Extended Kalman Filter (EKF) — Full Mathematical Description

1. True State (Ground Truth)

$$\mathbf{x}_t = egin{bmatrix} x \ y \ heta \end{bmatrix} \in \mathbb{R}^3$$

This represents the actual (unobservable) system state.

2. State Estimate (Mean and Covariance)

We assume a Gaussian belief over the state:

$$\mathbf{x}_t \sim \mathcal{N}(oldsymbol{\mu}_t, \Sigma_t)$$

Where:

- \$\boldsymbol{\mu}_t \in \mathbb{R}^3\$: estimated state mean
- \$\Sigma_t \in \mathbb{R}^{3} \times 3}\$: covariance of the estimate

3. Control Input

$$\mathbf{u}_t = egin{bmatrix} v \ \omega \end{bmatrix} \in \mathbb{R}^2$$

4. Motion Model (Nonlinear)

The robot follows a nonlinear motion model:

$$ar{m{\mu}}_t = g(m{\mu}_{t-1}, \mathbf{u}_t) = egin{bmatrix} x + v \cdot \Delta t \cdot \cos(heta) \ y + v \cdot \Delta t \cdot \sin(heta) \ heta + \omega \cdot \Delta t \end{bmatrix}$$

In reality, the motion is subject to Gaussian noise:

$$\mathbf{x}_t = g(\mathbf{x}_{t-1}, \mathbf{u}_t) + \mathbf{w}_t, \quad \mathbf{w}_t \sim \mathcal{N}(\mathbf{0}, R_t)$$

With Jacobian (w.r.t. state):

$$G_t = rac{\partial g}{\partial oldsymbol{\mu}}igg|_{oldsymbol{\mu}_{t-1}, \mathbf{u}_t} = egin{bmatrix} 1 & 0 & -v \cdot \Delta t \cdot \sin(heta) \ 0 & 1 & v \cdot \Delta t \cdot \cos(heta) \ 0 & 0 & 1 \end{bmatrix}$$

5. Observation Model

Assuming we can observe position and orientation \$(x, y, \theta)\$:

$$\hat{\mathbf{z}}_t = h(ar{oldsymbol{\mu}}_t) = egin{bmatrix} x \ y \ heta \end{bmatrix}$$

And the actual observation is:

$$\mathbf{z}_t = h(\mathbf{x}_t) + \mathbf{v}_t, \quad \mathbf{v}_t \sim \mathcal{N}(\mathbf{0}, Q_t)$$

With observation Jacobian:

$$H_t = rac{\partial h}{\partial \mathbf{x}}igg|_{ar{oldsymbol{\mu}}_t} = egin{bmatrix} 1 & 0 & 0 \ 0 & 1 & 0 \ 0 & 0 & 1 \end{bmatrix}$$

6. Covariances

- \$R_t\$: process noise covariance matrix (uncertainty in motion model)
- \$Q_t\$: measurement noise covariance matrix (sensor uncertainty)

7. EKF Algorithm (with Formula Blocks)

Prediction step:

$$egin{aligned} ar{oldsymbol{\mu}}_t &= g(oldsymbol{\mu}_{t-1}, \mathbf{u}_t) \ ar{\Sigma}_t &= G_t \, \Sigma_{t-1} \, G_t^ op + R_t \end{aligned}$$

Correction step:

$$egin{aligned} K_t &= ar{\Sigma}_t \, H_t^ op \Big(H_t \, ar{\Sigma}_t \, H_t^ op + Q_t \Big)^{-1} \ oldsymbol{\mu}_t &= ar{oldsymbol{\mu}}_t + K_t \, (\mathbf{z}_t - h(ar{oldsymbol{\mu}}_t)) \ \Sigma_t &= (I - K_t H_t) \, ar{\Sigma}_t \end{aligned}$$