

# Space feedback control

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# Summary

## 1 State feedback control

- Reference tracking
- Integral action
- Example 1
- Example 2

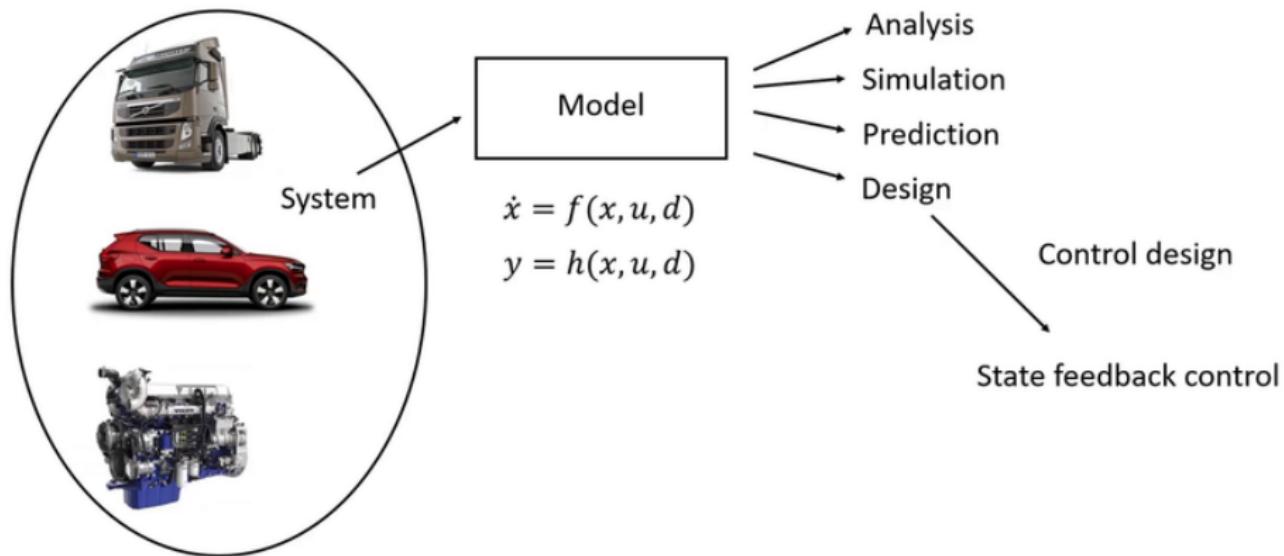
## 2 Reachability

- Definition
- Reachability matrix

## 3 Tuning or Pole placement

- Pole placement for time domain analysis
- Ackermann's formula
- Optimal control (LQR)
- Optimal control, method 1
- Optimal control, method 2
- Optimal control, method 3
- Optimal control, method 4
- Optimal control, example

## State feedback control



# State feedback control

Consider a linear time-invariant state-space model given by:

$$\dot{x}(t) = Ax(t) + Bu(t)$$

$$y(t) = Cx(t) + Du(t)$$

where  $x(t) \in \mathbb{R}^n$  is the state (vector),  $u(t) \in \mathbb{R}^p$  is the input or control signal and  $y(t) \in \mathbb{R}^q$  is the output signal. (For SISO case,  $p = 1, q = 1$ )

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The system poles are given by the eigenvalues of the system matrix  $A \in \mathbb{R}^{n \times n}$ .

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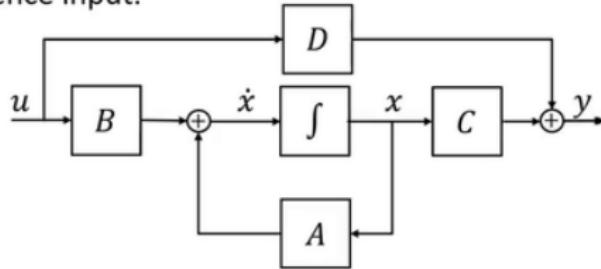
where  $K \in \mathbb{R}^{p \times n}$  is the feedback gain,  $k_r \in \mathbb{R}^{p \times r}$  is the steady-state reference gain and  $r(t) \in \mathbb{R}^r$  is the reference input.

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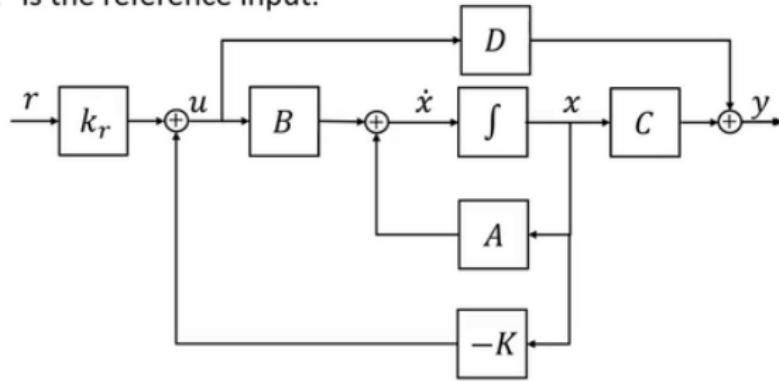


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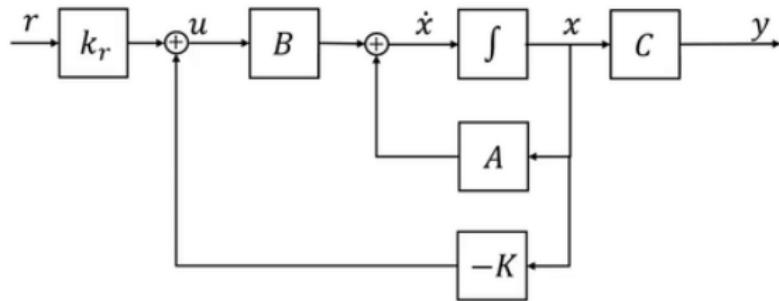


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SISO case:  $n$  parameters in  $K$  and  $n$  eigenvalues in  $A$ , so it might be possible!

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If  $y(t) \approx r(t)$  as  $t \rightarrow \infty$ , then  $k_r$  should be chosen as

$$k_r = -(C(A - BK)^{-1}B)^{-1} \quad \text{or} \quad k_r = -1/C(A - BK)^{-1}B$$

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Given the new state-space model, we design a controller in the usual fashion and the resulting controller becomes:

$$u(t) = -Kx(t) - K_I z(t) + k_r r(t)$$

## Example 1

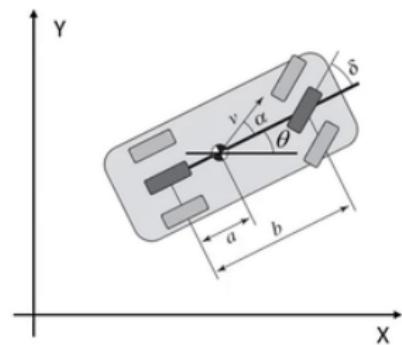
## Example 1 - Vehicle steering (Ex 7.4)

Consider the following system:

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where  $x_1$  is the lateral position  $Y$ ,  $x_2$  is the heading orientation  $\theta$  and  $u$  is the steering angle  $\delta$ .



Vehicle data:  $v_0 = 12 \text{ m/s}$

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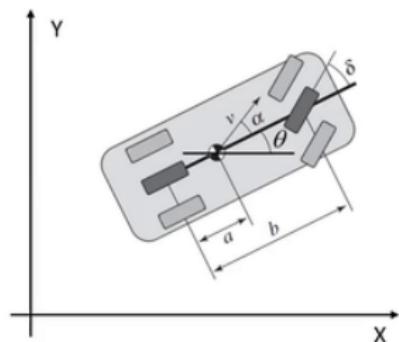
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The idea is to design a controller that ***stabilizes*** the dynamics and ***tracks*** a given lateral position of the vehicle.



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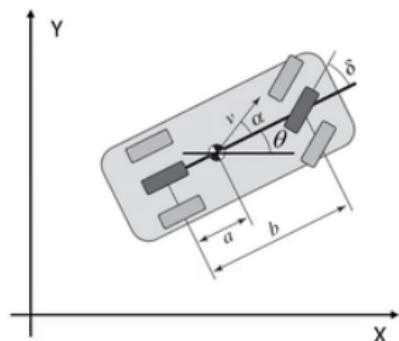
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**Specification:** Desired characteristic polynomial:

$$p_{des}(\lambda) = \lambda^2 + 2\zeta\omega_n\lambda + \omega_n^2$$



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The closed loop system has the characteristic polynomial

$$\det(\lambda I - A + BK) = \dots = \lambda^2 + \frac{v_0}{b}(ak_1 + k_2)\lambda + \frac{k_1 v_0^2}{b}$$

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Matching with desired characteristic polynomial gives:

$$\lambda^2 + 2\zeta\omega_n\lambda + \omega_n^2 \equiv \lambda^2 + \frac{v_0}{b}(ak_1 + k_2)\lambda + \frac{k_1 v_0^2}{b}$$

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The steady-state gain can be determined:

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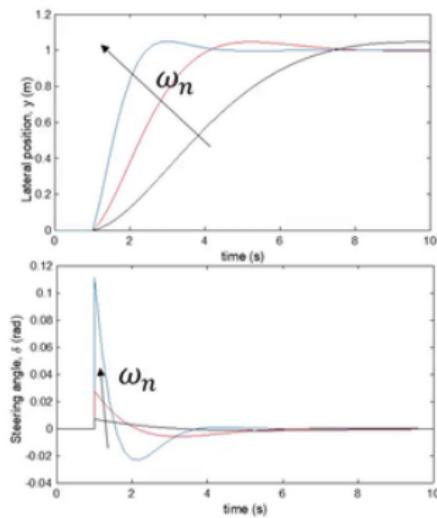
Inserting these control design parameters into the feedback controller gives:

$$u = -k_1x_1 - k_2x_2 + k_r r = -\frac{b\omega_n^2}{v_0^2}x_1 - \left(\frac{2\zeta\omega_n b}{v_0} - \frac{ab\omega_n^2}{v_0^2}\right)x_2 + \frac{b\omega_n^2}{v_0^2}r$$

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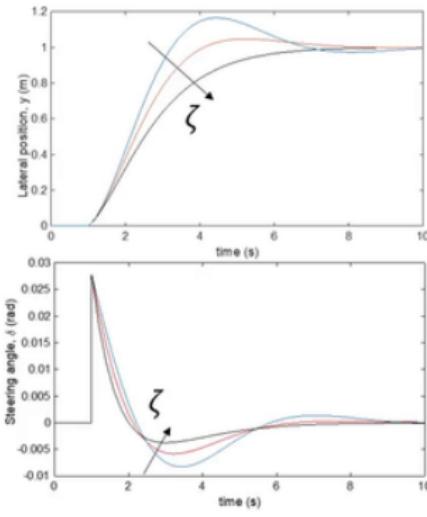
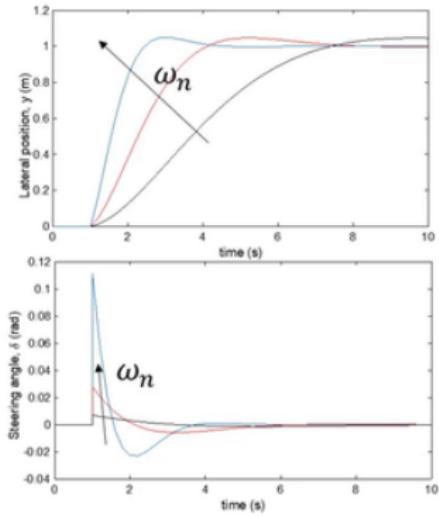
Simulations with different values of  $\zeta$  and  $\omega_n$ :



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Consider the following system (similar to Example 1 with one difference):

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u$$
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Again, the idea is to design a controller that **stabilizes** the dynamics and **tracks** a given reference signal.

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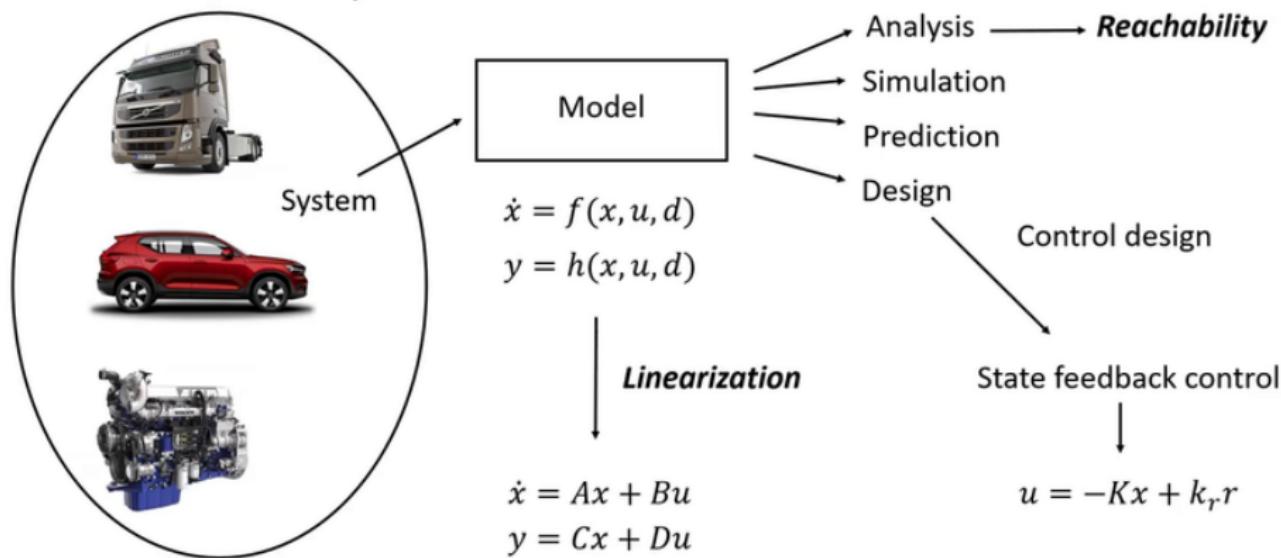
While matching with the desired characteristic polynomial

$$\lambda^2 + 2\zeta\omega_n\lambda + \omega_n^2 \equiv \lambda^2 + k_1\lambda$$

we notice that it is not possible to make them identical to each other.

It is not possible to control all the eigenvalues (shape the dynamics). We say that the system is not **controllable** or not **reachable**. Furthermore, one eigenvalue is always 0, which means that the closed loop system is unstable.

## Reachability



## Revisit - Example

Consider the following system:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u$$

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

State feedback control:  $u = -Kx + k_r, r = -k_1x_1 - k_2x_2 + k_rr$

The closed loop system dynamics becomes

$$\dot{x} = (A - BK)x + Bk_rr = \begin{bmatrix} -k_1 & 1 - k_2 \\ 0 & 0 \end{bmatrix}x + \begin{bmatrix} k_r \\ 0 \end{bmatrix}r$$

and the characteristic polynomial is given as

$$\det(\lambda I - A + BK) = \det\begin{pmatrix} \lambda + k_1 & k_2 - 1 \\ 0 & \lambda \end{pmatrix} = \lambda^2 + k_1\lambda = \lambda(\lambda + k_1)$$

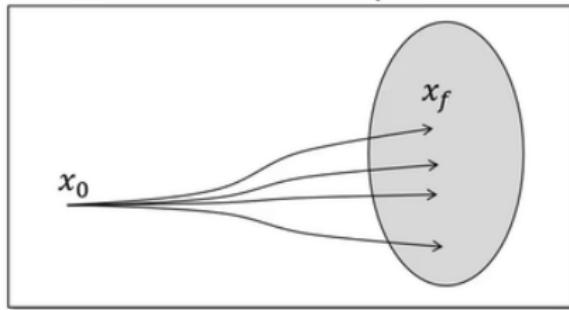
Uncontrollable  
Controllable

# Reachability

**Definition** (Reachability): A linear system is **reachable** if for any  $x_0, x_f \in \mathbb{R}^n$  there exists a  $T > 0$  and  $u: [0, T] \rightarrow \mathbb{R}$  such that if  $x(0) = x_0$  then the corresponding solution satisfies  $x(T) = x_f$ .

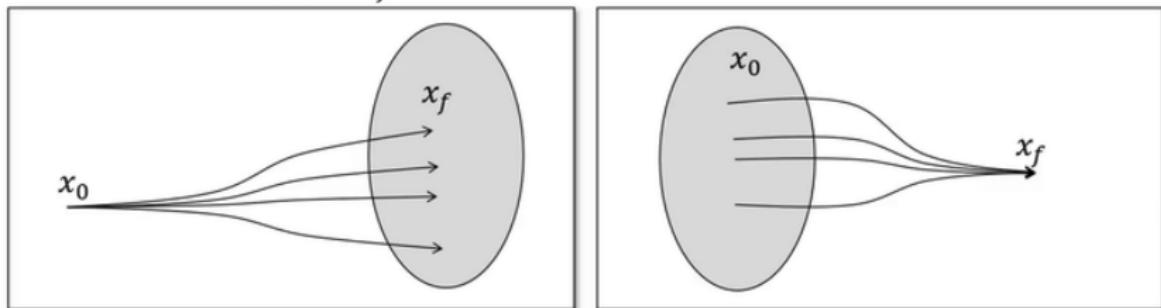
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Sometimes the definition of **controllable** and **controllability** is used, and that is similar.

## Linear system representations

$$\begin{array}{ccc}
 a\left(\frac{d}{dt}\right)y(t) = b\left(\frac{d}{dt}\right)u(t) & \xrightarrow{\mathcal{L}} & a(s)Y(s) = b(s)U(s) \\
 & & \downarrow G(s) = \frac{b(s)}{a(s)} \\
 y(t) = \int_0^t g(t-\tau) u(\tau) d\tau & \xleftarrow{\mathcal{L}^{-1}} & Y(s) = G(s)U(s) \\
 & \uparrow g(t) = Ce^{At}B + D\delta(t) & \uparrow G(s) = C(sI - A)^{-1}B + D \\
 \dot{x}(t) = Ax(t) + Bu(t) & \xrightarrow{\mathcal{L}} & sX(s) - x(0) = AX(s) + BU(s) \\
 y(t) = Cx(t) + Du(t) & & \quad \quad \quad Y(s) = CX(s) + DU(s)
 \end{array}$$

# Reachability

To see that an arbitrary point can be reached, we can use the convolution equation.

Assume that the system starts from zero, the state of a linear system is given by:

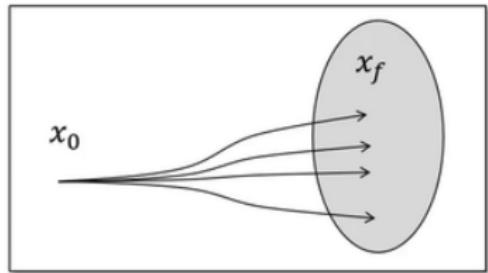
$$x(t) = \int_0^t e^{A(t-\tau)} B u(\tau) d\tau = \int_0^t e^{A\tau} B u(t-\tau) d\tau$$

From linear theory it can be shown that

$$e^{A\tau} = I\alpha_0(\tau) + A\alpha_1(\tau) + \cdots + A^{n-1}\alpha_{n-1}(\tau)$$

where  $\alpha_i(t)$  are scalar functions, so that

$$\begin{aligned} x(t) = & B \int_0^t \alpha_0(\tau) u(t-\tau) d\tau + AB \int_0^t \alpha_1(\tau) u(t-\tau) d\tau + \cdots \\ & + A^{n-1}B \int_0^t \alpha_{n-1}(\tau) u(t-\tau) d\tau \end{aligned}$$



# Reachability

By writing it in "vector form", we get:

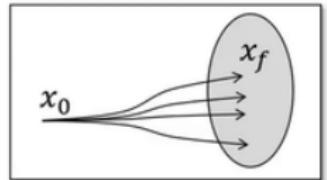
$$x(t) = [B \quad AB \quad \dots \quad A^{n-1}B] \underbrace{\left[ \begin{array}{c} \int_0^t \alpha_0(\tau) u(t-\tau) d\tau \\ \int_0^t \alpha_1(\tau) u(t-\tau) d\tau \\ \vdots \\ \int_0^t \alpha_{n-1}(\tau) u(t-\tau) d\tau \end{array} \right]}$$

$W_r$

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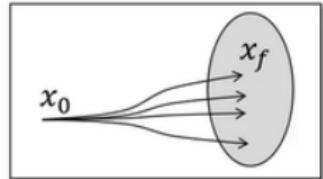


To reach an arbitrary point in state-space, we require that  $W_r$  is nonsingular. The matrix  $W_r$  is called the **reachability matrix**.

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To reach an arbitrary point in state-space, we require that  $W_r$  is nonsingular. The matrix  $W_r$  is called the **reachability matrix**.

**Theorem** (Reachability rank condition): *A linear system is reachable if and only if the reachability matrix is invertable (has full rank).*

## Revisit - Example

Return to our example, with the following system:

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} u$$
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Note: A square matrix  $M (n \times n)$  has full rank  $n$  iff  $\det(M) \neq 0$

Compute the determinant:

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$$\det(W_r) = \begin{vmatrix} 1 & 0 \\ 0 & 0 \end{vmatrix} = 1 \cdot 0 - 0 \cdot 0 = 0$$

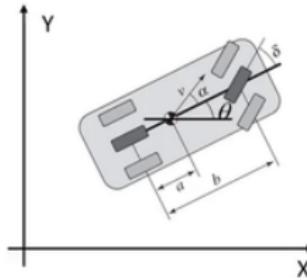
*The system is not reachable!*

## Revisit Example - Vehicle steering (Ex 7.4)

Consider the following system:

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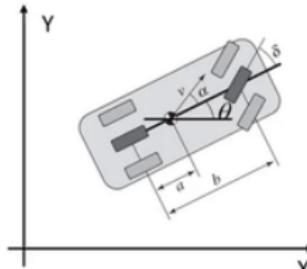
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Reachability matrix:

$$W_r = [B \quad AB] = \begin{bmatrix} av_0/b & [av_0/b \\ v_0/b] \\ v_0/b & [0 \quad 0] \begin{bmatrix} av_0/b \\ v_0/b \end{bmatrix} \end{bmatrix}$$



## Revisit Example - Vehicle steering (Ex 7.4)

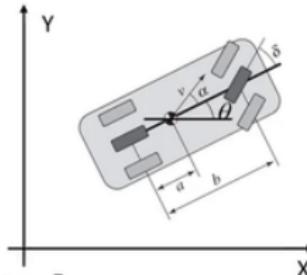
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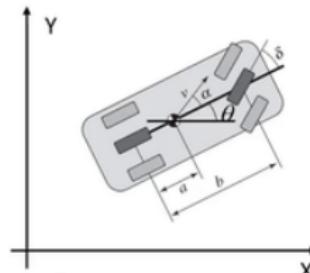
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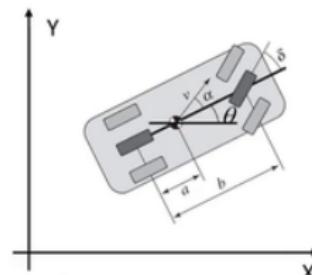
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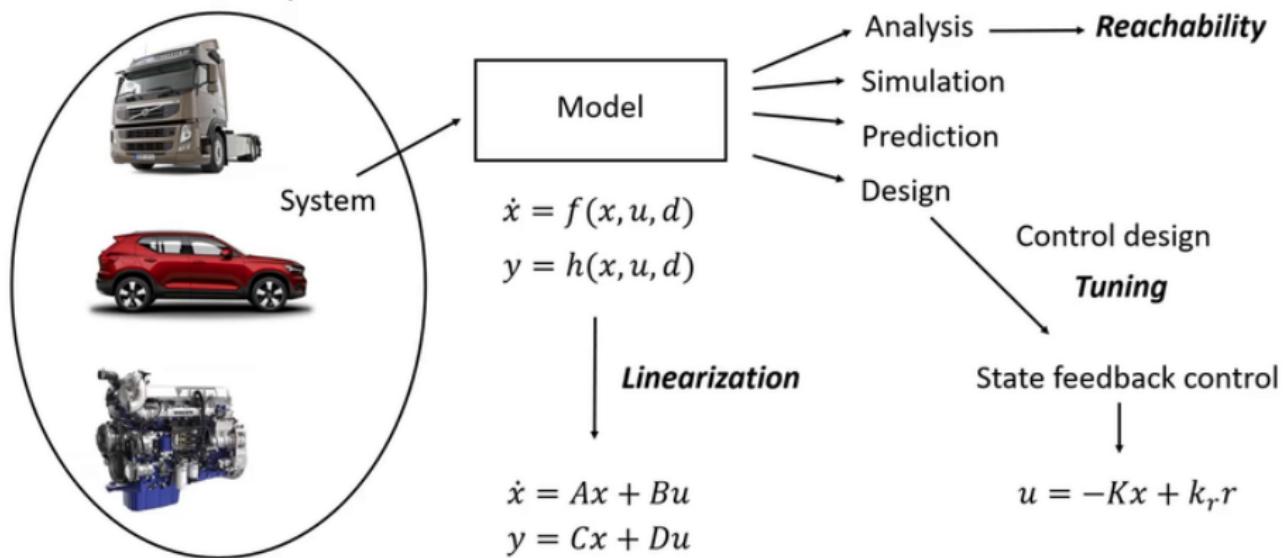
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The system is reachable, as long as  $v_0 \neq 0$ .



## Summary - state feedback control



## Pole placement

So far we have learnt how a state feedback looks like and when it is possible to design a state feedback controller to stabilize a system:

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

$$u = -Kx + k_r r$$

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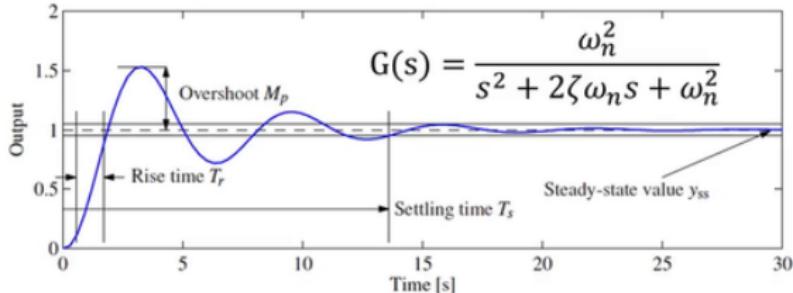
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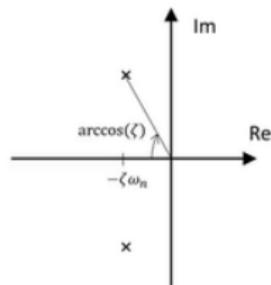
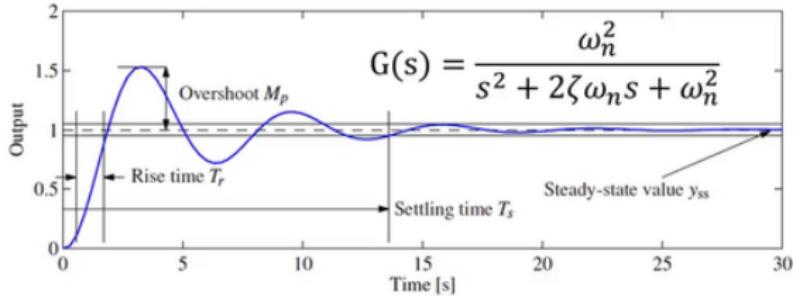
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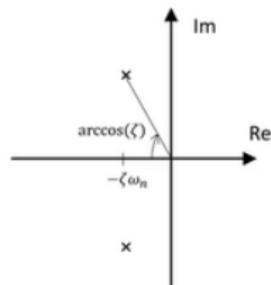
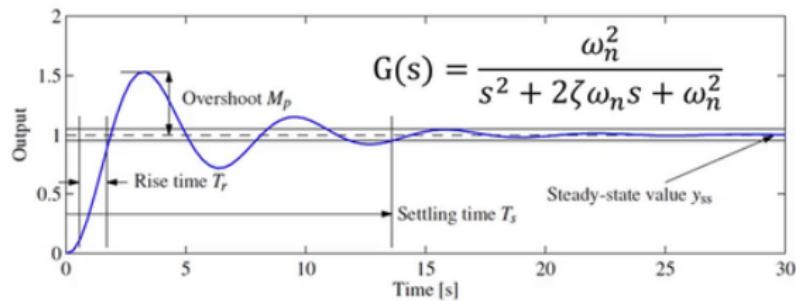
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# Specifications and pole placement

Property	Value	$\zeta = 0.5$	$\zeta = 1/\sqrt{2}$	$\zeta = 1$
Rise time	$T_r \approx 1/\omega_n \cdot e^{\arccos\zeta/\tan(\arccos\zeta)}$	$1.8/\omega_n$	$2.2/\omega_n$	$2.7/\omega_n$
Overshoot	$M_p \approx e^{-\pi\zeta\sqrt{1-\zeta^2}}$	16%	4%	0%
Settling time (2%)	$T_s \approx 4/\zeta\omega_n$	$8.0/\omega_n$	$5.9/\omega_n$	$4.0/\omega_n$



## Pole placement

*Where do we place the closed loop system's poles?*

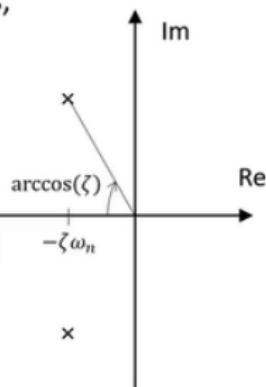
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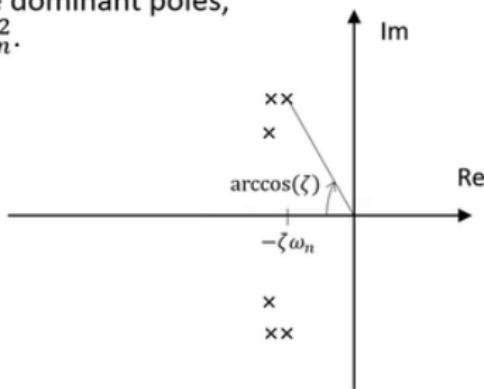


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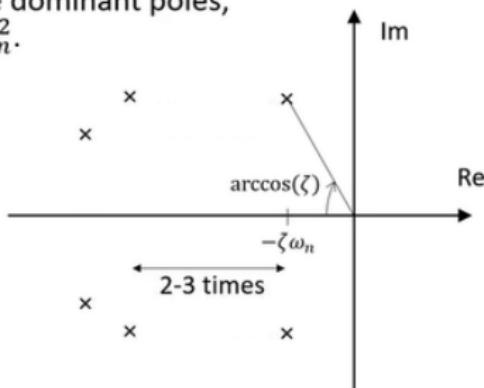


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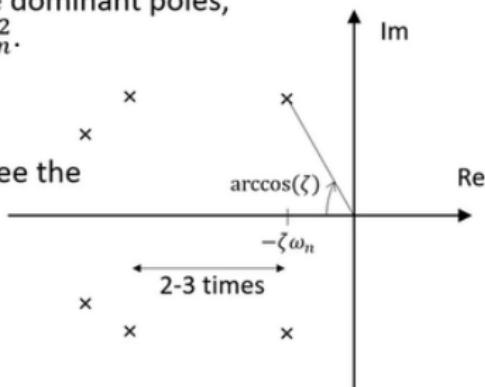
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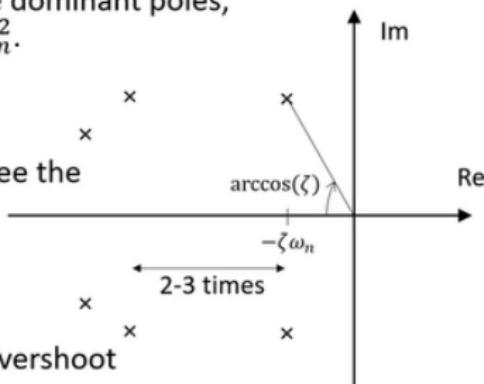
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Usually you end up with some zeros as well:

- Zeros in the left half plane give additional overshoot
- Zeros in the right half plane give a negative undershoot



## Pole placement (Ackermann's formula)

Pole placement is performed by matching the desired characteristic polynomial with the closed loop system's characteristic polynomial.

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$$k_1 = \frac{b\omega_n^2}{v_0^2} \quad k_2 = \frac{2\zeta\omega_n b}{v_0} - \frac{ab\omega_n^2}{v_0^2}$$

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For low order systems it is ok, but for larger systems this is boring work.

*Ackermann's formula offers us a method to do this in one computational step.*

## Pole placement (Ackermann's formula)

Consider a system  $\dot{x} = Ax + Bu$  with the characteristic polynomial

$$a(s) = s^n + a_1 s^{n-1} + \cdots + a_{n-1} s + a_n.$$

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Consider a system  $\dot{x} = Ax + Bu$  with the characteristic polynomial

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If the system is reachable, then there exist a control law,  $u = -Kx$ , that gives a closed loop system with the characteristic polynomial

$$p(s) = s^n + p_1 s^{n-1} + \cdots p_{n-1} s + p_n.$$

## Pole placement (Ackermann's formula)

The feedback gain is given by

$$K = [p_1 - a_1 \quad p_2 - a_2 \quad \dots \quad p_n - a_n] \tilde{W}_r W_r^{-1}$$

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$$W_r = [B \quad AB \quad \dots \quad A^{n-1}B]$$

and

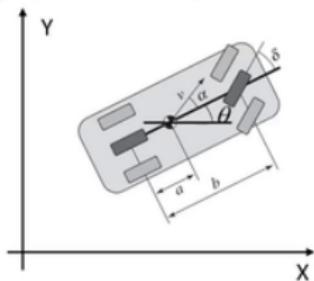
$$\tilde{W}_r = \begin{bmatrix} 1 & a_1 & a_2 & \cdots & a_{n-1} \\ 0 & 1 & a_1 & \cdots & a_{n-2} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 & a_1 \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix}^{-1}$$

This is called **Ackermann's formula**.

## Revisit Example - Vehicle steering (Ex 7.4)

Consider the following system:

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$$y = [1 \quad 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + [0] u$$



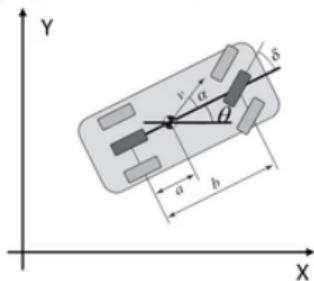
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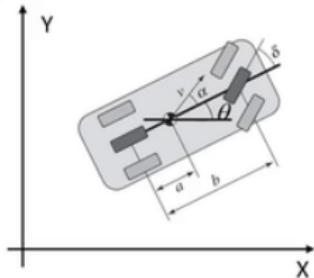
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Desired characteristic polynomial for the closed loop system:

$$p(s) = s^2 + 2\zeta\omega_n s + \omega_n^2$$



## Revisit Example - Vehicle steering (Ex 7.4)

The feedback gain is given by

$$K = [p_1 - a_1 \quad p_2 - a_2] \tilde{W}_r W_r^{-1} = [2\zeta\omega_n \quad \omega_n^2] \tilde{W}_r W_r^{-1}$$

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$$A^T S + S A - S B Q_u^{-1} B^T S + Q_x = 0$$

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  $Q_x \geq \mathbf{0}$  and  $Q_u > \mathbf{0}$ .

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## Linear Quadratic Regulator

3. Diagonal weighting.

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

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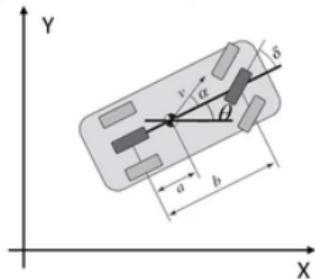
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### 4. Trial and error

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Vehicle data:  $v_0 = 12 \text{ m/s}$   
 $a = 2 \text{ m}$   
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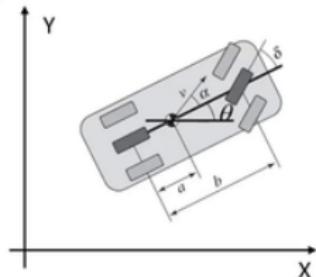
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where

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

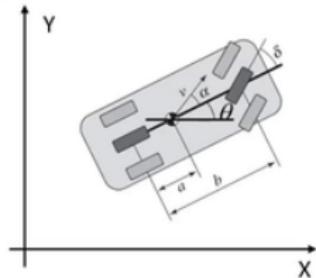


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For the case when

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



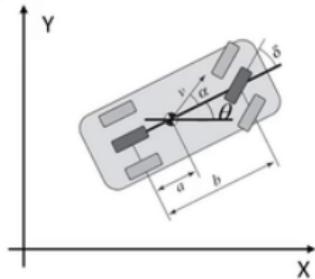
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In MATLAB: The LQR problem can be solved using the `lqr` command

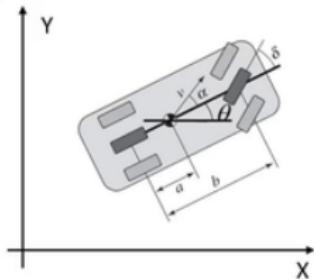
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$$S = \begin{bmatrix} 0.292 & 0.470 \\ 0.470 & 2.754 \end{bmatrix}$$



In MATLAB: The LQR problem can be solved using the `lqr` command

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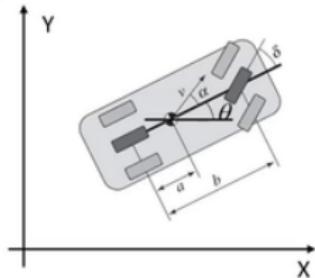
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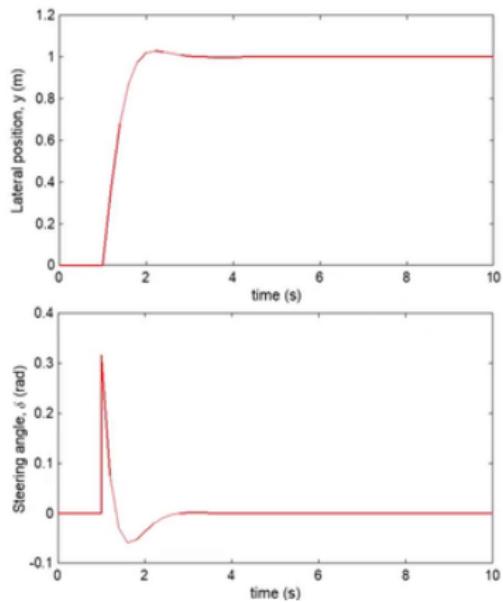
and the corresponding control law becomes

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

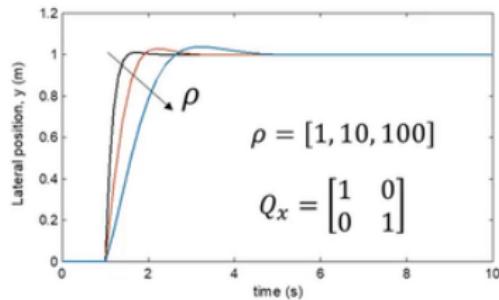


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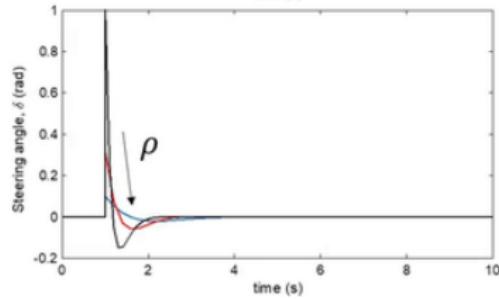
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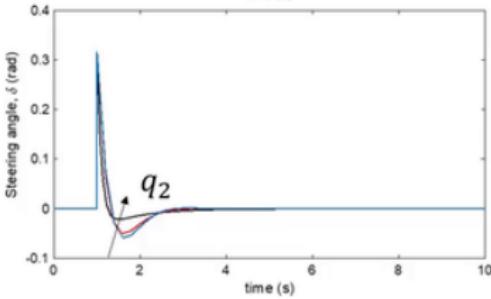
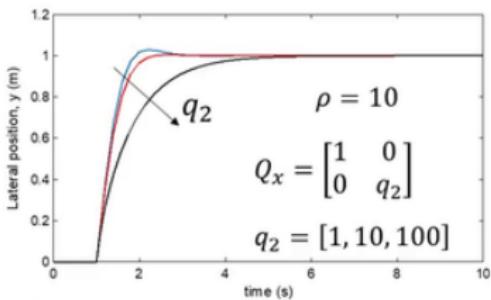
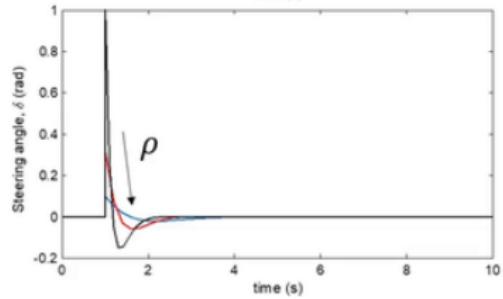
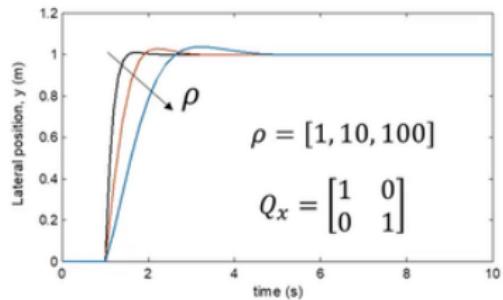
$$Q_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$



# Tuning or Pole placement

## Optimal control, example

### Revisit Example - Vehicle steering (Ex 7.4)



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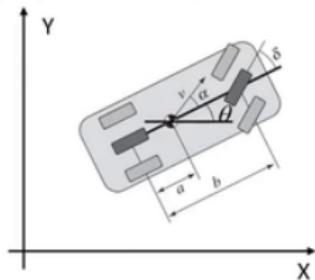
$$Q_x = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad Q_u = 10$$

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In MATLAB: The LQR problem can be solved using the `lqr` command

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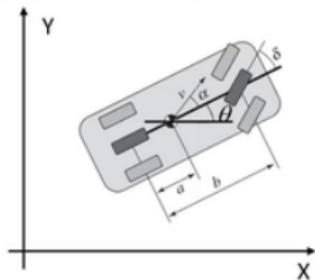
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$$u = -Kx, \quad K = Q_u^{-1}B^T S = [0.316 \quad 1.108]$$

The closed loop system poles are

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



In MATLAB: The LQR problem can be solved using the `lqr` command

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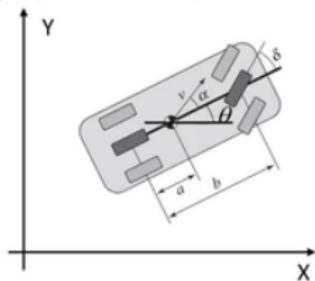
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Compared to the pole placement design, this corresponds to  $\zeta = 0.77$  and  $\omega_n = 3.44$ .



In MATLAB: The LQR problem can be solved using the `lqr` command

# Bibliography

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