ECE276A PR2 Report

1st Weixiao Zhan

weixiao-zhan[at]ucsd[dot]edu

I. INTRODUCTION

In this project, I implemented Simultaneous Localization and Mapping (SLAM) on a differential-drive robot equipped with a wheel encoder, an Inertial Measurement Unit (IMU), 2-D LiDAR, and an RGBD camera.

Initially, I constructed a motion model trajectory based on the kinematics of the differential-drive and utilizing data from the wheel encoder and IMU. Concurrently, I constructed an observation model trajectory using LiDAR scans through the Iterative Closest Points (ICP) method. Following this, I applied a Factor Graph and loop closure techniques to refine and optimize the trajectory. Finally, I leveraged the optimized trajectory to generate occupancy and texture maps of the environment.

II. PROBLEM FORMULATION

In this project, the pose of the robot can be represented in both 2d and 3d (with $z = 0$). Denote the robot pose at time stamp t as P_t:

$$
P_t = \begin{cases} \underline{\underline{2D}} \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} & \in \mathbb{R}^3 \\ \underline{\underline{3D}} \begin{bmatrix} R_{yaw}(\theta) & \begin{bmatrix} x \\ y \end{bmatrix} \\ 0 & 1 \end{bmatrix} & \in \mathbb{R}^{[4\times 4]} \end{cases}
$$

The 2d and 3d representation are interchangeable. The world frame is defined as robot frame at time 0, i.e.

$$
P_0 = \begin{cases} \vec{0}_3 \\ I_4 \end{cases}
$$

A. Motion Model: IMU & Differential-drive Kinematics

For the small time interval τ between two time stamp, the motion of robot can be approximate as a arc:

$$
P_{t+1}^{(M)} = P_t^{(M)} + \tau \begin{bmatrix} v_t \text{sinc}\left(\frac{w_t\tau}{2}\right)\cos\left(\theta_t + \frac{w_t\tau}{2}\right) \\ v_t \text{sinc}\left(\frac{w_t\tau}{2}\right)\sin\left(\theta_t + \frac{w_t\tau}{2}\right) \\ w_t \end{bmatrix}
$$

$$
= P_t^{(M)} + \begin{bmatrix} \delta d \cdot \text{sinc}\left(\frac{\delta\theta}{2}\right)\sin\left(\theta_t + \frac{\delta\theta}{2}\right) \\ \delta d \cdot \text{sinc}\left(\frac{\delta\theta}{2}\right)\sin\left(\theta_t + \frac{\delta\theta}{2}\right) \\ \delta\theta \end{bmatrix}
$$

in which, the superscript $^{(M)}$ means this is the motion model trajectory, δd is inferred from wheel encoder, and $\delta\theta$ is inferred from IMU's yaw reading.

B. Observation Model: LiDAR & ICP

The ICP algorithm can estimate relative transformation between source point cloud S and target point cloud T. It achieved this by iterates over these steps:

1) Find data association for all source points using closest points:

$$
\Delta = \left\{ \left(s, \arg\min_{t\in T} \|s - t\|\right) |\forall s \in S \right\}
$$

2) Estimate relative transformation $_tT_s$ using Kabsch algorithm:

$$
_tT_s = \arg\min_T \sum_{(s,t)\in\Delta} \|t - Ts\|
$$

3) Update $S \leftarrow {}_tT_sS$ and repeat step 1 until no improvement.

One 2d-LiDAR scan can be represented as a set of range and angle tuple $L = \{(r_i, \phi_i)\}$, and converted to a set of point cloud in body frame:

$$
\text{PC}_{\text{LiDAR frame}} = \left\{ \begin{bmatrix} r_i \sin\phi_i \\ r_i \cos\phi_i \\ 0 \end{bmatrix} |\forall(r_i, \phi_i) \in L \right\}
$$

$$
\begin{bmatrix} \text{PC} \\ 1 \end{bmatrix} =_{\text{body}} T_{\text{LidAR}} \begin{bmatrix} \text{PC}_{\text{LidAR frame}} \\ 1 \end{bmatrix}
$$

Leveraging ICP, I can estimate relative transformation between two LiDAR scan and compose observation model trajectory:

$$
_tT_{t+1}^{(O)} = \text{ICP}(S = \text{PC}_{t+1}, T = \text{PC}_t)
$$

$$
P_t^{(O)} = P_0 \prod_{f=1}^{t} {}_{f-1}T_f^{(O)}
$$

in which, the superscript $^{(O)}$ means this is the observation trajectory.

C. Factor Graph and Loop Closure

D. Mapping

1) Occupancy:
2) Texture:

III. TECHNICAL APPROACH

[25 pts] Technical Approach: Describe your technical approach to SLAM and texture mapping.

A. Time Stamp

IV. Results

[15 pts] Results: Present your results, and discuss them – what worked, what did not, and why. Analyze the impact of loop closure detection and pose graph optimization on the accuracy of the robot trajectory estimate and the resulting map quality. Make sure your results include (a) images of the trajectory and occupancy grid map over time constructed by your SLAM algorithm and (b) textured maps over time. If you have videos, include them in your submission zip file and refer to them in your report.