

Lecture 12 CE 697 Adv. Data Adj. 12-1  
Tues. 12 July 2016

next class Thurs. 14<sup>th</sup>

Schedule

5	M	T	W	Th	F	S
	11	12	13	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	29	30
31	1	2	3	4	5	6
7	8	9	10	11	12	13

grades due  
22<sup>nd</sup>

Kalman Filter 3 examples:

- 1 linear tracking target in image
- 2 NL radar tracking
- 3 NL attitude estimation

Jul 12-7:16 PM

Seq. LS — adding rows to B matrix 12-2  
usual interp.

can also add columns to B matrix  
example is adding new obs. or photos of  
new point

missing:

- (1) state vector, new copy @ each epoch
- (2) dynamic model (Eq. of Motion)

KF is really just Seq. Linear LS with 3 kinds of eq.

(1) observation

(2) error propagation

(3) prediction equation

NL KF	linearized	LKF
	extended	EKF
	iteratively extended	IEKF
	unscented	UKF

Jul 12-7:16 PM

our instinct from NL LS - make Taylor series approx, then left with "incremental" (correctors)  
 $\Delta x_j, \Delta \beta_j, \dots$  to refine full parameters  
 $x_j, \beta$

often in practice with NL KF, there are techniques to keep full variables.

good reference: KF for beginners  
 w/ matlab examples  
 Phil Kim  
 AUTN Publ. 2010

ls-kf.pdf LS  $\rightarrow$  conv. eqns for KF

12-3

Jul 12-7:16 PM

epoch 1  $B_1 x_1 = f_1$  obs  $R$  12-4  
 $x_2 = \Phi_1 x_1$  prediction  $Q$

---

epoch 2  $B_2 x_2 = f_2$   
 $x_3 = \Phi_2 x_2$

---

epoch 3  $B_3 x_3 = f_3$   
 $x_4 = \Phi_3 x_3$

!

$x_1$	$x_2$	$x_3$	$x_4$	$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix}$	$=$	$\begin{bmatrix} f_1 \\ 0 \\ f_2 \\ 0 \\ f_3 \\ 0 \\ f_4 \end{bmatrix}$
$B_1$	$\Phi_1$	$I$	$\dots$			
$\dots$	$B_2$	$\Phi_2$	$I$			
$\dots$	$\dots$	$B_3$	$\Phi_3$	$I$		
$\dots$	$\dots$	$\dots$	$\Phi_4$	$I$		
$\dots$	$\dots$	$\dots$	$\dots$	$B_4$		

Gilbert Strang

[ it theory would do big batch LS solutions ]

Jul 12-7:16 PM

Linear Case KF algo 12-5

$$z_k = H_k x_k + v_k \quad (v \sim \mathcal{B}_0 = f)$$

$$E(v_k v_j^T) = \begin{cases} R_k & j=k \\ 0 & j \neq k \end{cases}$$


---


$$x_{k+1} = \Phi_k x_k + w_k$$

$$E(w_k w_j^T) = \begin{cases} Q & \text{if } j=k \\ 0 & j \neq k \end{cases}$$


---


$$\hat{x}_{k+1}^- = \Phi_k \hat{x}_k^-$$

$$P_{k+1}^- = \Phi_k P_k \Phi_k^T + Q$$

Process model for  $x$

$$Y = Ax$$

$$z_{yy} = A S_{xx} A^T$$

Jul 12-7:16 PM

need to start  $\hat{x}_0^-$ ,  $P_0^-$  initial values 12-6

compute k. gain

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

update est w/ new meas.

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - H \hat{x}_k^-)$$

cov. for updated est.

$$P_{1k} = (I - K_k H_k) P_k^-$$

project ahead

$$\hat{x}_{k+1}^- = \Phi_k \hat{x}_k$$

$$P_{1k+1}^- = \Phi_k P_{1k} \Phi_k^T + Q$$

state vector  $\begin{bmatrix} x \\ y \end{bmatrix}$   $\begin{bmatrix} \hat{x} \\ \hat{y} \end{bmatrix}$   $\begin{bmatrix} x \\ \hat{x} \\ \hat{y} \\ y \\ \hat{y} \end{bmatrix}$  ...  $x$  is state vector

Jul 12-7:16 PM

KF algo for Nonlinear case (EKF) 12-7

$$z_k = h(x_k) + v_k, \quad h(x_k) \text{ is NL, } R$$

$$H = \frac{\partial h}{\partial x}$$


---


$$x_{k+1} = \Phi(x_k) + w_k \quad \Phi(x) \text{ is NL } \Phi$$

$$\Phi = \frac{\partial \Phi}{\partial x}$$


---


$$Hx \rightarrow h(x)$$

$$\Phi x \rightarrow \Phi(x)$$

Note: revised some things here. will be inconsistent with video. This is better notation. mostly replace  $g$  with  $\Phi$  replace  $G$  with  $\Phi$

Jul 12-7:16 PM

$\hat{x}_0^-, P_0^-$  12-8

comp k. gain

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \quad H = \frac{\partial h}{\partial x} \Big|_{\hat{x}}$$

update state ved. est.

$$\hat{x}_k = \hat{x}_k^- + K_k (z_k - h(\hat{x}_k^-))$$

empy prop

$$P_k = P_k^- - K_k H P_k^-$$

project ahead

$$\hat{x}_{k+1}^- = \Phi(\hat{x}_k)$$

edits here as well

$$P_{k+1}^- = \Phi P_k \Phi^T + Q$$

Jul 12-7:16 PM