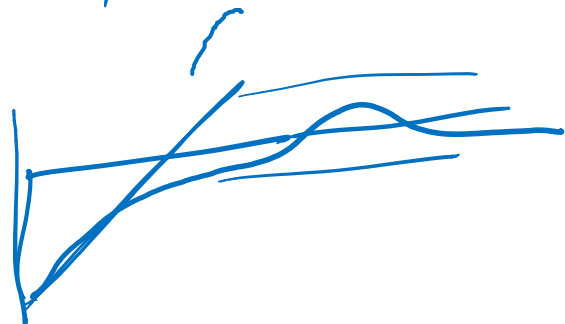
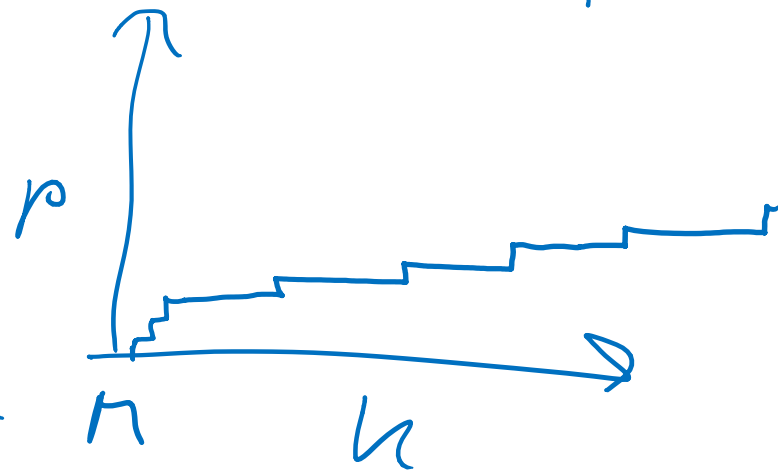
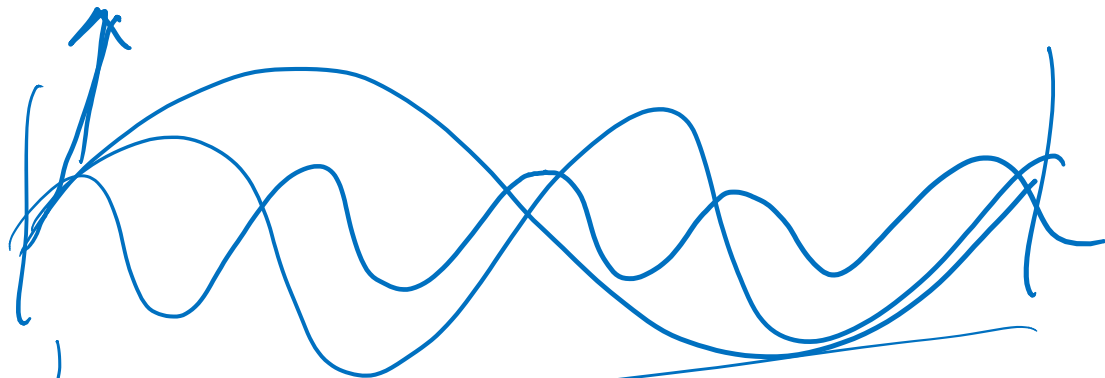
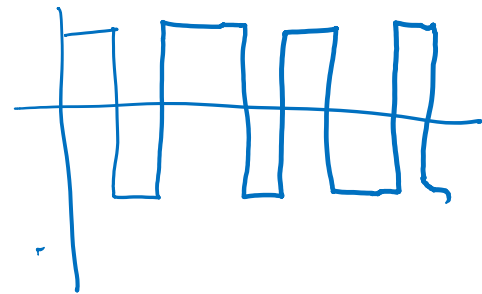


MULTI SINES



$u \xrightarrow{\text{FFT}} U(j\omega_0 \cdot k(p))$

$y \xrightarrow{\text{FFT}} Y(j\omega_0 \cdot k(p))$

$G(j\omega_0 \cdot k(p)) = \frac{Y(\cdot)}{U(\cdot)}$

PRBN

CH 9 ONLINE ESTIMATION (OF STATE)

TIME DOMAIN
DISCRETE TIME

LT1

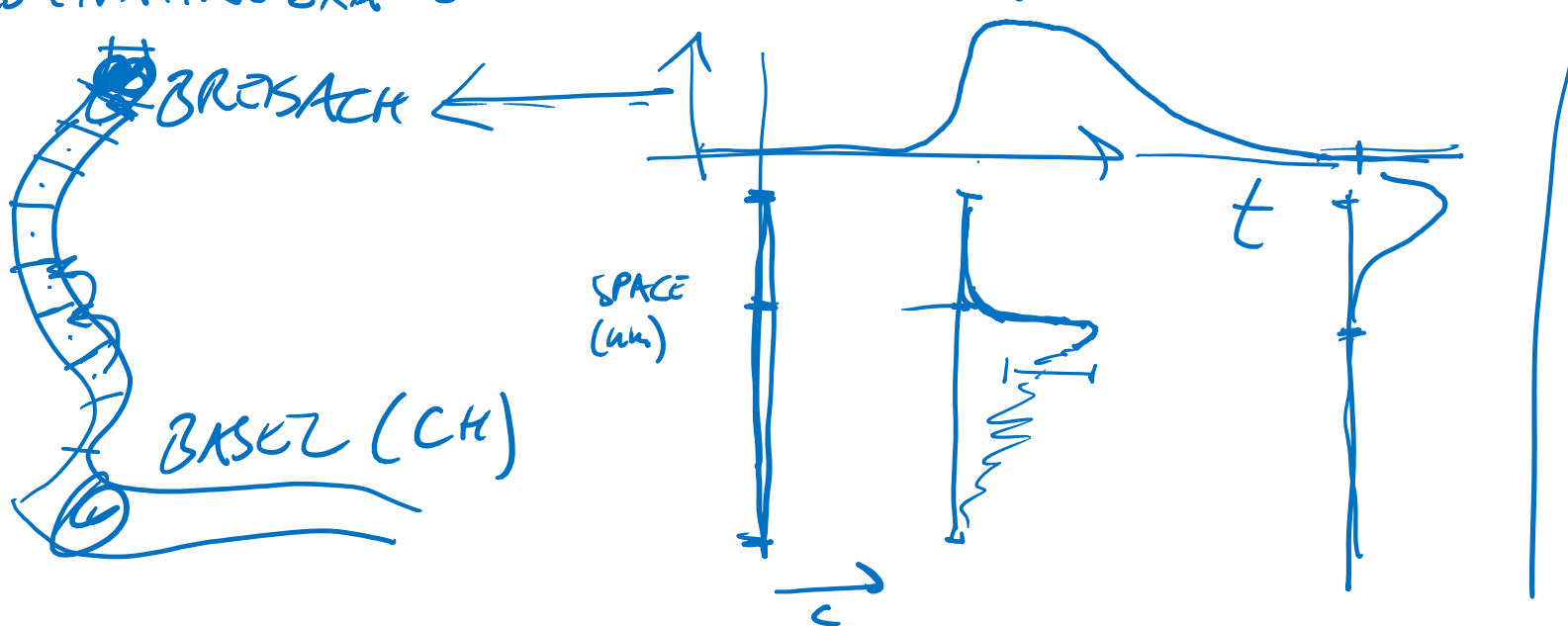
(DETERMINISTIC MODEL)
MEASUREMENT NOISE

$$\begin{aligned} x_{k+1} &= A_k \cdot x_k \\ y_k &= C_k \cdot x_{k+1} \end{aligned}$$

$$x_k = A_{k-1} \cdot A_{k-2} \cdots A_0 \cdot x_0$$

GIVEN y_0, y_1, \dots, y_k
FIND x_k
(RECURSIVELY)
(RESULT: KALMAN FILTER)

MOTIVATING EXAMPLE: POLL. EST. IN RHINE



RECURSIVE
RECALL: LIN. L.S. (RLS)

$$y_1, y_2, \dots \quad (y(n) \rightarrow y_n)$$

θ

$$y_n = \underline{\underline{\phi_n^T}} \theta + \varepsilon_n$$

Accm: $\theta \equiv x_0$
 $\phi_n^T \theta \equiv C_n \cdot x_n$
 $= C_n A_{n-1} \cdot A_{n-2}$
 $\varepsilon_n \equiv v_n \quad \dots A_0 \cdot x_0$

START: A-PRIORI INFORMATION ~~$\theta_0 \sim \mathcal{N}$~~ $\theta \sim \mathcal{N}(\hat{\theta}_0, Q_0^{-1})$

IT: ~~update~~

$Q_n = Q_{n-1} + \phi_n \phi_n^T$

$\hat{\theta}_n = \hat{\theta}_{n-1} + Q_n^{-1} \phi_n (y_n - \phi_n^T \hat{\theta}_{n-1})$

$$\hat{\theta}_n = \arg$$

min
 θ

$$\underbrace{\sum_0^k (\theta - \hat{\theta}_0)^T Q_0 (\theta - \hat{\theta}_0)} + \underbrace{\sum_{i=1}^k (y_i - \phi_i^T \theta)^2}$$

↑ cov
 Q_0 : INF.

$$Q_u = Q_{u-1} + \Phi_u \Phi_u^T$$

$$= Q_{u-1} + (C_u A_{u-1} \dots A_0)^T (C_u A_{u-1} \dots A_0)$$

$$\Phi_u^T = C_u \cdot A_{u-1} \dots A_0$$

$$\hat{\Theta}_u = \hat{\Theta}_{u-1} + Q_u^{-1} (C_u A_{u-1} \dots A_0)^T (y_u - C_u A_{u-1} A_{u-2} \dots A_0 \hat{\Theta}_{u-1})$$

$$\hat{\Theta}_u \equiv \hat{x}_{[0|u]}$$

"AT TIME u"

NEW NOTATION: $\hat{x}_{[k|m]}$: ESTIM. OF STATE AT TIME k
GIVEN ALL MEASUREMENTS UP TO TIME m

$$\hat{x}_{[k|m]} = A_{u-1} \cdot A_{u-2} \dots A_0 \hat{\Theta}_m$$

$$= A_{u-1} \dots A_0 \cdot \hat{x}_{[0|m]}$$

$$\text{cov}(\hat{x}_{[k|m]}) = (A_{k-1} \dots A_0) Q_m^{-1} (A_0^T \dots A_{u-1}^T)$$

$$=: P_{[k|m]}$$

$$\hat{x}_{[k|k]} = A_{u-1} \dots A_0 \cdot \hat{\Theta}_k = \underbrace{A_{u-1} \cdot A_{u-2} \dots A_0 \hat{\Theta}_{k-1}}_{\hat{x}_{[k|k-1]}} + \underbrace{(A_{u-1} \dots A_0) Q_k^{-1} (A_0^T \dots A_{u-1}^T) C_k^T}_{P_{[k|k]}} (y_k - C_k \cdot A_{u-1} \dots A_0 \hat{\Theta}_{k-1})$$

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

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

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

$$P_{[k|k]} = \cancel{P_{[k|k]}} \quad \cancel{P_{[k|k-1]}} \quad A_{k-1} \dots A_0 Q_0^{-1} A_0^T \dots A_{k-1}^T$$

$$\hat{x}_{[k|k]} \\ P_{[k|k]}$$

$$Q_k = Q_{k-1} + (A_0^T \dots A_{k-1}^T) C_k^T C_k (A_{k-1} \dots A_0) \cdot (\quad)^{-1}$$

$$(A_{k-1} \dots A_0)^{-T} Q_k (A_{k-1} \dots A_0)^{-1} = (A_{k-1} \dots A_0)^{-T} Q_{k-1} (A_{k-1} \dots A_0)^{-1} + C_k^T C_k$$

(ASS: $(A_{k-1} \dots A_0)$ INVERTIBLE)

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

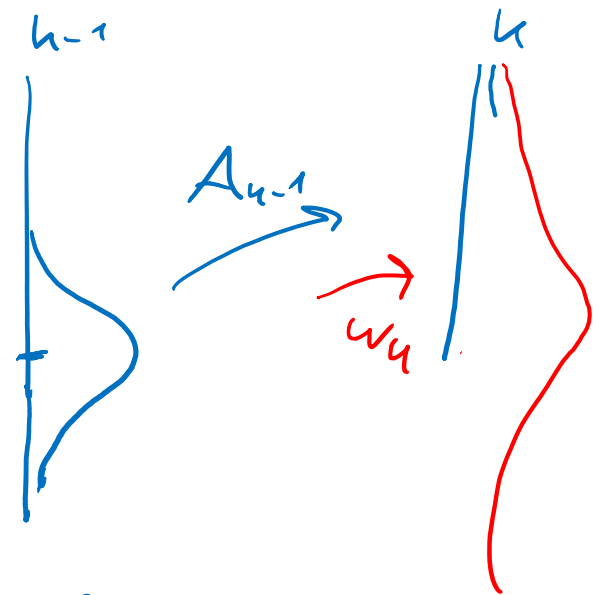
$$P_{[k|k]} = (P_{[k|k-1]}^{-1} + C_k^T C_k)^{-1}$$

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

(A) PREDICTION STEP (BEFORE MEASUREMENT):

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

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



(B) INNOVATION UPDATE STEP (AFTER MEASUREMENT):

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

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

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

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

9.3 KALMAN FILTER

GIVEN MODEL

$$\begin{aligned} x_{k+1} &= A_k \cdot x_k + w_k \\ y_k &= C_k \cdot x_k + v_k \end{aligned}$$

+ b_k KNOWN AFFINE DRIFT TERMS

STATE

NOISE: $w_k \sim N(0, W_k)$

MEASUREMENT

NOISE: $v_k \sim N(0, V_k)$

VERY SIMPLE IF $A_k \equiv A$
 (CONSTANT IN TIME) $C_k \equiv C$
 $W_k = W$
 $V_k = V$
 $P_{[k|k]} \rightarrow P$ (SOL ALG. RICK. ETC.)

① PREDICTION STEP (AS BEFORE)

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

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

② INNOV.

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

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

FOR CONST. MATRICES

$$P_{[k|k]} \stackrel{!}{=} P_{[k-1|k-1]} \stackrel{!}{=} P$$

$$P = \left((A P A^T + W)^{-1} + C^T V^{-1} C \right) \quad (\text{ALG. RICC. EQ.})$$

$$\hat{x}_{[k|k]} = \underbrace{A}_{=} \cdot \hat{x}_{[k-1|k-1]} + \underbrace{\delta_k}_{} + \underbrace{P \cdot C^T \cdot V^{-1}}_{=: L} \left(\underbrace{y_k}_{=} - C \cdot A \cdot \hat{x}_{[k-1|k-1]} \right)$$