

$$\hat{x}_k = \hat{x}_{k-1} + K(z_k - H\hat{x}_{k-1})$$

\hat{x}_k (最终估计值) \hat{x}_{k-1} (模型) z_k (测量) $H\hat{x}_{k-1}$ (模型 (算出来的))
 same.

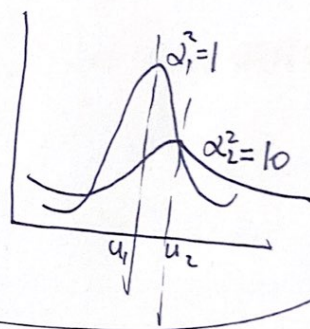
目标: 寻找 K , 使 $\hat{x}_k \rightarrow x_k$

$$e_k = x_k - \hat{x}_k$$

$$p(e_k) \sim (0, P)$$

$$P = E[ee^T] = \begin{bmatrix} \sigma_{e_1}^2 & \sigma_{e_1}\sigma_{e_2} \\ \sigma_{e_2}\sigma_{e_1} & \sigma_{e_2}^2 \end{bmatrix}$$

因此, e_k 要越小, 且 $p(e_k)$ 最小
 方差越小, 越靠近 0 \Rightarrow 误差最小



合适的 K , $\text{tr}(P)$ 最小

$$\text{tr}(P) = \sigma_{e_1}^2 + \sigma_{e_2}^2 \text{ 最小}$$

$$P = E[ee^T] = E[(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T]$$

DEF.

$$\Rightarrow x_k - \hat{x}_k = x_k - \hat{x}_{k-1} - K(z_k) + K H \hat{x}_{k-1}$$

$z_k = Hx_k + v_k$

$$= x_k - \hat{x}_{k-1} - K_k H x_k - K_k v_k + K_k H \hat{x}_{k-1}$$

$$= x_k - \hat{x}_{k-1} - K_k H (x_k - \hat{x}_{k-1}) - K_k v_k$$

$$= (I - K_k H) (x_k - \hat{x}_{k-1}) - K_k v_k$$

$= e_k$

$$\Rightarrow E[(x - \hat{x}) (x - \hat{x})^T]$$

$$= E[(I - K_k H) \tilde{e}_k - K_k v_k] [(I - K_k H) \tilde{e}_k - K_k v_k]^T]$$

$$= E[(I - K_k H) \tilde{e}_k - K_k v_k] [\tilde{e}_k^T (I - K_k H)^T - v_k^T K_k^T]]$$

$$= E \left[(I - K_k H) \tilde{e}_k \tilde{e}_k^T (I - K_k H)^T - (I - K_k H) \tilde{e}_k v_k^T K_k^T - K_k v_k \tilde{e}_k^T (I - K_k H)^T + K_k v_k v_k^T K_k^T \right]$$

$$\downarrow = 0$$

$$E(AB) = E(A)E(B)$$

\tilde{e}_k 和 v_k 相互独立

$$E(\tilde{e}_k) = 0 \quad E[v_k] = 0$$

$$\Rightarrow 0$$

$$= E[(I - K_k H) \tilde{e}_k \tilde{e}_k^T (I - K_k H)^T + K_k E(v_k v_k^T) K_k^T]$$

$$\Downarrow$$

$$P_k^-$$

$$\text{因为 } E(\tilde{e}_k \tilde{e}_k^T) = P_k^-$$

$$\Downarrow$$

R (测量噪声)

$$E(v_k v_k^T) = R$$

$$= (I - K_k H) P_k^- (I - K_k H)^T + K_k R K_k^T$$

3.

$$\Rightarrow P_k = (I - K_k H) P_k^- (I - K_k H)^T + K_k R_k K_k^T$$

$$\Rightarrow (P_k^- - K_k H P_k^-) (I^T - H_k^T K_k^T) + K_k R_k K_k^T$$

$$\Rightarrow P_k^- - \underline{K_k H P_k^-} - \underline{P_k^- H_k^T K_k^T} + K_k H P_k^- H_k^T K_k^T + K_k R_k K_k^T$$

$$\Rightarrow \text{s.t. min}_K \text{tr}(P_k)$$

$$\left. \begin{aligned} & \rightarrow K_k H P_k^- = ((P_k^- H^T) K_k^T)^T \\ & \Rightarrow \text{tr}(K_k H P_k^-) = \text{tr}(P_k^- H_k^T K_k^T) \end{aligned} \right\}$$

$$\Rightarrow \text{tr}(P_k) = \text{tr}(P_k^-) - 2 \text{tr}(K_k H P_k^-) + \text{tr}(K_k H P_k^- H_k^T K_k^T) + \text{tr}(K_k R_k K_k^T)$$

~~proof of~~

$$\text{tr} \left(\frac{d \text{tr}(AB)}{dA} \right) = B^T$$

$$\frac{d \text{tr}(ABA^T)}{dA} = 2AB$$

$$\text{proof} : \Rightarrow \text{tr} \left[\begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \right] = \text{tr} \begin{bmatrix} a_{11}b_{11} + a_{12}b_{21} & \\ & a_{21}b_{12} + a_{22}b_{22} \end{bmatrix}$$

$$\text{tr}(AB) = a_{11}b_{11} + a_{12}b_{21} + a_{21}b_{12} + a_{22}b_{22}$$

$$\frac{d \text{tr}(AB)}{dA} = \begin{bmatrix} \frac{d \text{tr}(AB)}{\partial a_{11}} & \frac{\partial \text{tr}(AB)}{\partial a_{12}} \\ \frac{d \text{tr}(AB)}{\partial a_{21}} & \frac{d \text{tr}(AB)}{\partial a_{22}} \end{bmatrix}$$

$$= \begin{bmatrix} b_{11} & b_{21} \\ b_{12} & b_{22} \end{bmatrix}$$

$$\Rightarrow \frac{d \text{tr}(P_k)}{dK_k} = 0 - 2(H P_k^-)^T + 2K_k H P_k^- H^T + 2K_k R_k = 0$$

$$\Rightarrow -P_k^{-T} H^T + K_k (H P_k^- H^T + R_k) = 0$$

$$\Rightarrow K_k (H P_k^- H^T + R_k) = P_k^{-T} H^T$$

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