

### Discretizing Motion Models Sensor Fusion

#### Fredrik Gustafsson fredrik.gustafsson@liu.se

Gustaf Hendeby gustaf.hendeby@liu.se

Linköping University

## Purpose

To make physical models derived in continuous time useful in filtering and sensor fusion applications.

- Given a continuous time physical model  $\dot{x}(t) = Ax(t) + Bu(t)$
- How to get a discrete time model  $x_{k+1} = Fx_k + Gu_k$ ?
- General methodology for discretizing (sampling) linear and nonlinear continuous time models.
- Examples from sensor fusion practice to illustrate.

イロト イロト イヨト イヨト ヨー シック

# Solving an ODE

What is the solution to the ODE  $\dot{x} = Ax + Bu$ ? Same methodology as in scalar case in calculus.

- 1. Multiply with integrating factor  $e^{-At}$  on both sides
- 2. Note that

$$\frac{d}{dt}\left(e^{-At}x(t)\right) = e^{-At}\left(\dot{x}(t) - Ax(t)\right)$$

3. Then, the solution by integrating both sides of

$$\int_0^t \frac{d}{ds} \left( e^{-As} x(s) \right) = \int_0^t e^{-As} u(s) ds$$

4. The solution is

$$x(t) = e^{At}x(0) + \int_0^t e^{-A(s-t)}u(s)ds$$

5. We get  $F = e^{AT}$  and, if u is piece-wise constant,  $G = \int_0^T e^{A\tau} d\tau B$ .

#### Example 1: Newton's II law (revisited)

Linear motion governed by Newtons II law,  $F = ma = m\ddot{X}$ . Using  $x = (p, v)^T$ ,

$$\dot{x} = \begin{pmatrix} v \\ a \end{pmatrix} = \begin{pmatrix} x_2 \\ \frac{F}{m} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} x + \begin{pmatrix} 0 & \frac{1}{m} \end{pmatrix}^T u = Ax + Bu$$

Solving the ODE over one sampling interval T gives

$$F = e^{AT} = I + AT + \frac{1}{2}A^2T^2 + \dots = \begin{pmatrix} 1 & T \\ 0 & 1 \end{pmatrix} \quad \{A^2 = 0\}$$
$$G = \int_0^T e^{A\tau} d\tau \begin{pmatrix} 0 \\ \frac{1}{m} \end{pmatrix} = \int_0^T \begin{pmatrix} 1 & \tau \\ 0 & 1 \end{pmatrix} d\tau \begin{pmatrix} 0 \\ \frac{1}{m} \end{pmatrix} = \begin{pmatrix} \frac{1}{2}T^2 \\ T \end{pmatrix} \frac{1}{m}.$$

◆□▶ ◆□▶ ◆三▶ ◆三▶ 三三 - のへぐ

# Inter-sample behaviour

How to treat the input u (control signal or process noise) in a linear continuous time model when discretizing

$$\dot{x} = Ax + Bu, \qquad x_{k+1} = Fx_k + Gu_k y = Cx + e, \qquad y_k = Hx_k + Ju_k + e_k$$

•  $F = e^{AT}$  is the unique solution to the ODE.

But G depends on the assumption or knowledge of the inter-sample behaviour. Most important assumptions:

- Piece-wise constant input: ZOH, zero order hold.
- Piece-wise linear input: FOH, first order hold.
- Band-limited according the the Nyquist criterium: BIL, the bilinear transformation.
- Use c2d in Matlab for converting a linear continuous time model to a linear discrete time model.
- It also holds that H = C, the measurement relation does not change with discretization, but note the input leakage term  $Ju_k$  that may appear.

### **Different Sampled Models of Double Integrator**

Models  $\dot{x} = Ax + Bu$  $x_{k+1} = Fx_k + Gu_k$ v = Cx + Du $v_k = H x_k + J u_k$ State:  $x = \begin{pmatrix} p(t) \\ y(t) \end{pmatrix}$ Continuous  $A = \begin{pmatrix} 0_n & I_n \\ 0_n & 0_n \end{pmatrix} \qquad B = \begin{pmatrix} 0_n \\ I_n \end{pmatrix} \qquad C = (I_n, 0_n) \qquad D = 0_n$ time  $F = \begin{pmatrix} I_n & TI_n \\ 0_n & I_n \end{pmatrix} \quad G = \begin{pmatrix} \frac{T^2}{2}I_n \\ TI_n \end{pmatrix} \quad H = (I_n, 0_n) \qquad J = 0_n$ ZOH  $F = \begin{pmatrix} I_n & TI_n \\ 0_n & I_n \end{pmatrix} \quad G = \begin{pmatrix} T^2 I_n \\ TI_n \end{pmatrix} \quad H = (I_n, 0_n) \quad J = \frac{T^2}{6} I_n$  $F = \begin{pmatrix} I_n & TI_n \\ 0_n & I_n \end{pmatrix} \quad G = \begin{pmatrix} \frac{T^2}{4} I_n \\ \frac{T}{2} I_n \end{pmatrix} \quad H = (I_n, \frac{T}{2} I_n) \quad J = \frac{T^2}{2} I_n$ FOH BIL

< □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □ > < □

### Translational Motion with *n* Integrators

Translational kinematics models in nD, where p(t) denotes:

- Position: X(t),  $(X(t), Y(t))^T$ , or  $(X(t), Y(t), Z(t))^T$
- Rotation:  $\psi(t)$  or  $(\phi(t), \theta(t), \psi(t))^T$

The signal w(t) is process noise for a pure kinematic model and a motion input signal in position, velocity, and acceleration, respectively, for the case of using sensed motion as an input rather than as a measurement.

State, x	Continuous time, 🗴	Discrete time, $x(t + T)$
р	W	x + Tw
$\begin{pmatrix} p \\ v \end{pmatrix}$	$\begin{pmatrix} 0_n & I_n \\ 0_n & 0_n \end{pmatrix} \times + \begin{pmatrix} 0_n \\ I_n \end{pmatrix} w$	$\begin{pmatrix} I_n & TI_n \\ 0_n & I_n \end{pmatrix} \times + \begin{pmatrix} \frac{T^2}{2} I_n \\ TI_n \end{pmatrix} w$
$\begin{pmatrix} p \\ v \\ a \end{pmatrix}$	$\begin{pmatrix} 0_n & I_n & 0_n \\ 0_n & 0_n & I_n \\ 0_n & 0_n & 0_n \end{pmatrix} \times + \begin{pmatrix} 0_n \\ 0_n \\ I_n \end{pmatrix} w$	$\begin{pmatrix} I_n & TI_n & \frac{T^2}{2}I_n \\ 0_n & I_n & TI_n \\ 0_n & 0_n & I_n \end{pmatrix} x + \begin{pmatrix} \frac{T^3}{6}I_n \\ \frac{T^2}{2}I_n \\ TI_n \end{pmatrix} w$

# Nonlinear models

Classification	Nonlinear	Linear
Continuous time	$\dot{x} = a(x, u) + v$	$\dot{x} = Ax + Bu + v$
	y = c(x, u) + e	y = Cx + Du + e
Discrete time	$x_{k+1} = f(x, u) + \bar{v}$	$x_{k+1} = Fx + Gu + \bar{v}$
	y = h(x, u) + e	y = Hx + Ju + e

- Nonlinear filters require a discrete time model.
- The Kalman filter requires a linear discrete time model.
- There are two paths from a nonlinear continuous time model to a linear discrete time model:
  - Discretized linearization: LInearize first, then apply the explicit discretization formulas.
  - Linearized discretization: Try to discretize first, and then linearize.

# Exact Discretization of Coordinated Turn Models

- Coordinated turn models popular in target tracking applications.
- Good compromize between model flexibility and simplicity.
- Possibility of exact sampling one reason for its success.
- Exact sampling even possible for two different choices of state vectors:
  - *Polar velocity* with speed v and heading h as states.
  - Cartesian velocity with  $v^X, v^Y$  as states.



San

► < Ξ >

< E.

# Coordinated Turns in 2D World Coordinates

Cartesian velocity	Polar velocity				
$\dot{X} = v^X$	$\dot{X} = v \cos(h)$				
$\dot{Y} = v^{Y}$	$\dot{Y} = v \sin(h)$				
$\dot{oldsymbol{v}}^{oldsymbol{X}}=-\omegaoldsymbol{v}^{oldsymbol{Y}}$	$\dot{v} = 0$				
$\dot{\mathbf{v}}^{\mathbf{Y}} = \omega \mathbf{v}^{\mathbf{X}}$	$\dot{m{h}}=\omega$				
$\dot{\omega}=0$	$\dot{\omega} = 0$				
$\begin{pmatrix} 0 & 0 & 1 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & \cos(h) & -v\sin(h) & 0 \end{pmatrix}$				
	$0  0  \sin(h)  v \cos(h)  0$				
$A = \begin{bmatrix} 0 & 0 & 0 & -\omega & -v^Y \end{bmatrix}$	$A = \begin{bmatrix} 0 & 0 & 0 & 0 \end{bmatrix}$				
$0 0 \omega 0 v^{X}$					
$\begin{pmatrix} 0 & 0 & 0 & 0 \end{pmatrix}$	(0 0 0 0 0 <i>)</i>				
$\overline{X_{t+T} = X + \frac{v^X}{\omega}\sin(\omega T) - \frac{v^Y}{\omega}(1 - \cos(\omega T))} X_{t+T} = X + \frac{2v}{\omega}\sin(\frac{\omega T}{2})\cos(h + \frac{\omega T}{2})$					
$Y_{t+T} = Y + \frac{v^X}{\omega}(1 - \cos(\omega T)) + \frac{v^Y}{\omega}\sin(\omega T)  Y_{t+T} = Y - \frac{2v}{\omega}\sin(\frac{\omega T}{2})\sin(h + \frac{\omega T}{2})$					
$v_{t+T}^X = v^X \cos(\omega T) - v^Y \sin(\omega T)$	$v_{t+T} = v$				
$v_{t+T}^Y = v^X \sin(\omega T) + v^Y \cos(\omega T)$	$h_{t+ au} = h + \omega T$				
$\omega_{t+T} = \omega$	$\omega_{t+T} = \omega$				

◆□ ▶ ◆昼 ▶ ◆臣 ▶ ◆臣 ● ○ ○ ○ ○ ○

# Summary

Classification	Nonlinear	Linear
Continuous-time	$\dot{x} = a(x, u) + v$	$\dot{x} = Ax + Bu + v$
	y = c(x, u) + e	y = Cx + Du + e
Discrete-time	$x_{k+1} = f(x, u) + v$	$x_{k+1} = Fx + Gu + v$
	y = h(x, u) + e	y = Hx + Ju + e

Discetized linearization: Linearize

$$A = a'_x(x, u), \quad B = a'_u(x, u), \quad C = c'_x(x, u), \quad D = c'_u(x, u),$$

and sample:  $F = e^{AT}$ ,  $G = \int_0^T e^{At} dt B$  (ZOH), H = C and J = D.

■ Linearized discretization: Sample by solving (if and when possible) the integral

$$x(t+T) = f(x(t), u(t)) = \int_t^{t+T} a(x(\tau), u(\tau)) d\tau,$$

and then linearize using  $F = f'_x(x_k, u_k)$  and  $G = f'_u(x_k, u_k)$ .

Statistical Sensor Fusion

Chapter 12

- ▲ ロ ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 回 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ 国 ▶ ▲ ■

11 / 11