

Exercise Sheet 4

Topic: EKF-SLAM

Exercise 4.1: EKF-SLAM

In this exercise, you will implement an EKF-SLAM algorithm. We assume the robot moves in the 2D plane, for example, a wheeled robot with differential drive that moves on the floor inside a building. This means the robot state $\xi_t = (x_t, y_t, \theta_t)^T$ is 3-dimensional and composed of the 2-dimensional position x_t, y_t in the plane and the robot heading θ_t . We model the robot motion with an odometry-based motion model in this exercise, i.e. the state-transition model is

$$\xi_t = g(\xi_{t-1}, \mathbf{u}_t) + \epsilon_t := \xi_{t-1} + \begin{pmatrix} u_{tr} \cos(\theta_{t-1} + u_{r1}) \\ u_{tr} \sin(\theta_{t-1} + u_{r1}) \\ u_{r1} + u_{r2} \end{pmatrix} + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(\mathbf{0}, \Sigma_{dt})$$

The action $\mathbf{u}_t = (u_{tr}, u_{r1}, u_{r2})^T$ is given by translational (u_{tr}) and rotational (u_{r1}, u_{r2}) motion measurements obtained from wheel odometry. For the noise covariance of the state-transitions, we assume

$$\Sigma_{dt} = \begin{pmatrix} 0.1 & 0 & 0 \\ 0 & 0.1 & 0 \\ 0 & 0 & 0.01 \end{pmatrix}$$

The robot measures the range r and bearing ϕ to 2D landmark points $\mathbf{l}_j = (l_{j,x}, l_{j,y})^T$ in the environment in the horizontal plane. The full state vector \mathbf{x} of the EKF is the vector stacked from robot state ξ_t and all landmark points \mathbf{l}_j . The robot measures multiple landmarks in a time step for which we assume the association $c_{t,i} = j$ of measurements $\mathbf{z}_{t,i} = (r_{t,i}, \phi_{t,i})^T$ to landmarks j known. The observation model is

$$\mathbf{z}_{t,i} = h(\mathbf{x}_t, c_{t,i}) + \delta_{t,i} := \begin{pmatrix} \|(x_t, y_t)^T - (l_{j,x}, l_{j,y})^T\|_2 \\ \text{atan2}(l_{j,y} - y_t, l_{j,x} - x_t) - \theta_t \end{pmatrix} + \delta_{t,i}, \quad \delta_{t,i} \sim \mathcal{N}(\mathbf{0}, \Sigma_{mt,i})$$

For the observation noise of an individual landmark measurement, we assume

$$\Sigma_{mt,i} = \begin{pmatrix} 0.1 & 0 \\ 0 & 0.1 \end{pmatrix}$$

The complete observation model in each time step, $\mathbf{z}_t = h(\mathbf{x}_t) + \delta_t$ with $\delta_t \sim \mathcal{N}(\mathbf{0}, \Sigma_{mt})$ stacks the M measurements in a single vector $\mathbf{z}_t = (\mathbf{z}_{t,0}^T, \dots, \mathbf{z}_{t,M-1}^T)^T$. Analogously, we write $h(\mathbf{x}_t) := (h(\mathbf{x}_t, x_{t,0})^T, \dots, h(\mathbf{x}_t, x_{t,M-1})^T)^T$. The covariance Σ_{mt} is formed from the individual measurement covariances,

$$\Sigma_{mt} = \begin{pmatrix} \Sigma_{mt,0} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \Sigma_{mt,1} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \Sigma_{mt,M-1} \end{pmatrix}$$

- a) Determine the analytic Jacobians of the state-transition function $g(\mathbf{x}_{t-1}, \mathbf{u}_t)$ and the observation function $h(\mathbf{x}_t)$ for the robot pose ξ and landmark positions \mathbf{l}_j .
- b) Obtain the code sample and data for this part of the exercise from the course webpage. The archive contains three folders: data, matlab, plots. Implement EKF prediction and correction to localize the robot and map the landmarks by finalizing the code in the files **prediction_step.m** and **correction_step.m**.
- c) Run your code and visualize the robot pose and landmark position estimates using the provided plotting functions.