

Lecture 19: Model Systems w/ Stochasticity

So far $\dot{x} = f(x, u)$ $x[n+1] = f(x[n], u[n])$
 $\dot{x} = f(x, u, w)$ $x[n+1] = f(x[n], u[n], w[n])$

$w[n]$ output of some
random process

$w[n]$

- disturbances
- model uncertainty

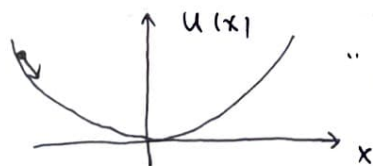
also known as process noise
distinct from measurement noise

Additive noise:

$$x[n+1] = f(x[n], u[n]) + B_w w[n]$$

Ex. Particle in a bowl

w/ Brownian motion



$$U(x) = \frac{1}{2} \alpha x^2$$

$$x[n+1] - x[n] = - \left. \frac{\partial U}{\partial x} \right|_{x[n]} + w[n]$$

$$\frac{\partial U(x)}{\partial x} = \alpha x$$

$$x[n+1] = (1 - \alpha) x[n] + w[n]$$

$$w = 0 \quad \text{fixed pt } x^* = 0$$

Exp stable for $0 < \alpha < 2$

$w[n]$ is Gaussian white noise (i.i.d)

$$E[w[n]] = 0 \quad E[w[i]w[j]] = \begin{cases} \sigma^2 & i=j \\ 0 & \text{otherwise} \end{cases}$$

Given $x[0]$ what is $x[n]$? what is $x[\infty]$?

$x[n]$ is a random variable

described by $P_{x[n]}(\cdot)$ density function

$$P_w(w) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{w^2}{2\sigma^2}}$$

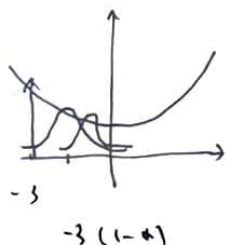
$$P_{x[n+1]|x[n],w[n]}(x[n+1]|x[n],w[n])$$

$$= P_{x[n+1]|x[n]}(x[n+1]|x[n]) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(y - (1-\alpha)x)^2}{2\sigma^2}}$$

"master eq"

$$P_{x[n+1]}(y) = \int_{-\infty}^{\infty} P_{x[n+1]|x[n]}(y|x) P_{x[n]}(x) dx$$

Gaussian ← Gaussian + it Gaussian



$$x[0] = -3$$

$$P_{x[0]}(x) = \delta(x+3)$$

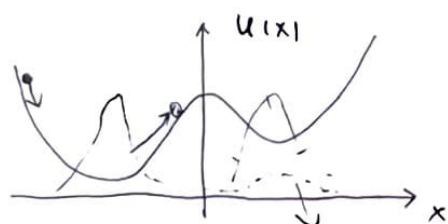
$P_{x[1]}$ Gaussian centered $-3(1-\alpha)$

distribution goes to a fixed point

Steady state distribution $P_{x^*}(\cdot)$

$$\mu^* = 0, (\sigma^*)^2 = \frac{\sigma^2}{2\alpha - \alpha^2}$$

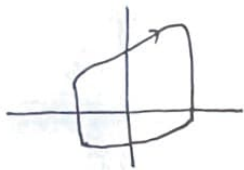
Nonlinear dynamics



"escape attempts"

final distribution

thought experiment:



Van der Pol oscillator with Gaussian noise

close to even on steady cycle



rimless wheel on rough terrain

$\alpha[n] \sim \text{Gaussian}$

Apex-to-apex

Poincaré map



a range of possible next state

Stationary distribution is standing still

no transition out, prob accumulates

"meta-stable" distribution

long-living transients in $P_x[n](\cdot)$

"mean first passage time" to another region

stability may not be a good metric

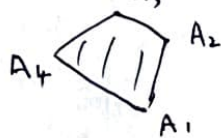
1) Worst case design / analysis

Typically for bounded uncertainty

$P_w(\cdot)$ has finite domain

e.g. via common Lyapunov function

$$\dot{x} = Ax \quad A = \sum_i \beta_i A_i \quad \sum_i \beta_i = 1, \beta_i \geq 0$$



for all $w \quad \dot{V} < 0 \quad$ Can be conservative

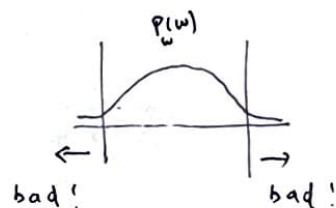
2) Stochastic control

with my objective on $P_{X[n]}()$

most common is expected performance

Risk - aware control

"chance constraints"



Expected Value

$$J = \sum_{n=0}^{\infty} g(x, u)$$

$$\min_{u(\cdot)} E[J] = \sum_{n=0}^{\infty} E[g(x, u)]$$

$$\text{now } J \text{ is a random variable} = \sum_{n=0}^{\infty} \left(\int_x g(x, u) P_X(x) dx \right)$$

compass gait \rightarrow J with stochasticity
policy is more robust

LQR problem J may not converge when sum to ∞
if never stabilize ~~around~~ goal

Stochastic LQR

$$x[n+1] = Ax[n] + Bu[n] + B_w w[n]$$

\uparrow non-zero

Gaussian iid

$$\min_u E \left[\sum_{n=0}^{\infty} x^T Q x + u^T R u \right]$$

$u = -Kx$ when is the same K as
deterministic LQR

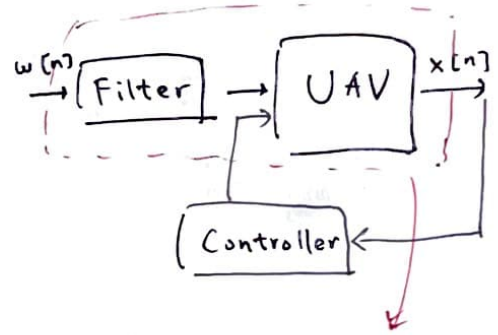
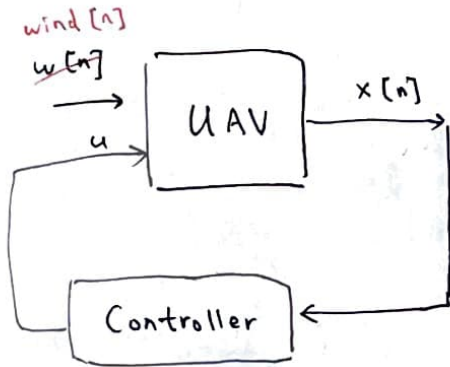
but control different for non-linear dynamics

$$J = \infty \quad x^T S x + c \quad \uparrow \quad \sum_{n=0}^{\infty} E[w[n] w^T[n]]$$

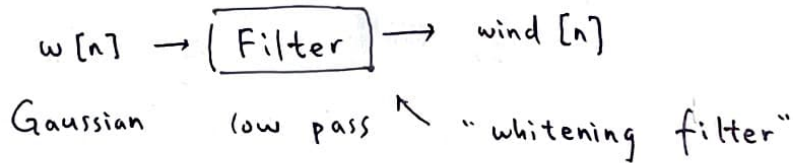
original S

stochastic changes
control law

Ex. A UAV in wind



wind is not Gaussian iid



system with i.i.d. input
do stochastic LQR

$u = -Kx$
↑
low pass filter
has state

No guaranteed margins for LQG Regulators

John C. Doyle 1978 paper