

# Today (12/6/05)

- **Today**
  - **Another way to find feedback gain: linear quadratic regulator (LQR)**
  - **Application to observer design: Kalman Filter**
  - **Combining LQR and Kalman Filter: Linear Quadratic Gaussian (LQG) controller**

# Quadratic Optimization

Choosing desired closed poles could be a tedious trial-and-error / hit-and-miss process. Another way to find the feedback gain is to pose the following optimization problem:

$$\min_u \int_0^{\infty} \left( \underbrace{x^T Q x}_{\text{State Penalty}} + \underbrace{u^T R u}_{\text{Control Penalty}} \right) dt$$

Cost Function

This is called the linear quadratic regulator problem, or LQR.

# Quadratic Optimization

Solution to the optimization problem:

$$u = -Fx$$

$$F = R^{-1}B^T P$$

where  $P$  solves a matrix quadratic equation called the Riccati Equation.

$$A^T P + PA + Q - PB^T R^{-1}BP = 0$$

$P$  is a symmetric positive definite matrix (i.e.,  $x^T P x$  is positive for all nonzero  $x$ ).

Optimal cost:  $x_0^T P x_0$  for the initial state  $x_0$

# MATLAB Command

```
F=lqr(A,B,Q,R); % feedback gain
```

```
[F,P,E]=lqr(A,B,Q,R);
```

```
% P = solution of Riccati Equation
```

```
% E = closed loop eigenvalues (i.e.,
```

```
%     eig(A-B*F) )
```

# Single Link Example

Consider the single link pendulum:

$$\min_u \int_0^{\infty} \left( \underbrace{q_1 x_1^2(t)}_{\text{Weighted position error}} + \underbrace{q_2 x_2^2(t)}_{\text{Weighted velocity error}} + \underbrace{ru^2(t)}_{\text{Weighted control effort}} \right) dt$$

Tuning parameters are now the relative weights,  $(q_1, q_2, r)$ , instead of the closed loop poles.

Large  $q_2 \rightarrow$  slower position response

Small  $r \rightarrow$  faster overall response

```
Q=diag([1,.1]);R=.01;
```

```
F=lqr(A,B,Q,R); % feedback gain
```

# Robustness

Property of LQR:

Guaranteed  $(-60^\circ, 60^\circ)$  phase margin and  $(-6\text{dB}, \text{inf dB})$  gain margin (allowable gain variation from  $-1/2$  to infinity).

So we get the robustness for free! We can concentrate on choosing  $Q$  and  $R$  to get the time domain performance.

# Kalman Filter

We can use the same approach to choose the observer gain. Consider a state space system corrupted by noise:

$$\dot{x} = Ax + Bu + w$$

$$y = Cx + Du + v$$

$w$  = state noise,  $v$  = output noise

Both are assumed to be zero mean, white, Gaussian noise with covariance  $W$  and  $V$ .

$w(t)$  and  $v(t)$  both are zero mean Gaussian random variables.

$$E[w(t)w^T(\tau)] = \delta(t - \tau)W, E[v(t)v^T(\tau)] = \delta(t - \tau)V$$

# Kalman Filter

We can use the same approach to choose the observer gain.

$$\dot{\hat{x}} = A\hat{x} + Bu - L(C\hat{x} + Du - y)$$

$$L = \Sigma C^T V^{-1}$$

where  $\Sigma$  solves the dual Riccati Equation:

$$A\Sigma + \Sigma A^T + W - \Sigma C^T V^{-1} C \Sigma = 0$$



# LQG Control

Combining LQR and Kalman Filter: Linear Quadratic Gaussian (LQG) controller

$$\dot{\hat{x}} = (A - LC - (B - LD)F)\hat{x} + Ly$$

where  $F$  is the optimal LQR gain and  
 $L$  is the Kalman gain

However, there is no longer guaranteed stability margin as in LQR.

# MATLAB Command

```
F=lqr(A,B,Q,R); % optimal lqr gain
```

```
[F,P,E]=lqr(A,B,Q,R);
```

```
L=lqr(A',C',W,V)'; % Kalman gain
```

```
% other related commands
```

```
% kalman, lqg
```