

Lecture 13 ce697 Adv. Data Adj. | 3-1
14 July 2016, Thursday

Next meeting: Tuesday 19th
then decide whether we need to meet on 21st

Review some edits made to notes for Lect. 12

$$\dot{x} = f(x) \quad \left. \begin{array}{l} \text{integration} \\ \text{num. solution of Diff Eq. 1 step} \\ \text{convert to predictor formula} \end{array} \right\}$$

$$x_{i+1} = \Phi(x_i)$$

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

u.c. l.c.

$$\bar{P}_{i+1} = \Phi_i \bar{P}_i \Phi_i^T + Q$$

Reference
KF, LS, and
Modeling
- Bruce Gibbs
Wiley, 2011

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Dynamic Models 13-2
⇒ Diff. Equations
Kinematics of Motion

We need, predictor formula $x_{i+1} = \Phi x_i$
 $x_{i+1} = \Phi(x_i)$

linear $\dot{x} = Ax$
nonlinear $\dot{x} = f(x)$

→ example constant velocity model 1 axis

$$\begin{bmatrix} \dot{p} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} p \\ v \end{bmatrix}$$

$$\dot{x} = Ax$$

(Euler method)

$$\begin{bmatrix} p \\ v \end{bmatrix}_{k+1} = \begin{bmatrix} p \\ v \end{bmatrix}_k + \begin{bmatrix} \dot{p} \\ \dot{v} \end{bmatrix} \Delta t$$

$$\begin{bmatrix} p \\ v \end{bmatrix}_{k+1} = \begin{bmatrix} p \\ v \end{bmatrix}_k + \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} p \\ v \end{bmatrix} \Delta t$$

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$$\begin{pmatrix} p \\ v \end{pmatrix}_{k+1} = \begin{bmatrix} I + \begin{bmatrix} 0 & \Delta t \\ 0 & 0 \end{bmatrix} \end{bmatrix} \begin{pmatrix} p \\ v \end{pmatrix}_k \quad |3-3$$

$$\begin{pmatrix} p \\ v \end{pmatrix}_{k+1} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{pmatrix} p \\ v \end{pmatrix}_k$$

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

Example constant accel. model w/ improved euler method

$$\begin{pmatrix} \dot{p} \\ \dot{v} \\ \dot{a} \end{pmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} p \\ v \\ a \end{pmatrix}, \quad \begin{pmatrix} \ddot{p} \\ \ddot{v} \\ \ddot{a} \end{pmatrix} = \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} p \\ v \\ a \end{pmatrix}$$

$$x_{k+1} = x_k + \dot{x} \Delta t + \ddot{x} \frac{(\Delta t)^2}{2!} + \dots$$

$$\begin{pmatrix} p \\ v \\ a \end{pmatrix}_{k+1} = \begin{pmatrix} p \\ v \\ a \end{pmatrix}_k + \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} p \\ v \\ a \end{pmatrix}_k \Delta t + \begin{bmatrix} 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} p \\ v \\ a \end{pmatrix}_k \Delta t^2$$

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$$\begin{pmatrix} p \\ v \\ a \end{pmatrix}_{k+1} = \left[\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} + \begin{bmatrix} 0 & \Delta t & 0 \\ 0 & 0 & \Delta t \\ 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & \Delta t^2/2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \right] \begin{pmatrix} p \\ v \\ a \end{pmatrix}_k \quad |3-4$$

$$\begin{pmatrix} p \\ v \\ a \end{pmatrix}_{k+1} = \begin{bmatrix} 1 & \Delta t & \Delta t^2/2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} p \\ v \\ a \end{pmatrix}_k$$

$$x_{k+1} = \Phi x_k$$

$$\Phi = e^{A \Delta t} = I + A \Delta t + \frac{(A \Delta t)^2}{2!} + \frac{(A \Delta t)^3}{3!} + \dots$$

$$e^x = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

matlab expm

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What if model nonlinear? $\dot{x} = f(x)$ 135

euler steps: $x_{k+1} = x_k + \dot{x} \Delta t$
 $x_{k+1} = x_k + \underbrace{f(x) \Delta t}_{\Phi(x)}$

improved euler method:
 $x_{k+1} = x_k + \dot{x} \Delta t + \ddot{x} \frac{\Delta t^2}{2!} + \dots$
 $\underbrace{\hspace{10em}}_{\Phi(x)}$

runge-kutta 4th order also widely used

3 axis w/c.a. model

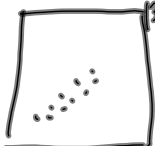
$$\begin{bmatrix} \dot{p}_x \\ v_x \\ a_x \\ p_y \\ v_y \\ a_y \\ \dot{p}_z \\ v_z \\ a_z \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & \phi & \phi \\ 0 & 0 & 1 & \phi & \phi \\ 0 & 0 & 0 & 0 & 0 \\ \phi & 0 & 1 & \phi & \phi \\ 0 & 0 & 0 & 0 & 0 \\ \phi & \phi & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_x \\ v_x \\ a_x \\ p_y \\ v_y \\ a_y \\ p_z \\ v_z \\ a_z \end{bmatrix}$$

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description of model for first HW prob. 136

constant vel. model

state vector = $\begin{bmatrix} p_x \\ v_x \\ p_y \\ v_y \end{bmatrix}$



C.V. model

$$\begin{bmatrix} \dot{p}_x \\ \dot{v}_x \\ \dot{p}_y \\ \dot{v}_y \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} p_x \\ v_x \\ p_y \\ v_y \end{bmatrix}, \quad \dot{x} = Ax$$

$$\Phi = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} p_x \\ v_x \\ p_y \\ v_y \end{bmatrix}_{k+1} = \Phi \begin{bmatrix} p_x \\ v_x \\ p_y \\ v_y \end{bmatrix}_k$$

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measurement / obs. model

13-7

$$z_k = H_k x_k + v_k$$

$$\begin{pmatrix} x_{\text{obs.}} \\ y_{\text{obs.}} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} p_x \\ v_x \\ p_y \\ v_y \end{pmatrix}$$

H

linear KF algo

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

obs. pred obs.

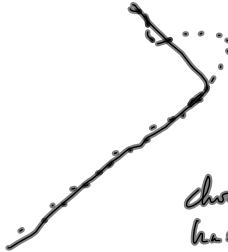
misclosure

$$\text{compare to } R : \begin{pmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{yx} & \sigma_y^2 \end{pmatrix}$$

compute σ_x, σ_y

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should look out for divergence from model 13-8



one approach to address this
 run multiple filters in parallel
 choose the lowest order model which
 has acceptable misclosure.

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