

TAM 598 Lecture 20:

State Space Models - Kalman Filters

Announcements:

- HW 5 covers lectures 17-20; due on Fri Apr 18

last time:

initial conditions $\underline{x}_0 = \underline{u}_0 + \underline{z}_0$

transitions $\underline{x}_{t+1} = \underline{A} \underline{x}_t + \underline{B} \underline{u}_t + \underline{z}_t$

emissions $y_t = C x + w_t$

Kalman Filter - recursively computes the posterior distribution
 $P(\underline{x}_t | \underline{y}_{1:t}, \underline{u}_{1:t})$ using two steps:

prediction step goal $p(\underline{x}_t | \underline{y}_{1:t-1}, \underline{u}_{1:t})$

say we have $p(\underline{x}_{t-1} | \underline{y}_{1:t-1}, \underline{u}_{1:t-1}) = N(\underline{x}_{t-1} | \underline{\mu}_{t-1}, \underline{V}_{t-1})$

we use our update rules and marginalize over \underline{x}_{t-1} :

update step

goal: $p(\underline{x}_t | \underline{y}_{1:t}, \underline{u}_{1:t})$

we now condition our prior on a new measurement \underline{y}_t
to obtain the posterior using Bayes' Rule:

SMOOTHING - now we want the posterior $p(\underline{x}_t \mid \underline{y}_{1:T}, \underline{u}_{1:T})$
of the distribution of the state at t , given all measurements
and control inputs up to some future time T .

$$p(\underline{x}_{T-1} | \underline{x}_T, \underline{y}_{1:T}, \underline{u}_{1:T})$$

from here:

- ① our joint distribution $P(\underline{x}_T, \underline{x}_{T-1} \mid \underline{y}_{1:T}, \underline{x}_{1:T})$ is gaussian
- ② integrate out \underline{x}_T to get our smoothed distribution

- ③ Result is gaussian with
mean
covariance