

AA 549: Estimation and Kalman Filtering
Kalman Filters

• **Discrete-Time Kalman Filter**

| | |
|---------------------|--|
| Model: | $x_{k+1} = \Phi_k x_k + \Gamma_k u_k + \Upsilon_k w_k, \quad w_k \sim \mathcal{N}(0, R_k)$ |
| | $\tilde{y}_k = H_k x_k + v_k, \quad v_k \sim \mathcal{N}(0, R_k)$ |
| Initialize: | $\hat{x}(t_0) = \hat{x}_0, \quad P_0 = E[(\hat{x}_0 - x_0)(\hat{x}_0 - x_0)^T]$ |
| Gain: | $K_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1}$ |
| Update: | $\hat{x}_k^+ = \hat{x}_k^- + K_k [\tilde{y}_k - H_k \hat{x}_k^-]$ |
| | $P_k^+ = [I - K_k H_k] P_k^-$ |
| Propagation: | $\hat{x}_{k+1}^- = \Phi_k \hat{x}_k^+ + \Gamma_k u_k$ |
| | $P_{k+1}^- = \Phi_k P_k^+ \Phi_k^T + \Upsilon_k Q_k \Upsilon_k^T$ |

Alternative Forms:

$$P_k^+ = [I - K_k H_k] P_k^- [I - K_k H_k]^T + K_k R_k K_k^T$$

$$P_k^+ = P_k^- - P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1} H_k P_k^-$$

$$P_k^+ = [(P_k^-)^{-1} + H_k^T R_k^{-1} H_k]^{-1}$$

$$K_k = P_k^+ H_k^T R_k^{-1}, \quad [I - K_k H_k] = P_k^+ (P_k^-)^{-1}, \quad \hat{x}_k^+ = P_k^+ [(P_k^-)^{-1} \hat{x}_k^- + H_k^T R_k^{-1} \tilde{y}_k]$$

Combined Form

$$\hat{x}_{k+1} = \Phi_k \hat{x}_k + \Gamma_k u_k + \Phi_k K_k [\tilde{y}_k - H_k \hat{x}_k]$$

$$K_k = P_k H_k^T [H_k P_k H_k^T + R_k]^{-1}$$

Discrete Riccati Eqn.

$$P_{k+1} = \Phi_k P_k \Phi_k^T - \Phi_k P_k H_k^T [H_k P_k H_k^T + R_k]^{-1} H_k P_k \Phi_k^T + \Upsilon_k Q_k \Upsilon_k^T$$

Other forms

$$P_{k+1} = \Phi_k P_k \Phi_k^T - \Phi_k K_k [H_k P_k H_k^T + R_k] K_k^T \Phi_k^T + \Upsilon_k Q_k \Upsilon_k^T$$

$$= \Phi_k P_k \Phi_k^T - \Phi_k K_k H_k P_k \Phi_k^T + \Upsilon_k Q_k \Upsilon_k^T$$

Infinite Horizon

$$K_\infty = P_\infty H^T [H P_\infty H^T + R]^{-1}$$

DT Alg. Riccati Eqn. (DARE)

$$P_\infty = \Phi P_\infty \Phi - \Phi P_\infty H^T [H P_\infty H^T + R]^{-1} H P_\infty \Phi^T + \Upsilon Q \Upsilon^T$$

DARE other forms

$$P_\infty = \Phi P_\infty \Phi - \Phi K_\infty [H P_\infty H^T + R] K_\infty^T \Phi^T + \Upsilon Q \Upsilon^T$$

$$= \Phi P_\infty \Phi - \Phi K_\infty H P_\infty \Phi^T + \Upsilon Q \Upsilon^T$$

- **Continuous-Time Kalman Filter**

Model: $\dot{x}(t) = F(t)x(t) + B(t)u(t) + G(t)w(t), \quad w(t) \sim \mathcal{N}(0, Q(t))$
 $\tilde{y}(t) = H(t)x(t) + v(t), \quad v(t) \sim \mathcal{N}(0, R(t))$
 $E[w(t)w(\tau)^T] = Q(t)\delta(t - \tau)$
 $E[v(t)v(\tau)^T] = R(t)\delta(t - \tau)$
 $E[v(t)w(\tau)^T] = 0$

Initialize: $\hat{x}(t_0) = \hat{x}_0, \quad P_0 = E[(\hat{x}(0) - x(0))(\hat{x}(0) - x(0))^T]$

Gain: $K(t) = P(t)H^T(t)R^{-1}(t)$

Covariance: $\dot{P}(t) = F(t)P(t) + P(t)F^T(t) - P(t)H^T(t)R^{-1}(t)H(t)P(t) + G(t)Q(t)G^T(t)$

Estimate: $\dot{\hat{x}} = F(t)\hat{x}(t) + B(t)u(t) + K(t)[\tilde{y}(t) - H(t)\hat{x}(t)]$

Alternative Forms:

$$\dot{P}(t) = F(t)P(t) + P(t)F^T(t) + K(t)R(t)K^T(t) + G(t)Q(t)G^T(t)$$

Infinite Horizon

$$K_\infty = P_\infty H^T R^{-1}$$

CT Alg. Riccati Eqn. (CARE) $0 = FP_\infty + P_\infty F^T - P_\infty H^T R^{-1} H P_\infty + GQG^T$

$$0 = FP_\infty + P_\infty F^T + K_\infty R K_\infty^T + GQG^T$$

- **Continuous/Discrete Kalman Filter**

Model: $\hat{x}(t) = F(t)x(t) + B(t)u(t) + G(t)w(t), \quad w(t) \sim \mathcal{N}(0, Q(t))$
 $\tilde{y}_k = H_k x_k + v_k, \quad v_k \sim \mathcal{N}(0, R_k)$

Initialize: $\hat{x}(t_0) = \hat{x}_0, \quad P_0 = E[(\hat{x}(0) - x(0))(\hat{x}(0) - x(0))^T]$

Gain: $K_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1}$

Update: $\hat{x}_k^+ = \hat{x}_k^- + K_k [\tilde{y}_k - H_k \hat{x}_k^-]$

$$P_k^+ = [I - K_k H_k] P_k^-$$

Propagation: $\dot{\hat{x}}(t) = F(t)\hat{x}(t) + B(t)u(t)$

$$\dot{P}(t) = F(t)P(t) + P(t)F^T(t) + G(t)Q(t)G^T(t)$$

- **Continuous-Time Extended Kalman Filter**

Model: $\dot{x}(t) = f(x, u, t) + G(t)w(t), \quad w(t) \sim \mathcal{N}(0, Q(t))$
 $\tilde{y}(t) = h(x, t) + v(t), \quad v(t) \sim \mathcal{N}(0, R(t))$

Initialize: $\hat{x}(t_0) = \hat{x}_0, \quad P_0 = E[(\hat{x}(0) - x(0))(\hat{x}(0) - x(0))^T]$

Gain: $K(t) = P(t)H(t)^T R(t)^{-1}$

Covariance: $\dot{P}(t) = F(t)P(t) + P(t)F(t)^T - P(t)H(t)^T R(t)^{-1} H(t)P(t) + G(t)Q(t)G(t)^T$
 $F(t) = \left. \frac{\partial f}{\partial x} \right|_{\hat{x}(t), u(t)}, \quad H(t) = \left. \frac{\partial h}{\partial x} \right|_{\hat{x}(t)}$

Estimate: $\dot{\hat{x}}(t) = f(\hat{x}, u, t) + K(t)[\tilde{y}(t) - h(\hat{x}, t)]$

- **Continuous-Discrete Extended Kalman Filter**

Model: $\dot{x}(t) = f(x, u, t) + G(t)w(t), \quad w(t) \sim \mathcal{N}(0, Q(t))$
 $\tilde{y}_k = h(x_k) + v_k, \quad v_k \sim \mathcal{N}(0, R_k)$

Initialize: $\hat{x}(t_0) = \hat{x}_0, \quad P_0 = E[(\hat{x}(0) - x(0))(\hat{x}(0) - x(0))^T]$

Gain: $K_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1}, \quad H_k = \left. \frac{\partial h}{\partial x} \right|_{\hat{x}_k^-}$

Update: $\hat{x}_k^+ = \hat{x}_k^- + K_k [\tilde{y}_k - h(\hat{x}_k^-)]$
 $P_k^+ = [I - K_k H_k] P_k^-$

Propagation: $\dot{\hat{x}}(t) = f(\hat{x}, u, t)$
 $\dot{P}(t) = F(t)P(t) + P(t)F(t)^T + G(t)Q(t)G(t)^T, \quad F(t) = \left. \frac{\partial f}{\partial x} \right|_{\hat{x}(t), u(t)}$

• Unscented Kalman Filter

Model: $x_{k+1} = f(x_k, u_k, w_k, k), \quad w(t) \sim \mathcal{N}(0, Q_k)$
 $\tilde{y}_k = h(x_k, u_k, v_k, k), \quad v_k \sim \mathcal{N}(0, R_k)$

Sample: $x_k^a = \begin{bmatrix} x_k \\ w_k \\ v_k \end{bmatrix}, \quad \hat{x}_k^a = \begin{bmatrix} \hat{x}_k \\ 0 \\ 0 \end{bmatrix}, \quad P_k^a = \begin{bmatrix} P_k^+ & P_k^{xw} & P_k^{xv} \\ (P_k^{xw})^T & Q_k & P_k^{wv} \\ (P_k^{xv})^T & (P_k^{wv})^T & R_k \end{bmatrix}$

$P = MM^T, \quad M = \sqrt{P_k^a}, \quad \text{using Cholesky, SVD, etc...}$

$\sigma_k^{(i)} = \text{cols of } \pm\gamma\sqrt{P_k^a}$

$\chi_k^{a(0)} = \hat{x}_k^a, \quad \chi_k^{a(i)} = \hat{x}_k^a + \sigma_k^{(i)}, \quad i = 1, 2, \dots, 2L, \quad \chi_k^{a(i)} = \begin{bmatrix} \chi_k^{x(i)} \\ \chi_k^{w(i)} \\ \chi_k^{v(i)} \end{bmatrix}$

Propagate: $\chi_{k+1}^{x(i)} = f(\chi_k^{x(i)}, \chi_k^{w(i)}, u_k, k)$
 $\gamma_k^{(i)} = h(\chi_k^{x(i)}, u_k, \chi_k^{v(i)}, k)$

Reconstruct: $\hat{x}_k^- = \sum_{i=0}^{2L} W_i^{\text{mean}} \chi_k^{x(i)}, \quad P_k^- = \sum_{i=0}^{2L} W_i^{\text{cov}} [\chi_k^{x(i)} - \hat{x}_k^-] [\chi_k^{x(i)} - \hat{x}_k^-]^T$
 $\hat{y}_k^- = \sum_{i=0}^{2L} W_i^{\text{mean}} \gamma_k^{(i)}, \quad P_k^{e_y e_y} = \sum_{i=0}^{2L} W_i^{\text{cov}} [\gamma_k^{(i)} - \hat{y}_k^-] [\gamma_k^{(i)} - \hat{y}_k^-]^T$

$P_k^{e_x e_y} = \sum_{i=0}^{2L} W_i^{\text{cov}} [\chi_k^{x(i)} - \hat{x}_k^-] [\gamma_k^{(i)} - \hat{y}_k^-]^T$

Gain: $K_k = P_k^{e_x e_y} (P_k^{e_y e_y})^{-1}$

Update: $\hat{x}_k^+ = \hat{x}_k^- + K_k e_k^- = \hat{x}_k^- + K_k (\tilde{y}_k - \hat{y}_k^-)$

$P_k^+ = P_k^- - K_k P_k^{e_y e_y} K_k^T$

Params/weights: L : length of $x_k^a, \quad \gamma = \sqrt{L + \lambda}, \quad \lambda = \alpha^2(L + \kappa) - L$

$10^{-4} \leq \alpha \leq 1, \quad \beta = 2$

$W_0^{\text{mean}} = \frac{\lambda}{L + \lambda}, \quad W_0^{\text{cov}} = \frac{\lambda}{L + \lambda} + (1 - \alpha^2 + \beta)$

$W_i^{\text{mean}} = W_i^{\text{cov}} = \frac{1}{2(L + \lambda)}, \quad i = 1, 2, \dots, 2L$