

# **The extended Kalman filter and the Iterative extended Kalman filter**

Sensor fusion & nonlinear filtering

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# THE EXTENDED KALMAN FILTER (EKF)

- The extended Kalman filter was developed almost immediately after the Kalman filter, in the early 1960s.

## The extended Kalman filter (EKF)

- **Idea:** Linearize  $\mathbf{f}_{k-1}(\mathbf{x}_{k-1})$  and  $\mathbf{h}_k(\mathbf{x}_k)$  and apply the Kalman filter on the linearized system!
- **Prediction:** linearize  $\mathbf{f}_{k-1}(\mathbf{x}_{k-1})$  around  $\hat{\mathbf{x}}_{k-1|k-1}$  and use the Kalman filter prediction.
- **Update:** linearize  $\mathbf{h}_k(\mathbf{x}_k)$  around  $\hat{\mathbf{x}}_{k|k-1}$  and use the Kalman filter update.

# TAYLOR SERIES EXPANSIONS

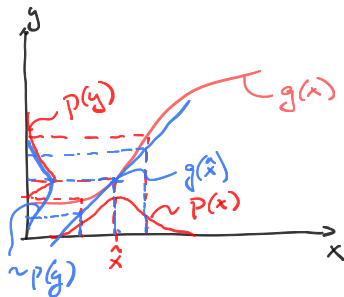
- Consider a Gaussian random variable  $\mathbf{x} \sim \mathcal{N}(\hat{\mathbf{x}}, \mathbf{P})$  and a nonlinear function  $\mathbf{y} = \mathbf{g}(\mathbf{x})$ .

## Taylor series expansions

- A first order Taylor expansion of  $\mathbf{g}(\mathbf{x})$  around  $\hat{\mathbf{x}}$  gives

$$\mathbf{y} \approx \mathbf{g}(\hat{\mathbf{x}}) + \underbrace{\mathbf{g}'(\hat{\mathbf{x}})}_{m \times n} (\mathbf{x} - \hat{\mathbf{x}})$$

where  $[\mathbf{g}'(\mathbf{x})]_{ij} = \frac{\partial g_i(\mathbf{x})}{\partial x_j}$  is the Jacobian matrix of  $\mathbf{g}$ .



- Note that we now get  $E\{\mathbf{y}\} = E\{\underbrace{\mathbf{g}(\hat{\mathbf{x}}) + \mathbf{g}'(\hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}})}_{=0}\} = \mathbf{g}(\hat{\mathbf{x}})$

$$\mathbb{E}\{\mathbf{y}\} \approx \mathbf{g}(\hat{\mathbf{x}})$$

$$\text{Cov}\{\mathbf{y}\} \approx \mathbf{g}'(\hat{\mathbf{x}}) \mathbf{P} \mathbf{g}'(\hat{\mathbf{x}})^T.$$

$$\text{Cov}\{\mathbf{y}\} = \text{Cov}\{\underbrace{\mathbf{g}(\hat{\mathbf{x}})}_{=0} + \underbrace{\mathbf{g}'(\hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}})}_{=0}\} = \mathbf{g}'(\hat{\mathbf{x}}) \underbrace{\text{Cov}\{\mathbf{x} - \hat{\mathbf{x}}\}}_{\mathbf{P}} \mathbf{g}'(\hat{\mathbf{x}})^T$$

## SELF ASSESSMENT

- What is  $g(\hat{\mathbf{x}})$  and  $g'(\hat{\mathbf{x}})$  when

$$\mathbf{x} = \begin{bmatrix} p_1 \\ p_2 \\ v_1 \\ v_2 \end{bmatrix}, \hat{\mathbf{x}} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} \text{ and } y = \sqrt{p_1^2 + p_2^2}?$$

- $g(\hat{\mathbf{x}}) = \sqrt{5}$  and  $g'(\hat{\mathbf{x}}) = \begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} & 0 & 0 \end{bmatrix}^T$
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# EKF: THE PREDICTION STEP

- We have

$$\mathbf{x}_{k-1} | \mathbf{y}_{1:k-1} \sim \mathcal{N}(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{P}_{k-1|k-1}).$$

- By using the approximation

$$\begin{aligned}\mathbf{x}_k &= \mathbf{f}(\mathbf{x}_{k-1}) + \mathbf{q}_{k-1} \\ &\approx \mathbf{f}(\hat{\mathbf{x}}_{k-1|k-1}) + \mathbf{f}'(\hat{\mathbf{x}}_{k-1|k-1}) (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1|k-1}) + \mathbf{q}_{k-1}\end{aligned}$$

we get:

## EKF: the prediction step

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{f}(\hat{\mathbf{x}}_{k-1|k-1})$$

$$\mathbf{P}_{k|k-1} = \underbrace{\mathbf{f}'(\hat{\mathbf{x}}_{k-1|k-1})}_{\tilde{\mathbf{F}}} \mathbf{P}_{k-1|k-1} \underbrace{\mathbf{f}'(\hat{\mathbf{x}}_{k-1|k-1})^T}_{\tilde{\mathbf{F}}^T} + \mathbf{Q}_{k-1}$$

## EKF: THE UPDATE STEP

- Similarly, if we approximate

$$\begin{aligned}\mathbf{y}_k &= \mathbf{h}(\mathbf{x}_k) + \mathbf{r}_k \\ &\approx \mathbf{h}(\hat{\mathbf{x}}_{k|k-1}) + \mathbf{h}'(\hat{\mathbf{x}}_{k|k-1}) (\mathbf{x}_k - \hat{\mathbf{x}}_{k|k-1}) + \mathbf{r}_{k-1},\end{aligned}$$

we get:

### EKF: the update step

$$\begin{aligned}\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k (\mathbf{y}_k - \mathbf{h}(\hat{\mathbf{x}}_{k|k-1})) \\ \mathbf{P}_{k|k} &= \mathbf{P}_{k|k-1} - \mathbf{K}_k \mathbf{S}_k \mathbf{K}_k^T \\ \mathbf{S}_k &= \mathbf{h}'(\hat{\mathbf{x}}_{k|k-1}) \mathbf{P}_{k|k-1} \mathbf{h}'(\hat{\mathbf{x}}_{k|k-1})^T + \mathbf{R}_k \\ \mathbf{K}_k &= \mathbf{P}_{k|k-1} \mathbf{h}'(\hat{\mathbf{x}}_{k|k-1})^T \mathbf{S}_k^{-1}\end{aligned}$$