

Kalman Filter and Extended Kalman Filter

Jungtaek Kim
(jtkim@postech.edu)

Machine Learning Group,
Department of Computer Science and Engineering, POSTECH,
77-Cheongam-ro, Nam-gu, Pohang-si 790-784,
Gyongsankbuk-do, Republic of Korea

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Kalman Filter

- ▶ Kalman filter uses a series of measurements observed over time, containing noise and other inaccuracies.
- ▶ It produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone.
- ▶ It operates recursively on streams of noisy input data.

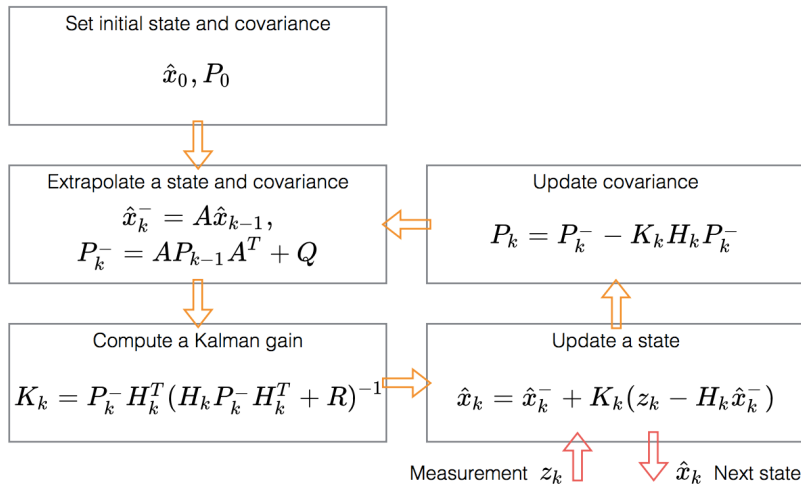


Preliminaries

- ▶ Input (Measurement) - z_k
- ▶ Output (State) - \hat{x}_k
- ▶ System Model - A, H_k, Q, R
- ▶ $z_k = H_k x_k + v_k$ where $v_k \sim \mathcal{N}(0, R)$
- ▶ $x_{k+1} = A x_k + w_k$ where $w_k \sim \mathcal{N}(0, Q)$



Block Diagram of Kalman Filter



Proof of Kalman Filter: State and Covariance Extrapolation

- ▶ State extrapolation is

$$\begin{aligned}\hat{x}_{k+1}^- &= \mathbb{E}[x_{k+1}|I_k] \\ &= \mathbb{E}[Ax_k + w_k|I_k] \\ &= A\hat{x}_k.\end{aligned}$$

- ▶ Covariance extrapolation is

$$\begin{aligned}P_{k+1}^- &= \mathbb{E}[(x_{k+1} - \hat{x}_k^-)(x_{k+1} - \hat{x}_k^-)^T|I_k] \\ &= \mathbb{E}[(x_{k+1} - \hat{x}_k^-)^2|I_k] \\ &= \mathbb{E}[(Ax_k + w_k - A\hat{x}_k)^2|I_k] \\ &= \mathbb{E}[(A(x_k - \hat{x}_k) + w_k)^2|I_k] \\ &= AP_kA^T + Q.\end{aligned}$$



Proof of Kalman Filter: State Update

- ▶ The next state given the current state and the measured state can be expressed by the equation with the given terms,

$$\hat{x}_{k+1} = K'_{k+1}\hat{x}_k + K_{k+1}z_{k+1}.$$

- ▶ The error term $\tilde{x}_k = \hat{x}_k - x_k$ has zero mean and covariance P_k .



Proof of Kalman Filter: State Update

- ▶ The error term is arranged to

$$\begin{aligned}\hat{x}_{k+1} - x_{k+1} &= K'_{k+1}\hat{x}_k + K_{k+1}z_{k+1} - x_{k+1} \\ &= K'_{k+1}\hat{x}_k + K_{k+1}(H_{k+1}x_{k+1} + v_{k+1}) \\ &\quad - x_{k+1} - K'_{k+1}x_k + K'_{k+1}x_k.\end{aligned}$$

- ▶ Rearranging term is

$$\begin{aligned}&= K'_{k+1}(\hat{x}_k - x_k) + K_{k+1}(H_{k+1}(Ax_k + w_k) + v_{k+1}) \\ &\quad - (Ax_k + w_k) + K'_{k+1}x_k \\ &= K'_{k+1}(\hat{x}_k - x_k) + (K_{k+1}H_{k+1}A - A + K'_{k+1})x_k \\ &\quad + (K_{k+1}H_{k+1} - I)w_k + K_{k+1}v_{k+1}.\end{aligned}$$



Proof of Kalman Filter: State Update

- ▶ The expectation of the error term is

$$\mathbb{E}[\hat{x}_{k+1} - x_{k+1}] = [K_{k+1}H_{k+1}A - A + K'_{k+1}]\mathbb{E}[x_k] = 0.$$

- ▶ Therefore,

$$\begin{aligned}K_{k+1}H_{k+1}A - A + K'_{k+1} &= 0 \\K'_{k+1} &= (I - K_{k+1}H_{k+1})A\end{aligned}$$

is satisfied.



Proof of Kalman Filter: State Update

- The next state is

$$\begin{aligned}\hat{x}_{k+1} &= (I - K_{k+1}H_{k+1})A\hat{x}_k + K_{k+1}z_{k+1} \\ &= \underbrace{A\hat{x}_k}_{\text{extrapolated state}} + \underbrace{K_{k+1}(z_{k+1} - H_{k+1}A\hat{x}_k)}_{\text{residual of measurement and prediction}} \\ &= \hat{x}_{k+1}^- + K_{k+1}(z_{k+1} - H_{k+1}\hat{x}_{k+1}^-) \quad \text{by } \hat{x}_{k+1}^- = A\hat{x}_k.\end{aligned}$$



Proof of Kalman Filter: Kalman Gain Computation

- (con'd)

$$P_{k+1} = P_{k+1}^- - K_{k+1}H_{k+1}P_{k+1}^- - P_{k+1}^-H_{k+1}^TK_{k+1}^T + K_{k+1}(H_{k+1}P_{k+1}^-H_{k+1}^T + R)K_{k+1}^T.$$

- It can be substituted from $k + 1$ to k ,

$$P_k = P_k^- - K_kH_kP_k^- - P_k^-H_k^TK_k^T + K_k(H_kP_k^-H_k^T + R)K_k^T.$$

- The trace of P_k is

$$\nabla_K \text{tr}(P_k) = -P_k^-H_k^T - P_k^-H_k^T + 2K_kH_kP_k^-H_k^T + 2K_kR = 0.$$

- Thus, Kalman gain is

$$K_k = P_k^-H_k^T(H_kP_k^-H_k^T + R)^{-1}.$$



Proof of Kalman Filter: Covariance Update

- ▶ The covariance of the error term can be expressed with substituting Kalman gain by

$$\begin{aligned} P_k &= P_k^- - K_k H_k P_k^- - P_k^- H_k^T K_k^T + K_k (H_k P_k^- H_k^T + R) K_k^T \\ &= P_k^- - K_k H_k P_k^- - P_k^- H_k^T K_k^T + P_k^- H_k^T K_k^T \\ &= (I - K_k H_k) P_k^-. \end{aligned}$$



Kalman Filter vs. Extended Kalman Filter

- ▶ Kalman Filter - a linear system
- ▶ Extended Kalman Filter - a nonlinear system



Extended Kalman Filter

- State and measurement are the functions of x_k ,

$$x_{k+1} = f_k(x_k) + w_k$$

$$y_k = h_k(x_k) + v_k,$$

where $w_k \sim \mathcal{N}(0, Q)$ and $v_k \sim \mathcal{N}(0, R)$.

- Let $F(k)$ and $H(k)$ be the Jacobian matrices of $f(\cdot)$ and $h(\cdot)$, denoted by

$$F(k) = \nabla f_k|_{\hat{x}(k|k)}$$

$$H(k+1) = \nabla h|_{\hat{x}(k=1|k)}.$$



Extended Kalman Filter

► Predict Cycle

$$\hat{x}(k+1|k) = f_k(\hat{x}(k|k))$$

$$P(k+1|k) = F(k)P(k|k)F^T(k) + Q(k)$$

► Filtered Cycle

$$\hat{x}(k+1|k+1) = \hat{x}(k+1|k)$$

$$+ K(k+1)(y_{k+1} - h_{k+1}(\hat{x}(k+1|k)))$$

$$K(k+1) = P(k+1|k)H^T(k+1)$$

$$* (H(k+1)P(k+1|k)H^T(k+1) + R(k+1))^{-1}$$

$$P(k+1|k+1) = (I - K(k+1)H(k+1))P(k+1|k)$$



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