. For some of us, it is the first time we are working with this kind of hardware and developing signal processing algorithms. The added physical element and lack of previous experience will likely add friction and might make it difficult for us to stick to the plan. We also might not be fully cognizant of extra background, research, or implementation needed to complete the final steps. Furthermore, we also need to prepare for the presentation by ironing out bugs and creating an interesting demo.



Timeline of the project

Extra features

The real-time processing of the data will be quite computationally expensive and might not be possible without a very powerful computer.

Should time permit, we could also explore the fusion of radar data with camera/LiDAR for improved accuracy and redundancy. This could be the development of a hybrid system that leverages the strengths of each sensing technology by selecting the optimal sensor for the task at hand or a deep learning system to get some common embedding space. Through this, we can create a more robust model for SLAM that performs well under a greater variety of scenarios, including those where individual sensors may fail or provide unreliable data.

Finally, we could use well-known deep learning algorithms to fill in the gaps in the 3D imaging process, not only achieving a better retrieval of the environment but also classifying objects in the 3D point cloud (e.g. detecting a car vs a pedestrian).