

2 CH 3, RECALL

$$x_{k+1} = A_k \cdot x_k + w_k$$

$$w_k \sim \mathcal{N}(0, W_k)$$

$$y_k = C_k \cdot x_k + v_k$$

$$v_k \sim \mathcal{N}(0, V_k)$$

KALMAN FILTER : ^{TAKING} ~~GOING~~ $y_0, y_1, y_2, \dots$ $\Rightarrow$ CORR. $\hat{x}_0, \hat{x}_1, \hat{x}_2, \dots$

PRED. $\hat{x}_{[k|k-1]} = A_{k-1} \cdot \hat{x}_{[k-1|k-1]}$

$$P_{[k|k-1]} = A_{k-1} \cdot P_{[k-1|k-1]} \cdot A_{k-1}^T + W_k$$

INNOV. $P_{[k|k]} = \left(P_{[k|k-1]}^{-1} + C_k^T V_k^{-1} C_k \right)^{-1}$

$$\hat{x}_{[k|k]} = \hat{x}_{[k|k-1]} + P_{[k|k]} \cdot C_k^T V_k^{-1} (y_k - C_k \cdot \hat{x}_{[k|k-1]})$$

DISCR.

CONT. TIME

LIN.
(KALMAN FILTER)

$$x_{k+1} = A_k \cdot x_k + w_k$$

$$y_k = C_k \cdot x_k + v_k$$

①

② $x_{k+1} = f_k(x_k) + w_k$

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

NONLIN.
(EXTENDED KALMAN FILTER)

$$\dot{x} = A(t) x(t) + w(t)$$

$$y(t) = C(t) \cdot x(t) + v(t)$$

③

④

$$\dot{x} = f(x, t) + w(t)$$

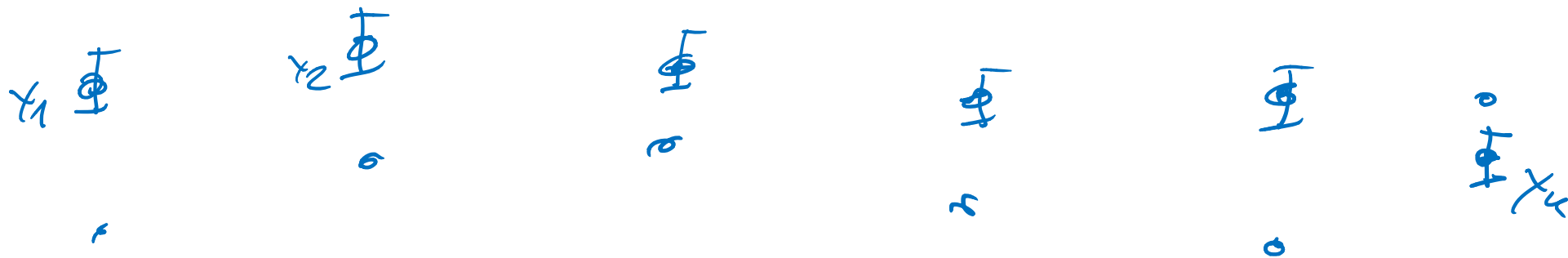
$$y(t) = h(x, t) + v(t)$$

$$A^c = \frac{\partial f}{\partial x}$$

$$C^c = \frac{\partial h}{\partial x}$$

WHICH OPT. PROBLEM DOES THE KF SOLVE?

$$\hat{x}_{0|k} \quad \hat{x}_{[1|k]} \quad \hat{x}_{[2|k]} \quad \dots \quad x_{[k|k]}$$



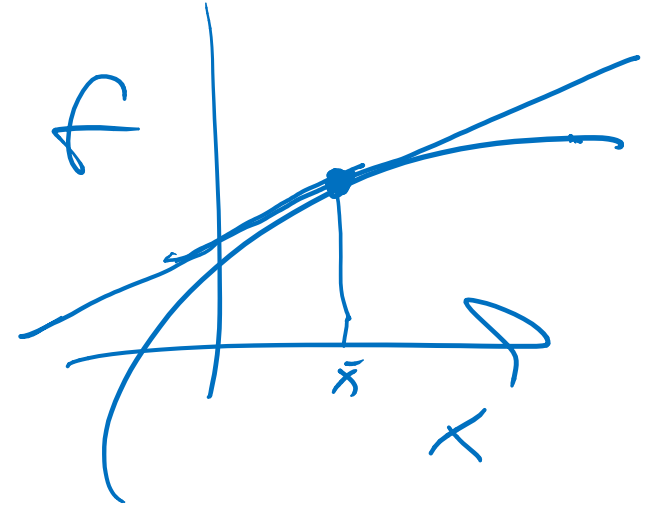
$$(\hat{x}_{[0|k]}, \dots, \hat{x}_{[k|k]}) = \arg \min_{x_0, \dots, x_k} (x_0 - \hat{x}_0)^T P_0^{-1} (x_0 - \hat{x}_0) + \sum_{i=1}^k \|y_i - C_i x_i\|_{V_i^{-1}}^2 + \sum_{i=1}^k \|x_i - A_{i-1} \cdot x_{i-1}\|_{W_{i-1}^{-1}}^2$$

TRAJECTORY ESTIMATION BASED ON ML / BAYESIAN / MAP

KF FIND ONLY $\hat{x}_{[k|k]}$, I.E. LAST STATE OF THE TRAJECTORY, VERY EFFICIENTLY

EXTENDED KF (DISCRETE TIME)

$$\begin{cases} x_{n+1} = f_n(x_n) + w_n \\ y_n = h_n(x_n) + v_n \end{cases}$$



IDEA: APPROX. f_n, h_n BY FIRST ORDER TAYLOR SERIES (LINEARIZE)

$$f_n(x) \approx f_n(\bar{x}) + \frac{\partial f_n}{\partial x}(\bar{x}) \cdot (x - \bar{x})$$

AT BEST AVAILABLE ^{"A_n"} ESTIMATE SO FAR

$$h_n(x) \approx h_n(\bar{x}) + \frac{\partial h_n}{\partial x}(\bar{x}) (x - \bar{x})$$

↓
C_n

PRED

KF

$$\hat{x}_{[k|k-1]} = A_{k-1} \hat{x}_{[k-1|k-1]}$$

$$P_{[k|k-1]} = A_{k-1} P_{[k-1|k-1]} A_{k-1}^T + W_k$$

EKF

$$x_{[k|k-1]} = \boxed{f_{k-1}(x_{[k-1|k-1]})}$$

SAME, WITH $\boxed{A_{k-1} = \frac{\partial f_{k-1}}{\partial x}(\cdot)}$

INNOV.

$$P_{[k|k]} = \left(P_{[k|k-1]}^{-1} + C_k^T V_k^{-1} C_k \right)^{-1}$$

SAME, WITH $\boxed{C_k = \frac{\partial h_k}{\partial x}(x_{[k|k-1]})}$

.....

$$\hat{x}_{[k|k]} = \hat{x}_{[k|k-1]} + P_{[k|k]} \cdot C_k^T \cdot V_k^{-1} \cdot \left(y_k - \boxed{h_k(\hat{x}_{[k|k-1]})} \right)$$

NOTE: EVEN FOR τ_1 f AND h , $A_k = \frac{\partial f}{\partial x}(\hat{x}_{[k|k]}) \neq A_{k+1} = \frac{\partial f}{\partial x}(\hat{x}_{[k+1|k+1]})$
BECAUSE WE LINEARIZE AT DIFFERENT POINTS.

Memory of EKF: Same as KF

$\hat{x}_{k|k}$, $P_{k|k}$

9.4 KF IN CONT. TIME

$$\begin{aligned}\dot{x}(t) &= A^c(t) \cdot x(t) + \cancel{w(t)} w^c(t) \\ y(t) &= C^c(t) \cdot x(t) + v^c(t)\end{aligned}$$

①

↓ DISCRETE TIME, WITH SAMPLING TIME Δt

②
↓ $\lim_{\Delta t \rightarrow 0}$..

$$\dot{\hat{x}} = \dots$$

$$\dot{\hat{p}} = \dots$$

$$\begin{aligned}\text{cov}(w^c(t_1), w^c(t_2)) \\ = \delta(t_1 - t_2) \cdot W^c\end{aligned}$$

$$[W^c] = \frac{[x]^2}{[t]}$$

WHITE NOISE IN CONT. TIME.

$$\begin{aligned}\text{cov}(v^c(t_1), v^c(t_2)) \\ = \delta(t_1 - t_2) \cdot V^c\end{aligned}$$

$$[V^c] = [t] \cdot [y]^2$$

① TRANSF. SYSTEM FROM CONT. TO DISCR TIME

IDEA: USE EULER INTEGRATION SCHEME

$$t_n = k \cdot \Delta t$$

$$\dot{x} = A^c \cdot x + w^c$$

$$x_k \equiv x(t_n)$$

$$\boxed{x_{k+1} = x_k + \Delta t \cdot A^c \cdot x_k + \underbrace{\int_{t_n}^{t_{n+1}} w^c(t) dt}_{=: w_k}}$$

$$= \underbrace{(I + \Delta t A^c)}_{A_k} \cdot x_k + w_k$$

$$= A_k \cdot x_k + w_k$$

i.e. $\boxed{A_k = I + \Delta t \cdot A^c}$

$$\boxed{w_k = \Delta t \cdot w^c}$$
$$\boxed{[w_k] = [x]^2}$$

$$y = C^c \cdot x + v^c$$
$$y_k = C^c \cdot x_k + v_k$$

$$\boxed{C_k = C^c}$$

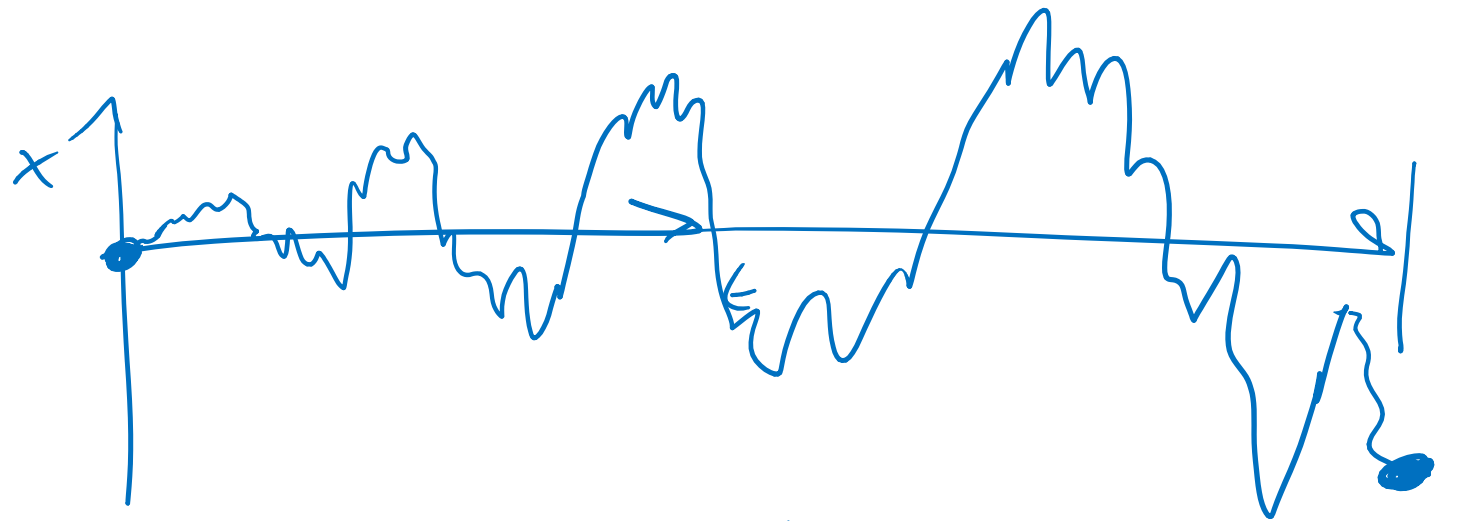
$$y_k = \left(\frac{1}{\Delta t} \right) \int_{t_n}^{t_{n+1}} y(t) dt$$

$$\boxed{v_k = \frac{v^c}{\Delta t}}$$

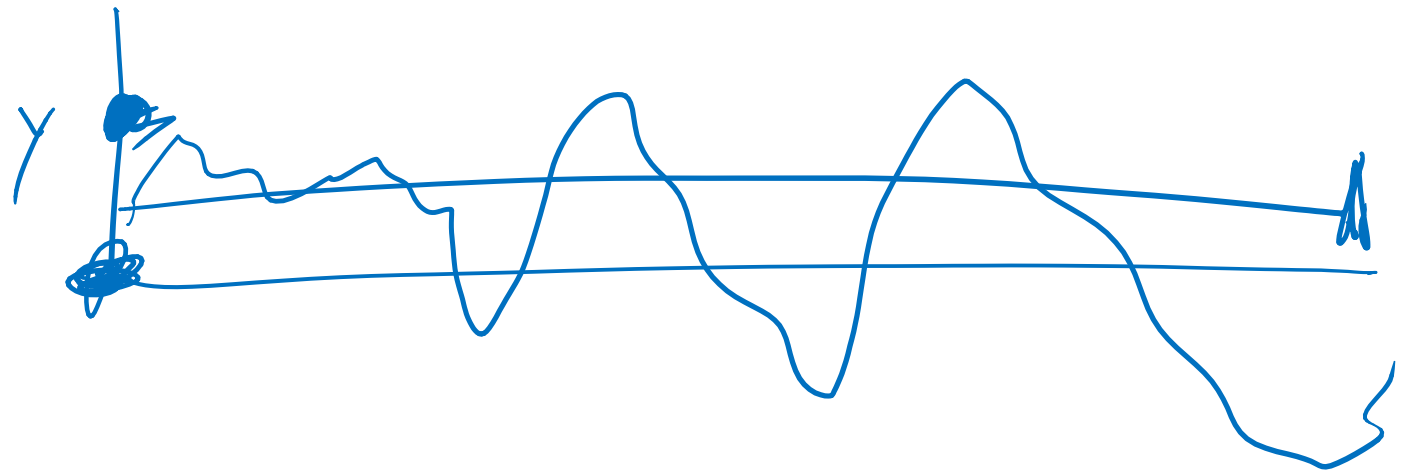
Ex:

$$\dot{x} = w$$

$$y = x$$



Δt



$$A_u = I + \Delta t A^c$$

$$W_u = \Delta t \cdot W^c$$

$$C_u = C^c$$

$$V_u = \frac{V^c}{\Delta t}$$

$$\text{Discr. KF: (pre)} x_{[k|k-1]} = (I + \Delta t A^c) \cdot x_{[k-1|k-1]} = x_{[k-1|k-1]} + \Delta t A^c \cdot x_{[k-1|k-1]}$$

$$\begin{aligned} \rightarrow P_{[k|k-1]} &= (I + \Delta t A^c) P_{[k-1|k-1]} (I + \Delta t A^c)^T + \Delta t \cdot W^c \\ &= P_{[k-1|k-1]} + \Delta t \cdot \underline{P_{[k-1|k-1]} \cdot A^{cT}} + \Delta t \cdot \underline{A^c \cdot P_{[k-1|k-1]}} + O(\Delta t^2) \end{aligned}$$

$$\begin{aligned} P_{[k|k]} &= (P_{[k|k-1]}^{-1} + C_u^T V_u^{-1} C_u)^{-1} = (P_{[k|k-1]}^{-1} + C^{cT} (V^c)^{-1} C^c + \Delta t \cdot W^c)^{-1} \\ &= (P_{[k|k-1]}^{-1} \cdot (I + P_{[k|k-1]} \cdot C^{cT} V^{c-1} C^c \Delta t))^{-1} P_{[k|k-1]} = (I + P_{[k|k-1]} \cdot C^{cT} V^{c-1} C^c)^{-1} \cdot P_{[k|k-1]} \\ &= (I - \Delta t P_{[k|k-1]} \cdot C^{cT} V^{c-1} C^c + O(\Delta t^2)) \cdot P_{[k|k-1]} \\ \rightarrow &= \underline{P_{[k|k-1]} - \Delta t P_{[k|k-1]} \cdot C^{cT} V^{c-1} C^c \cdot P_{[k|k-1]} + O(\Delta t^2)} \end{aligned}$$

$$x_{[k|k]} = x_{[k|k-1]} + P_{[k|k]} \cdot C^T \cdot V^{C^{-1}} \cdot \Delta t \cdot (y_k - C^C \cdot x_{[k|k-1]})$$

~~$x_{[k|k]}$~~

$$x_{[k-1|k-1]} \rightarrow x_{[k|k]}$$

$$x_{[k|k]} = x_{[k-1|k-1]} + \Delta t A^C \cdot x_{[k-1|k-1]} + \Delta t P C^T V^{C^{-1}} (y - C^C x)$$

$$x_{[k|k]} = x_{[k-1|k-1]} + \Delta t (A^C x + P C^T V^{C^{-1}} (y - C^C x))$$

$$\frac{x_{[k|k]} - x_{[k-1|k-1]}}{\Delta t} = A^C x + P C^T V^{C^{-1}} (y - C^C x) \rightarrow \boxed{\dot{\hat{x}} = A^C \hat{x} + \underline{\underline{P C^T V^{C^{-1}} (y - C^C \hat{x})}}}$$

$$\boxed{\dot{P} = \underline{\underline{P \cdot A^{CT}}} + \underline{\underline{A^C \cdot P}} - \underline{\underline{P C^T V^{C^{-1}} C \cdot P}}}$$

CONT. TIME KF.