

5 EKF SLAM

* Definition of SLAM Problem

Given

① The robot's controls

$$U_{1:T} = \{u_1, u_2, u_3 \dots u_T\}$$

② Observations

$$Z_{1:T} = \{z_1, z_2 \dots z_T\}$$

Wanted

① Map of the Environment
 m

② Path of the robot

$$x_{0:T} = \{x_0, x_1, \dots, x_T\}$$

Only this for
Online SLAM

* EKF Slam

Assumption: Known correspondences

⇒ State space (for 2D plane) is

$$x_t = (x, y, \theta, m_{1,x}, m_{1,y}, \dots, m_{n,x}, m_{n,y})^T$$

↑
Pose of
robot

↑
Positions of
all the
landmark

⇒ Map with n landmark: $(3+2n)$ -dimensional.

$$\mu = \begin{pmatrix} x \\ m \end{pmatrix} \quad \Sigma = \begin{pmatrix} \Sigma_{xx} & \Sigma_{xm} \\ \Sigma_{mx} & \Sigma_{mm} \end{pmatrix}$$

(state)

landmarks

* EKF SLAM : A

1. State prediction
2. Measurement
3. Measurement
4. Data association
5. Update

* Assumption

- ① Robot motion
- ② Velocity - 1
- ③ Robot observation
- ④ Range - b
- ⑤ Known
- ⑥ Known

* Initialization

⇒ Robot state
all landmarks

$$\mu_0 = \begin{pmatrix} x_0 \\ m_0 \end{pmatrix}$$

$$\Sigma_0 = \begin{pmatrix} \Sigma_{xx} & \Sigma_{xm} \\ \Sigma_{mx} & \Sigma_{mm} \end{pmatrix}$$

* EKF SLAM : Filter Cycle

- | | |
|---------------------------|-------------------|
| 1. State prediction | {Prediction step} |
| 2. Measurement prediction | |
| 3. Measurement | {Correction step} |
| 4. Data association | |
| 5. Update | |

* Assumptions

- ① Robot moves in 2D plane
- ② Velocity-based motion model
- ③ Robot observes point landmarks (x, y)
- ④ Range-bearing sensor
- ⑤ Known data association
- ⑥ Known number of landmarks

* Initialization

⇒ Robot starts in its own reference frame
(all landmarks unknown)

Step 1

$$\mu_0 = (0, 0, 0, \dots, 0)^T$$

$$\Sigma_0 = \begin{pmatrix} 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & \infty \end{pmatrix}$$

* Motion model (update step)

⇒ From the motion in the plane

$$\begin{pmatrix} x' \\ y' \\ \theta' \end{pmatrix} = \begin{pmatrix} x \\ y \\ \theta \end{pmatrix} + \begin{pmatrix} -\frac{v_t}{\omega_t} \sin \theta + \frac{v_t}{\omega_t} \sin(\theta + \omega_t \Delta t) \\ \frac{v_t}{\omega_t} \cos \theta + -\frac{v_t}{\omega_t} \cos(\theta + \omega_t \Delta t) \\ \omega_t \Delta t \end{pmatrix}$$

⇒ to the $2N+3$ dimensional Space:

$$\begin{pmatrix} x' \\ y' \\ \theta' \\ \vdots \end{pmatrix} = \begin{pmatrix} x \\ y \\ \theta \\ \vdots \end{pmatrix} + \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \end{pmatrix}^T \begin{pmatrix} -\frac{v_t}{\omega_t} \sin \theta + \frac{v_t}{\omega_t} \sin(\theta + \omega_t \Delta t) \\ \frac{v_t}{\omega_t} \cos \theta - \frac{v_t}{\omega_t} \cos(\theta + \omega_t \Delta t) \\ \omega_t \Delta t \\ \vdots \end{pmatrix}$$

Identity (3×3) $2N$ Cols

(Step 2)

$g(u_t, x_t)$

(Step 3): $\Sigma_t = G_t \Sigma_{t-1} G_t^T + R_t$

$$G_t = \begin{pmatrix} G_t^x & 0 \\ 0 & I \end{pmatrix}$$

Jacobian of the motion (3×3)

Identity $(2N \times 2N)$

$$G_t^x = \begin{pmatrix} 1 & 0 & -\frac{v_t}{\omega_t} \cos \theta + \frac{v_t}{\omega_t} \cos(\theta + \omega_t \Delta t) \\ 0 & 1 & -\frac{v_t}{\omega_t} \sin \theta + \frac{v_t}{\omega_t} \sin(\theta + \omega_t \Delta t) \\ 0 & 0 & 1 \end{pmatrix}$$

{ for Velocity motion model }

only change uncertainty in pose not in landmark

$(F_x^T R_t^x F_x) \leftarrow$ { Uncertainty of the motion model assumed to be given }

⇒ After putting everything in step 3 we get:

$$\Sigma_t = \begin{pmatrix} G_t^x \Sigma_{xx} (G_t^x)^T & G_t^x \Sigma_{xm} \\ (G_t^x \Sigma_{xm})^T & \Sigma_{mm} \end{pmatrix} + R_t$$

* EKF SLAM: Correction Step

→ Known data association.

→ $C_t^i = j$: i th measurement at time t observes the landmark with index j .

→ Initialize landmark if unobserved

→ Compute the expected observation

→ Compute the jacobian of h

→ Proceed with computing the Kalman gain.

⇒ for range-bearing observation model

$$\begin{pmatrix} \bar{\mu}_{j,x} \\ \bar{\mu}_{j,y} \end{pmatrix} = \begin{pmatrix} \bar{\mu}_{t,x} \\ \bar{\mu}_{t,y} \end{pmatrix} + \begin{pmatrix} r_t^i \cos(\phi_t^i + \bar{\mu}_{t,\theta}) \\ r_t^i \sin(\phi_t^i + \bar{\mu}_{t,\theta}) \end{pmatrix}$$

$\left\{ \begin{array}{l} \text{Observed} \\ \text{location of} \\ \text{landmark } i \end{array} \right\}$
 $\left\{ \begin{array}{l} \text{Estimated} \\ \text{Robot's} \\ \text{Location} \end{array} \right\}$
 $\left\{ \begin{array}{l} \text{Relative} \\ \text{Measurement} \end{array} \right\}$

$$Z_t^i = (r_t^i, \phi_t^i)^T$$

Predicted observation

⇒ Expected Observation

$$\delta = \begin{pmatrix} \delta_x \\ \delta_y \end{pmatrix} = \begin{pmatrix} \bar{\mu}_{j,x} - \bar{\mu}_{t,x} \\ \bar{\mu}_{j,y} - \bar{\mu}_{t,y} \end{pmatrix}$$

$$\text{Let } q = \delta^T \delta$$

$$\hat{Z}_t^i = \begin{pmatrix} \sqrt{q} \\ \text{atan2}(\delta_y, \delta_x) - \bar{\mu}_{t,\theta} \\ h(\bar{\mu}_t) \end{pmatrix}$$

* Jacobian for the Observation

$$\text{low } H_t^i = \frac{\partial h(\mu_t)}{\partial \mu_t}$$

low-dim space $(\alpha, \gamma, 0, m_{j,\alpha}, m_{j,\gamma})$

$$\text{low } H_t^i = \frac{1}{q} \begin{pmatrix} -\sqrt{q} \delta_{\alpha} & -\sqrt{q} \delta_{\gamma} & 0 & \sqrt{q} \delta_{\alpha} & \sqrt{q} \delta_{\gamma} \\ \delta_{\gamma} & -\delta_{\alpha} & -q & -\delta_{\gamma} & \delta_{\alpha} \end{pmatrix}_{2 \times 5}$$

⇒ Map it to the high dimensional space

$$H_t^i = \text{low } H_t^i F_{\alpha, j}$$

$$\begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \end{pmatrix}$$

$\underbrace{\hspace{10em}}_{2j-2} \quad \quad \quad \underbrace{\hspace{10em}}_{2N-2j}$

⇒ So we can now perform all the remaining steps: Step 4, Step 5, Step 6, Step 7

1 EKF-SLAM Algorithm ($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t, C_t, R_t$)

2
$$F_x = \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 1 & 0 & \dots & 0 \end{pmatrix}$$

2N columns

3
$$\bar{\mu}_t = \mu_{t-1} + F_x^T \begin{pmatrix} -\frac{v_t}{\omega_t} \sin(\mu_{t-1,0}) + \frac{v_t}{\omega_t} \sin(\mu_{t-1,0} + \omega_t \Delta t) \\ \frac{v_t}{\omega_t} \cos(\mu_{t-1,0}) - \frac{v_t}{\omega_t} \cos(\mu_{t-1,0} + \omega_t \Delta t) \\ \omega_t \Delta t \end{pmatrix}$$

4
$$G_t = I + F_x^T \begin{pmatrix} 0 & 0 & -\frac{v_t}{\omega_t} \cos(\mu_{t-1,0}) + \frac{v_t}{\omega_t} \cos(\mu_{t-1,0} + \omega_t \Delta t) \\ 0 & 0 & -\frac{v_t}{\omega_t} \sin(\mu_{t-1,0}) + \frac{v_t}{\omega_t} \sin(\mu_{t-1,0} + \omega_t \Delta t) \\ 0 & 0 & 0 \end{pmatrix} F_x$$

5
$$\Sigma_t = G_t \Sigma_{t-1} G_t^T + \underbrace{F_x^T R_x F_x}_{R_t}$$

6
$$Q_t = \begin{pmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_\phi^2 \end{pmatrix}$$

7 for all observed features $z_t^i = (x_t^i, \phi_t^i)^T$ do

10
$$\begin{pmatrix} \bar{\mu}_{j,x} \\ \bar{\mu}_{j,y} \end{pmatrix} = \begin{pmatrix} \bar{\mu}_{t,x} \\ \bar{\mu}_{t,y} \end{pmatrix} + \begin{pmatrix} x_t^i \cos(\phi_t^i + \bar{\mu}_{t,0}) \\ x_t^i \sin(\phi_t^i + \bar{\mu}_{t,0}) \end{pmatrix}$$

8 $j = C_t$
 9 if landmark j never seen before

11 ~~else~~ endif

12
$$\delta = \begin{pmatrix} \delta_x \\ \delta_y \end{pmatrix} = \begin{pmatrix} \bar{\mu}_{j,x} - \bar{\mu}_{t,x} \\ \bar{\mu}_{j,y} - \bar{\mu}_{t,y} \end{pmatrix}$$

13
$$a = \delta^T \delta$$

14
$$\hat{z}_t^i = \begin{pmatrix} \sqrt{a} \\ a \tan 2(\delta_y, \delta_x) - \bar{\mu}_{t,0} \end{pmatrix}$$

$$15 \quad F_{z,j} = \begin{pmatrix} 1 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 1 & 0 & 0 & \dots & 0 \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 1 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 0 & 0 & 0 & 0 & \dots & 0 \end{pmatrix}$$

$\underbrace{\quad\quad\quad}_{2j-2} \qquad \qquad \underbrace{\quad\quad\quad}_{2N-2j}$

$$16 \quad H_t^i = \frac{1}{q} \begin{pmatrix} -\sqrt{q} \delta_{x1} & -\sqrt{q} \delta_{y1} & 0 & \sqrt{q} \delta_{x1} & \sqrt{q} \delta_{y1} \\ \delta_{y1} & -\delta_{x1} & -q & -\delta_{y1} & \delta_{x1} \end{pmatrix} F_{x,i}$$

$$17 \quad K_t^i = \bar{\Sigma}_t H_t^{iT} (H_t^i \bar{\Sigma}_t H_t^{iT} + Q_t)^{-1}$$

$$18 \quad \bar{\mu}_t = \bar{\mu}_t + K_t^i (z_t^i - \hat{z}_t^i)$$

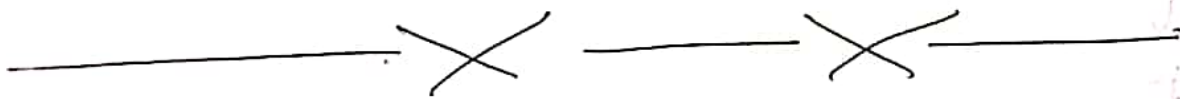
$$19 \quad \bar{\Sigma}_t = (I - K_t^i H_t^i) \bar{\Sigma}_t$$

20 end for

$$21 \quad \mu_t = \bar{\mu}_t$$

$$22 \quad \Sigma_t = \bar{\Sigma}_t$$

23 return μ_t, Σ_t



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