University of Bonn, IGG Prof. Dr. Cyrill Stachniss Graph-SLAM Tutorial

## Graph-Based SLAM Exercise

## Exercise

Implement a least-squares method to address SLAM in its graph-based formulation. To support this task, we provided a small Matlab/Octave framework. The framework contains the following folders:

data contains several datasets, each gives the measurements of one SLAM problem matlab contains the Matlab/Octave framework with stubs to complete.

**plots** this folder is used to store images.

The below mentioned tasks should be implemented inside the framework in the directory matlab by completing the stubs. After implementing the missing parts, you can run the optimizer by typing lsSLAM. The script will produce a plot showing the positions of the robot and (if available) the positions of the landmarks in each iteration. These plots will be saved in the plots directory.

- 1. Implement the missing code in compute\_global\_error.m for computing the current error value for a graph with constraints.
- 2. Implement the missing code in linearize\_pose\_constraint.m for computing the error and the Jacobian of a pose-pose constraint. Test your implementation with test\_jacobian\_pose\_pose.
- 3. Implement the missing code in linearize\_and\_solve.m for constructing and solving the linear approximation.
- 4. Implement the missing code in linearize\_pose\_landmark\_constraint.m for computing the error and the Jacobian of a pose-landmark constraint. Test your implementation with test\_jacobian\_pose\_landmark.
- 5. Implement the update of the state vector in lsSLAM.m.
- 6. Additional homework: For a deeper understanding, verify the error function and Jacobian for pose-pose as well as pose-landmark constraints as shown in the remainder of this document.

# **Expected Results**

Figure 1 depicts the result that you should obtain after convergence for each dataset. Additionally, the initial and the final error for each dataset should approximately take the values in the table below.

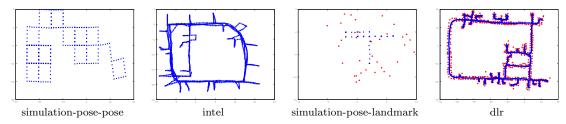


Figure 1: Result for each dataset.

dataset	initial error	final error
simulation-pose-pose.dat	138862234	8269
intel.dat	1795139	360
simulation-pose-landmark.dat	3030	474
dlr.dat	369655336	56860

## Hints

- The key elements in the graph datastructure g are the node poses/locations stored in g.x as well as the edge information g.edges consisting of the measurement (measurement) between the two nodes and the corresponding information matrix (information).
- The state vector (g.x) consists of a concatenation of robot poses (and possibly landmark positions), i.e.,  $\mathbf{x}_{1:N}$  with
  - pose of the robot:  $\mathbf{x}_i = (x_i \ y_i \ \theta_i)^T$ Hint: Use the function  $\mathrm{v2t}(\cdot)$  and  $\mathrm{t2v}(\cdot)$  that transform a vector into a transformation matrix  $(\mathrm{v2t}(\cdot))$  and vice versa  $(\mathrm{t2v}(\cdot))$ . The function invt $(\cdot)$  inverts a transformation.

$$v2t(\mathbf{x}_i) = \begin{pmatrix} R_i & \mathbf{t}_i \\ \mathbf{0} & 1 \end{pmatrix} = \begin{pmatrix} \cos(\theta_i) & -\sin(\theta_i) & x_i \\ \sin(\theta_i) & \cos(\theta_i) & y_i \\ 0 & 0 & 1 \end{pmatrix} = X_i \qquad t2v(X_i) = \mathbf{x}_i$$

- position of a landmark:  $\mathbf{x}_l = (x_l \ y_l)^T$
- We consider the following error functions:
  - pose-pose constraint:  $\mathbf{e}_{ij} = \text{t2v}(Z_{ij}^{-1}(X_i^{-1}X_j))$ , where  $Z_{ij} = \text{v2t}(\mathbf{z}_{ij})$  is the transformation matrix of the measurement  $\mathbf{z}_{ij}^T = (\mathbf{t}_{ij}^T, \theta_{ij})$ .
  - pose-landmark constraint:  $\mathbf{e}_{il}(\mathbf{x}) = X_i^{-1}\mathbf{x}_l \mathbf{z}_{il}$

# Further Information on the Error Functions and Jacobians for 2D Graph-Based SLAM

In the following we will provide the definitions and the derivations for the Jacobians to implement 2D graph-based SLAM.

#### Error Functions and Jacobians for a Pose-Pose Constraint

The basic entities of the poses of the robot and the constraint are defined as

$$\mathbf{x}_i^{\top} = (\mathbf{t}_i^{\top}, \theta_i) = (x_i, y_i, \theta_i) \tag{1}$$

$$\mathbf{x}_{i}^{\top} = (\mathbf{t}_{i}^{\top}, \theta_{j}) = (x_{j}, y_{j}, \theta_{j}) \tag{2}$$

$$\mathbf{x}_{i}^{\top} = (\mathbf{t}_{i}^{\top}, \theta_{i}) = (x_{i}, y_{i}, \theta_{i})$$

$$\mathbf{x}_{j}^{\top} = (\mathbf{t}_{j}^{\top}, \theta_{j}) = (x_{j}, y_{j}, \theta_{j})$$

$$\mathbf{z}_{ij}^{\top} = (\mathbf{t}_{ij}^{\top}, \theta_{ij}) = (x_{ij}, y_{ij}, \theta_{ij})$$

$$(1)$$

$$(2)$$

$$(3)$$

where  $\mathbf{t}_i$  and  $\mathbf{t}_{ij}$  are 2D vectors and  $\theta_i$  and  $\theta_{ij}$  are rotation angles which are normalized to  $[-\pi,\pi)$ .

#### **Error Function**

The error function is

$$\mathbf{e}_{ij}(\mathbf{x}) = \mathbf{t}2\mathbf{v}(Z_{ij}^{-1}(X_i^{-1}X_j)) \tag{4}$$

#### Jacobian

To derive the Jacobian, it is advantageous to start from:

$$\mathbf{e}_{ij}(\mathbf{x}) = \mathbf{e}_{ij}(\mathbf{x}_i, \mathbf{x}_j) = \begin{pmatrix} R_{ij}^{\top} (R_i^{\top} (\mathbf{t}_j - \mathbf{t}_i) - \mathbf{t}_{ij}) \\ \theta_j - \theta_i - \theta_{ij} \end{pmatrix},$$
(5)

where  $R_i$  and  $R_{ij}$  are the 2 × 2 rotation matrices of  $\theta_i$  and  $\theta_{ij}$  with the following structure

$$R_{i} = \begin{pmatrix} \cos(\theta_{i}) & -\sin(\theta_{i}) \\ \sin(\theta_{i}) & \cos(\theta_{i}) \end{pmatrix} \qquad R_{ij} = \begin{pmatrix} \cos(\theta_{ij}) & -\sin(\theta_{ij}) \\ \sin(\theta_{ij}) & \cos(\theta_{ij}) \end{pmatrix}. \tag{6}$$

The Jacobians of the error function become

$$\mathbf{A}_{ij} = \frac{\partial \mathbf{e}_{ij}(\mathbf{x})}{\partial \mathbf{x}_i} = \begin{pmatrix} -R_{ij}^{\top} R_i^{\top} & R_{ij}^{\top} \frac{\partial R_i^{\top}}{\partial \theta_i} (\mathbf{t}_j - \mathbf{t}_i) \\ \mathbf{0} & -1 \end{pmatrix}$$
(7)

$$\mathbf{B}_{ij} = \frac{\partial \mathbf{e}_{ij}(\mathbf{x})}{\partial \mathbf{x}_i} = \begin{pmatrix} R_{ij}^{\top} R_i^{\top} & \mathbf{0} \\ \mathbf{0} & 1 \end{pmatrix}. \tag{8}$$

And for  $\frac{\partial R_i^{\top}}{\partial \theta_i}$  we obtain

$$\frac{\partial R_i^{\top}}{\partial \theta_i} = \begin{pmatrix} -\sin(\theta_i) & \cos(\theta_i) \\ -\cos(\theta_i) & -\sin(\theta_i) \end{pmatrix}. \tag{9}$$

## Error Functions and Jacobians for a Pose-Landmark Constraint

The basic entities of the poses of the robot and the constraint are defined as

$$\mathbf{x}_{i}^{\top} = (\mathbf{t}_{i}^{\top}, \theta_{i})$$

$$\mathbf{x}_{l}^{\top} = (x_{l}, y_{l})^{\top}$$

$$(10)$$

$$\mathbf{x}_l^{\top} = (x_l, y_l)^{\top} \tag{11}$$

$$\mathbf{z}_{il} = (x_{il}, y_{il})^{\top}, \tag{12}$$

where  $\mathbf{t}_i$  is a 2D vector,  $\theta_i$  is a rotation angle which is normalized to  $[-\pi, \pi)$ , and  $(x_{il}, y_{il})^{\top}$  is the measurement of  $\mathbf{x}_l$  in the local frame of  $\mathbf{x}_i$ .

#### **Error Function**

The error function is

$$\mathbf{e}_{il}(\mathbf{x}) = X_i^{-1} \mathbf{x}_l - \mathbf{z}_{il} \tag{13}$$

#### Jacobian

To derive the Jacobian, it is advantageous to start from:

$$\mathbf{e}_{il}(\mathbf{x}) = R_i^{\mathsf{T}}(\mathbf{x}_l - \mathbf{t}_i) - \mathbf{z}_{il},\tag{14}$$

where  $R_i$  is the 2 × 2 rotation matrices of  $\theta_i$  with the following structure

$$R_i = \begin{pmatrix} \cos(\theta_i) & -\sin(\theta_i) \\ \sin(\theta_i) & \cos(\theta_i) \end{pmatrix}. \tag{15}$$

The Jacobians of the error function becomes

$$\mathbf{A}_{il} = \frac{\partial \mathbf{e}_{il}(\mathbf{x})}{\partial \mathbf{x}_i} = \begin{pmatrix} -R_i^{\top} & \frac{\partial R_i^{\top}}{\partial \theta_i} (\mathbf{x}_l - \mathbf{t}_i) \end{pmatrix}$$
(16)

$$\mathbf{B}_{il} = \frac{\partial \mathbf{e}_{il}(\mathbf{x})}{\partial \mathbf{x}_i} = R_i^{\mathsf{T}} \tag{17}$$

And for  $\frac{\partial R_i^\top}{\partial \theta_i}$  we obtain

$$\frac{\partial R_i^{\top}}{\partial \theta_i} = \begin{pmatrix} -\sin(\theta_i) & \cos(\theta_i) \\ -\cos(\theta_i) & -\sin(\theta_i) \end{pmatrix}. \tag{18}$$