NOW WE CAN FORM THE KALMAN FILTER ITERATION (RECURSION)

PRIOR ESTIMATES $\hat{X}_0(-), P_0(-)$

$\Downarrow$ $k=0$

CAN USE A's OR B's

① COMPUTE KALMAN GAIN

(1A) $$L_K = P_K(-)\, C_d^T \left[C_d\, P_K(-)\, C_d^T + R_K \right]^{-1}$$

(1-B1) OR.

$$P_K(+) = \left[P_K^{-1}(-) + C_d^T R_K^{-1} C_d \right]^{-1}$$

(1-B2) and.

$$L_K = P_K(+)\, C_d^T R_K^{-1}$$

② UPDATE ESTIMATE WITH Y_K

$$\hat{X}_K(+) = \hat{X}_K(-) + L_K\left(Y_K - C_d \hat{X}_K(-)\right)$$

③ UPDATE COVARIANCE.

(3A) $$P_K(+) = \left(I - L_K C_D\right) P_K(-)$$

OR

(3B) SAME AS 1-B1 !

PROPAGATE TO NEXT TIME (-)

(4-A1) $$\hat{X}_{K+1}(-) = A_d \hat{X}_K(+) + \left(B_d U_K\right)$$

(4-A2) $$P_{K+1}(-) = A_d P_K(+) A_d^T + Q_K$$

$K \leftarrow K+1$

EASY TO PERFORM ON DIGITAL COMPUTER.

Kalman Filter Steps

(1) Form & store the continuous system model

$$\dot{x} = Ax + B_w w_1 \quad ; \quad y = Cx + \nu$$

(2) If w_1 is colored process noise $\longrightarrow$ convert to augmented white noise driven continuous model

(3) Use C matrix Trick to find Q_d $\left(C = expm(S\Delta t)\right)$

(4) Use an initial state uncertainty estimate (P) and state estimate $(\hat{x})$

~~(5) Kalman Filter (p. 10-4)~~

(5) Look @ $\left(y_k - C_d \hat{x}_k\right)$ to get a "feel" for the process noise

(6) Simulate:

$$x_{k+1} = A_d x_k + G_d w_{k-1}$$

$$y_{k+1} = C_d x_k + \nu_k$$

$$w_{k-1} = sqrtm(Q_d)\,(randn(n,1))$$

$$G_d = I$$

(7) Kalman Filter (p. 10-1)

Note: Can Reinitialize P_k every so often

$$P_k = \frac{1}{2}\left(P_k + P_k^T\right)$$

(8) Check design w/ Incorrect Model $\hat{A}_d, \hat{Q}_d, \hat{R}_d$