Introduction to State Space techniques

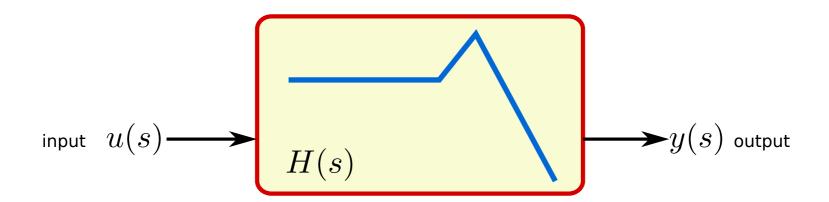
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GEO ISC meeting - December 2012

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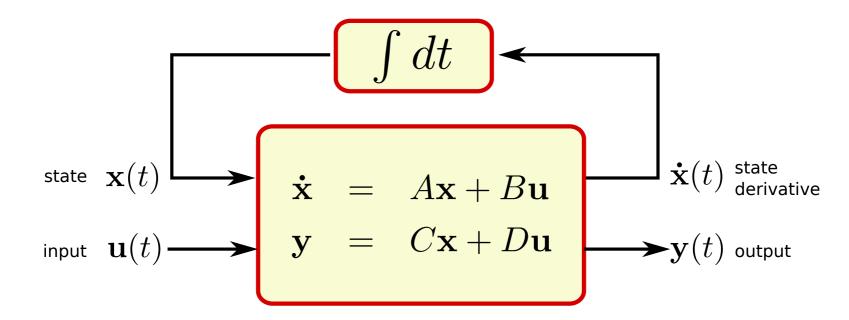


our friend the frequency domain



System represented as a linear transfer function

state space



System represented as a collection of coupled linear first-order differential equations.

A, B, C, D internal dynamics inputs state state $\mathbf{x}(t)$ $\dot{ extbf{X}}$ $A\mathbf{x} + B\mathbf{u}$ $C\mathbf{x} + D\mathbf{u}$ input $\mathbf{u}(t)$ $\mathbf{y}(t)$ output

"pass-through"

outputs

(i.e. sensors)

an example

$$\overbrace{F_{\text{ext}} - kx - \gamma \dot{x}}^{F} = \overbrace{m\ddot{x}}^{ma}$$

system state = {position, velocity}
$$\dot{\mathbf{X}}$$

$$egin{array}{c} oldsymbol{C} \\ y \end{array}) = egin{bmatrix} C \\ oldsymbol{1} & 0 \end{bmatrix} oldsymbol{C}$$

$$egin{array}{c|c} oldsymbol{D} & \mathbf{u} \ oldsymbol{u} & F_{ext} \end{array}$$

state estimation

Problem:

Not all state information is directly observable.

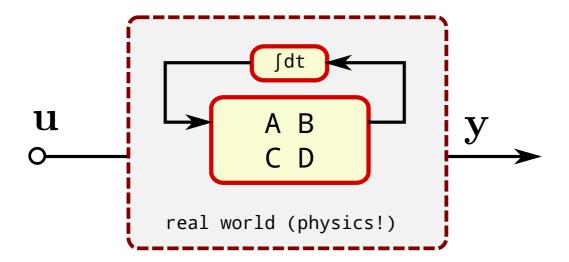
Example:

In a double suspension, you might only have sensors on one of the suspended masses.

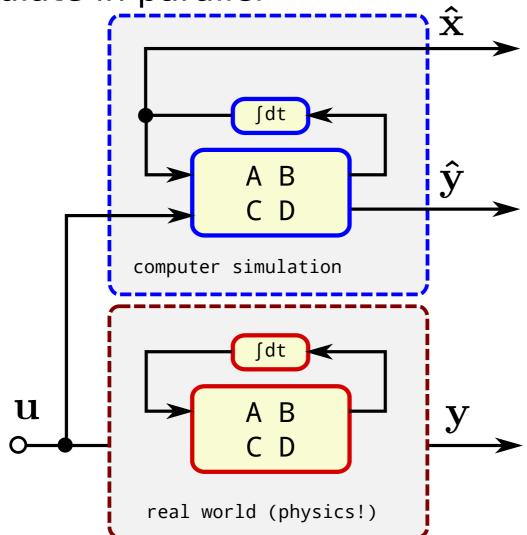
Solution:

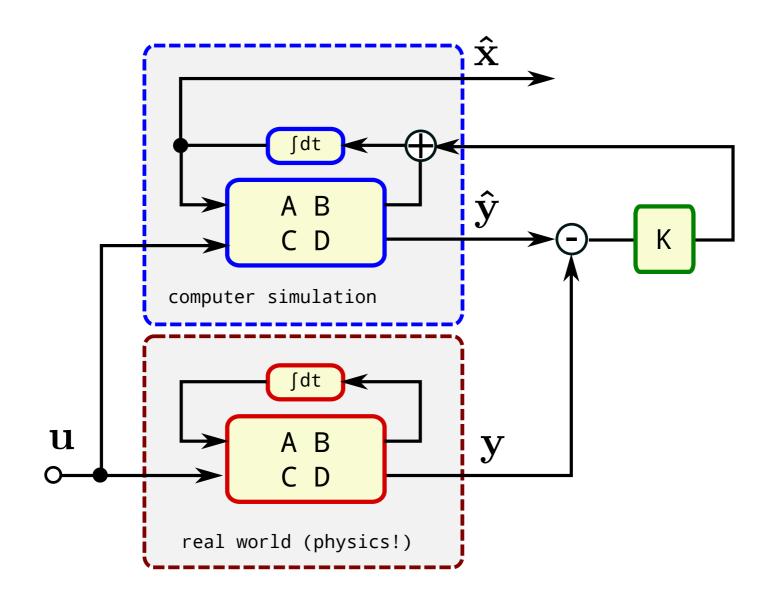
It turns out that there is a systematic way to estimate unsensed states.

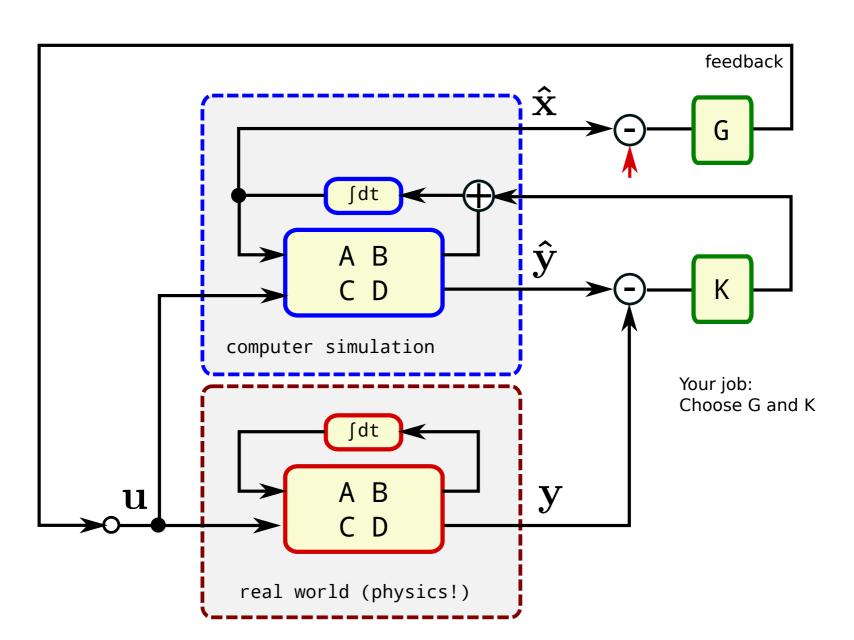
structure of state feedback...



simulate in parallel







robustness

Problem:

If your model does not match your system exactly, the resulting state estimator and controller might not work.

(See paper by Strain and Shapiro[1], and Fu's talk at the last GEO ISC meeting!)

Solution?

This seems to be an area of active research: "robust control".

Toy example

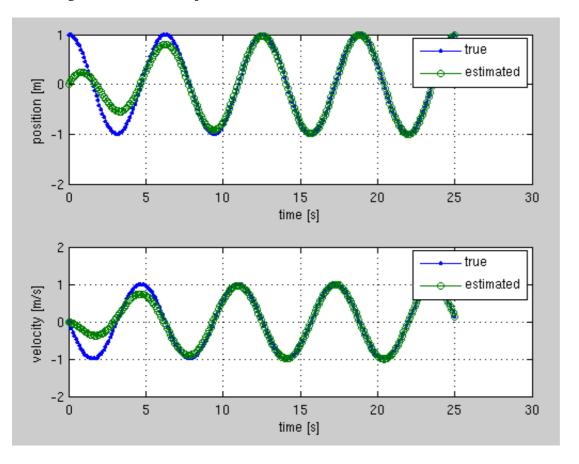
```
% State-Space Simple Harmonic Oscillator
1
2
3
4
       % This script simulates a damped simple harmonic oscillator (i.e. mass on a
       % spring) using a state-space description, and also implements a linear
5
       % observer.
7
       % Tobin Fricke
8
       % 2012-04-13
9
10
       % Parameters
11
12 -
       k = 1; % spring constant [m/s]
13 -
       m = 1: % mass [kg]
14 -
       b = 0: % damping constant [kg/m/s]
15
       % Define the state-space matrices
16
17
18
       % The dynamic system is defined by these matrices:
19
20
       % (d/dt) \times = A \times + B u
21
               v = C \times + D u
22
23
       % where
24
25
       % x: internal state
26
       % u: input to system
27
       % y: output from system
28
29 -
       A = [0 1; (-k/m) (-b/m)]; % state --> state derivative
30 -
       B = [0 ; (1/m)];
                                    % input --> state derivative
       C = \lceil 1 \ 0 \rceil:
                                    % state --> output
31 -
32 -
       D = 0;
                                    % input --> output
33
34
       % Define the gains matrix for the observer
35
36 -
       K = [0.5; -0.1];
                                    % residual --> state hat dot
37
38
       % Initial state
39
40 -
                                    % initial state
       x = [1 : 0]:
41 -
                                    % initial state estimate
       xhat = [0: 0]:
       t = 0;
                                    % initial time [s]
43 -
                                    % initial input
       u = 0:
```

```
% Simulation parameters
46
47 -
       N = 251:
                                    % number of time steps
48 -
       dt = 0.1;
                                   % time step [seconds]
49
50
       % allocate space for the results
51
52 -
       xs = nan(2, N):
                                    % time series of true state
53 -
       \timeshats = nan(2, N);
                                    % time series of estimated state
54 -
       ts = nan(1, N);
55
56
       % Do the simulation
57
     □ for ii=1:length(xs)
59
         % record the state
60 -
         xs(:. ii) = x:
61 -
         xhats(:,ii) = xhat:
62 -
         ts(ii) = t;
63
         % get the current outputs
         V = C^* \times + D^* u:
                                % output of physical system
         vhat = C*xhat + D*u; % expected output
67 -
                 = v - vhat;
                                    % residual
69
         % advance the state
70 -
               = e \times pm(A*dt)*(x + B*u*dt):
71 -
         xhat = expm(A*dt)*(xhat + B*u*dt + K*r*dt);
72 -
               = t + dt;
73
74 -
       end
75
76
       % Plot the results
77
78 -
       figure(1):
79 -
       subplot(2,1,1);
80 -
       plot(ts, xs(1,:), '.-', ts, xhats(1,:), 'o-');
       legend('true', 'estimated');
82 -
       ylabel('position [m]');
       xlabel('time [s]');
84 -
       arid on
85
86 -
       subplot(2,1,2);
```

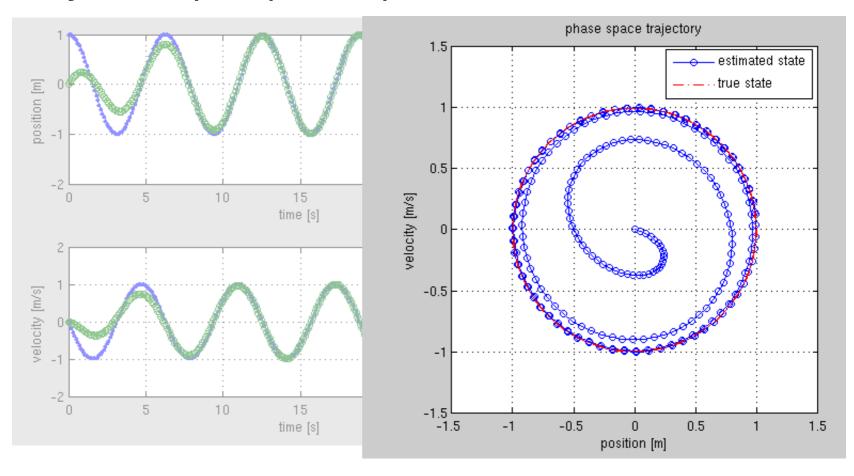


https://github.com/tobin/statespace-intro-talk

Toy example: time series



Toy example: phase plane



word cloud

step response

convolution

time domain

PID controllers

Bode plots

steady-state

overshoot

impulse response

settling time

frequency domain

Initial conditions

transfer functions

swept-sine

controllability and observability

state estimation

Nyquist diagram

poles and zeroes

Higher-order differential equations

nonlinear systems

multi-input,

internal state

multi-output (MIMO)

single-input, single-output

Wiener filters

Linear systems

first-order differential equations

state space

initial LIGO

Kalman filters

the moon landing

optimum control

Questions I have

- Is this useful to us?
 (My guesses: for single cavities, no. For suspensions, sometimes. For seismic isolation maybe? for interferometer lock acquisition could be very interesting!)
- Proof is system identification done in state space? Our measurements are made in the time domain (step response) or frequency domain (transfer functions). How do we use these measurements to improve the state space models?

What could we accomplish?

Thanks for your attention!



Control system design: an introduction to state-space-methods by Bernard Friedland

"How to do state space modeling" Note by Peter Nelson, on GEO-ISC wiki