Space feedback control Linear Quadratic Regulator (LQR control)

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Linear Quadratic Regulator

An alternative method to pole placement is to place the poles so that the closed loop system optimizes a cost function:

$$J = \int_0^\infty (x^T Q_x x + u^T Q_u u) dt$$

Linear Quadratic Regulator

Busca una función de costo que penalice las desviaciones de los estados del sistema y de los controles de accion sobre el sistema

An alternative method to pole placement is to place the poles so that the closed loop system optimizes a cost function:

$$J = \int_0^\infty (x^T Q_x x + u^T Q_u u) dt$$
 Qx def pos
Qu semidef pos

where x^TQ_xx is the **state cost** and u^TQ_uu is the **control cost**. The matrices Q_x and Q_u are symmetric, positive (semi-) definite matrices. This is called the **linear quadratic regulator (LQR)** problem.

The solution to the LQR problem is given by

definida positiva-autovalores>0
semidef pos -autovalores>=0

u = -Kx, $K = Q_u^{-1}B^TS$ La solución esta dada por where S is a positive definite, symmetric matrix given by encontrar K, es decir S

$$A^TS + SA - SBQ_u^{-1}B^TS + Q_x = 0$$

This equation is called the algebraic Riccati equation.

Linear Quadratic Regulator

The tuning of the LQR is to choose the weighting matrices Q_x and Q_u . To guarantee that a solution exists, the system must be **reachable** and that $Q_x \ge 0$ and $Q_u > 0$.

semidef pos

definida positiva

The tuning of the LQR is to choose the weighting matrices Q_x and Q_u . To guarantee that a solution exists, the system must be **reachable** and that $Q_x \ge 0$ and $Q_u > 0$.

1. Simplest choice: $Q_x = I$ and $Q_u = \rho I$ $J = \int_0^\infty (x^T x + \rho u^T u) dt \qquad \Rightarrow \qquad \text{trade-off} \implies \|x\|^2 \quad vs \quad \rho \|u\|^2$

This reduce the tuning to select ρ , which then becomes a trade-off between state cost and control cost.

Para rho grande penalizamos más acciones de control

Para rho grande penalizamos más acciones de control(más lentas o de menor valor) y si rho<1 penalizamos más acciones sobre los estados.

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Otro método es penalizar los estados que se ven reflejados en la salida del sistema

2. Output weighting. Let $z=\mathcal{C}_zx$ be the output you want to keep small.

Choose
$$Q_x = C_z^T C_z$$
, and $Q_u = \rho I$. \Rightarrow trade-off $\Rightarrow ||z||^2 vs \rho ||u||^2$

salida vs acciones de control

3. Diagnonal weighting.

$$Q_x = \begin{bmatrix} q_1 & & 0 \\ & \ddots & \\ 0 & & q_n \end{bmatrix} \qquad Q_u = \begin{bmatrix} \rho_1 & & 0 \\ & \ddots & \\ 0 & & \rho_p \end{bmatrix}$$

Choose the individual diagonal elements based on how much each state or input signal should contribute to the overall cost.

Elegimos valores individuales para los parámetros en la diagonal de estas matrices respetando características mencionadas antes

3er método

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Choose the individual diagonal elements based on how much each state or input signal should contribute to the overall cost.

Fijamos valores máx para estados y para salidas y alfa o beta distribuye

Alternative, (Bryson's rule) choose the diagonal weights as $q_i=\alpha_i^2/x_{i,max}^2$ and $\rho_i = \beta_i^2/u_{i,max}^2$, where $x_{i,max}$ and $u_{i,max}$ represents the largest response. α and eta are used for additional individual weighting of the state and control cost,

$$\sum_{i=1}^{n} \alpha_i^2 = 1 \qquad \sum_{i=1}^{p} \beta_i^2 = 1$$

Limitamos valores máximos para acciones de control y cada estado

Ox semidef pos, Qu def pos

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$$Q_x = \begin{bmatrix} q_1 & 0 \\ & \ddots \\ 0 & q_n \end{bmatrix} \quad Q_u = \begin{bmatrix} \rho_1 & 0 \\ & \ddots \\ 0 & \rho_p \end{bmatrix}$$

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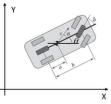
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Trial and error

Consider the following system:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & v_0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} av_0/b \\ v_0/b \end{bmatrix} u$$
$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \end{bmatrix} u$$



Vehicle data: $v_0 = 12 m/s$ a = 2 mb = 4 m

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$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 12 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 6 \\ 3 \end{bmatrix} u$$

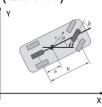
$$y = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \end{bmatrix} u$$

Place the poles so that the closed loop system optimizes the cost function:

$$J = \int_0^\infty (x^T Q_x x + u^T Q_u u) dt$$

where

$$Q_x = \begin{bmatrix} q_1 & 0 \\ 0 & q_2 \end{bmatrix} \qquad Q_u = \rho$$



Vehicle data:
$$v_0 = 12 \ m/s$$
 $a = 2 \ m$ $b = 4 \ m$

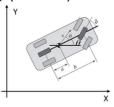
Optimal control (LQR) Optimal control, example

Revisit Example - Vehicle steering (Ex 7.4)

For the case when

$$Q_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q_u = 10$$

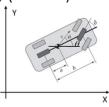


For the case when

$$Q_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad Q_u = 10$$

The solution to the algebraic Ricatti equation is

$$A^TS + SA - SBQ_u^{-1}B^TS + Q_x = 0$$



Optimal control, example

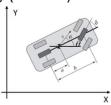
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For the case when

$$Q_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad Q_u = 10$$

The solution to the algebraic Ricatti equation is

$$S = \begin{bmatrix} 0.292 & 0.470 \\ 0.470 & 2.754 \end{bmatrix}$$



For the case when

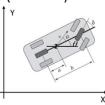
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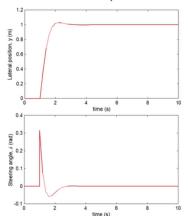
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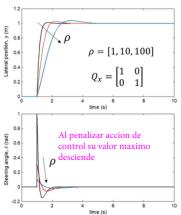
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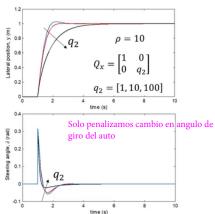
and the corresponding control law becomes

$$u = -Kx$$
, $K = Q_u^{-1}B^TS = [0.316 \ 1.108]$









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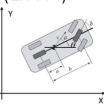
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The closed loop system poles are

$$E = \begin{bmatrix} -2.6110 + 2.1371i \\ -2.6110 - 2.1371i \end{bmatrix}$$



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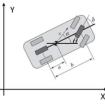
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Compared to the pole placement design, this corresponds to $\zeta=0.77$ and $\omega_n=3.44$.



Bibliography

Karl J. Astrom and Richard M. Murray Feedback Systems. Version v3.0i.
 Princeton University Press. September 2018. Chapter 7.