

# Chapter 7 Control

## Part 2

### 7.2 State Space Control



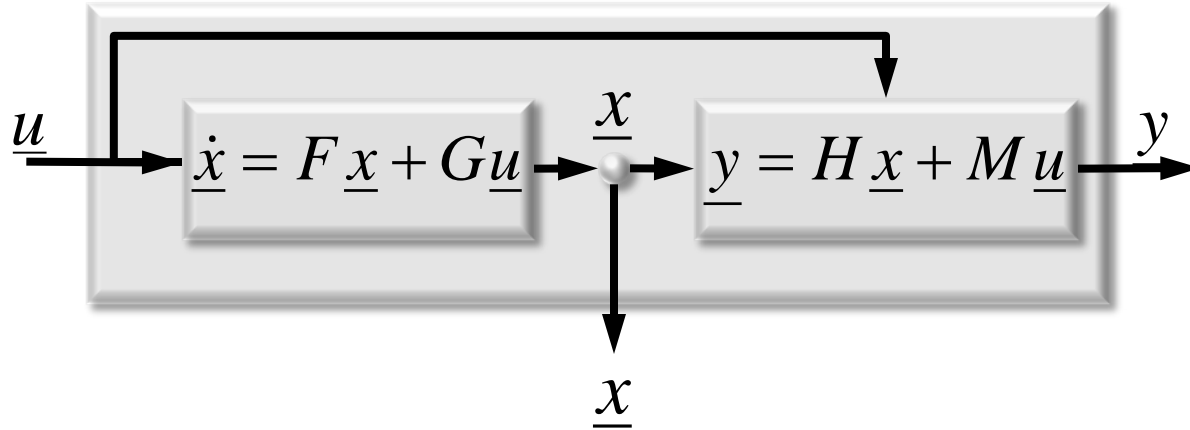
# Outline

- 7.2 State Space Control
  - 7.2.1 Introduction
  - 7.2.2 State Space Feedback Control
  - 7.2.3 Example: Robot Trajectory Following
  - 7.2.4 Perception Based Control
  - 7.2.5 Steering Trajectory Generation
  - Summary

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# 7.2 State Space Control



- Looks deeper at system behavior by exposing the states
- Tries to control the entire state vector

# 7.2.1 Introduction

(State Space Model)

- Recall the linear TI case:

$$\dot{\underline{x}}(t) = F(t)\underline{x}(t) + G(t)\underline{u}(t)$$

$$\underline{y}(t) = H(t)\underline{x}(t) + M(t)\underline{u}(t)$$

- $\underline{x}$  is  $n \times 1$
- $\underline{u}$  is  $r \times 1$
- $\underline{y}$  is  $m \times 1$

## 7.2.1.1 Controllability

- Completely controllable if there is a  $u(t)$  that drives the system:
  - From any  $x(t_1)$
  - To any  $x(t_2)$
  - In finite time  $Dt = t_2 - t_1$ .
- Totally controllable if  $Dt$  can be made as small as desired.
- Some use the word reachability for this concept.

# 7.2.1.1 Controllability

(Controllability Condition)

- Totally controllable iff this  $n \times nm$  matrix:

$$Q = [G | FG | FFG | \dots | F^{n-1}G]$$

- ... is of full rank.
- If  $F(t)$  and  $G(t)$  depend on time,  $Q$  can only lose rank at isolated points in time.

## 7.2.1.2 Observability

- Completely observable if  $\underline{x}(t_1)$  is fully determined by knowledge of
  - $\underline{u}(t)$  and
  - $\underline{y}(t)$
  - on an interval  $[t_1, t_2]$  where  $t_2 > t_1$  :
  - In finite time  $\Delta t = t_2 - t_1$ .
- Totally observable if  $\Delta t = t_2 - t_1$  can be made as small as desired.



## 7.2.1.2 Observability

(Observability Condition)

- Totally observable iff this  $m \times n$  matrix:

$$P = \begin{bmatrix} H \\ HF \\ HFF \\ \dots \\ HF^{n-1} \end{bmatrix}$$

- ... is of full rank.
- If  $F(t)$  and  $G(t)$  depend on time,  $P$  can only lose rank at isolated points in time.

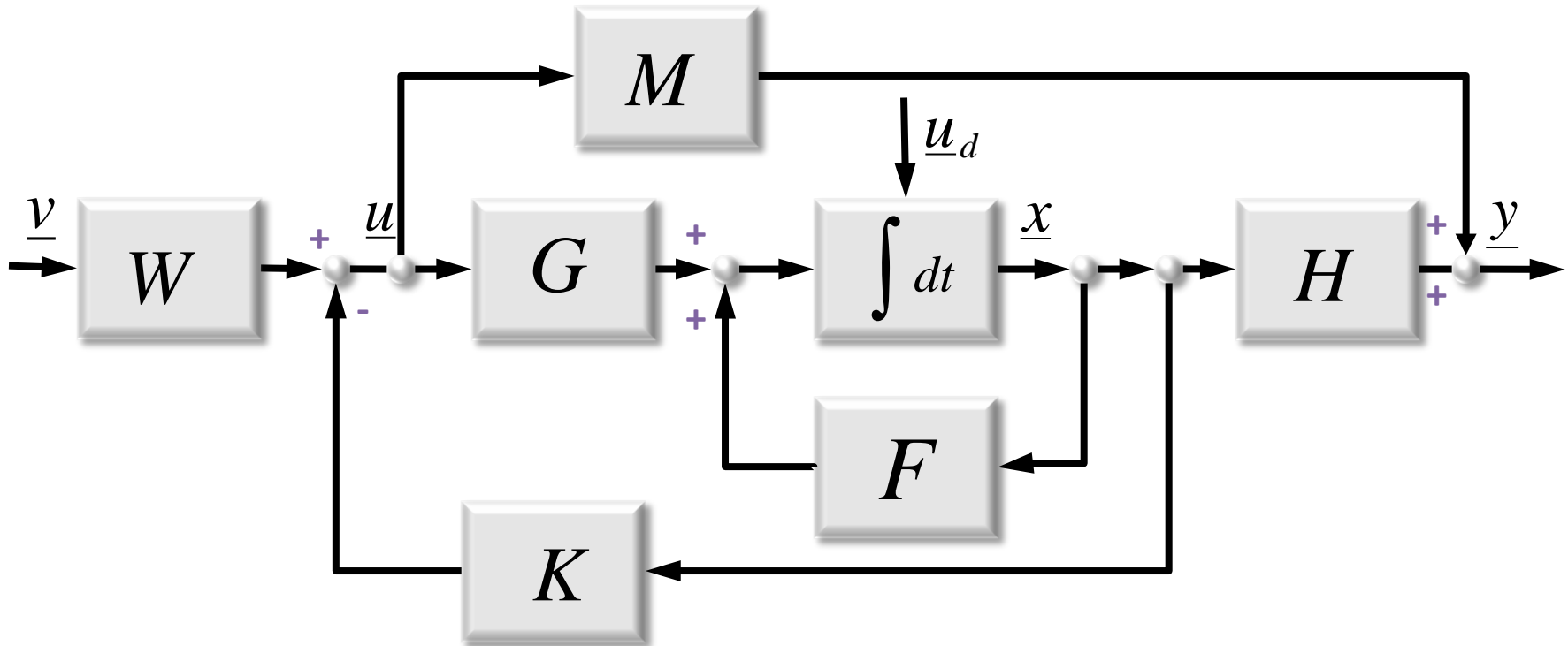
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# Feedback Control in State Space

- Two options: state and output feedback.
- Only the second seems relevant (since only  $y$  is accessible by definition)
- However:
  - Full state feedback is theoretically relevant
  - Sometimes you can measure all states
  - Often, you can reconstruct the states.

## 7.2.2.1 State Feedback



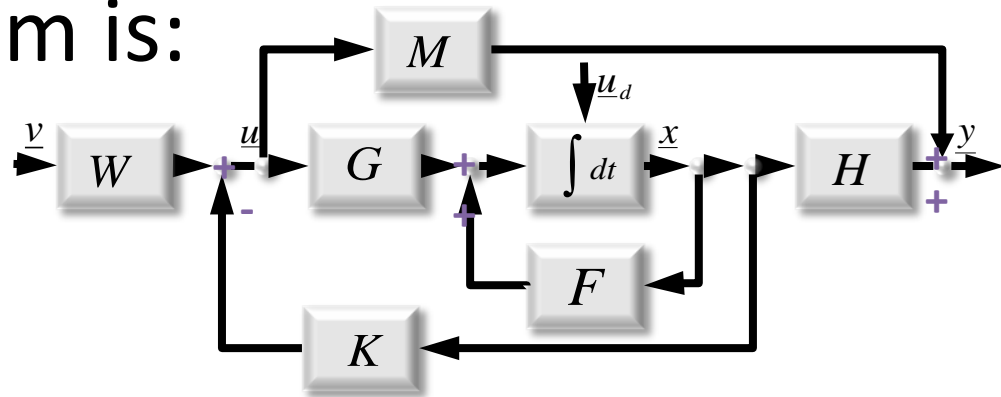
$$\underline{u}(t) = W\underline{v}(t) - K\underline{x}(t)$$

## 7.2.2.1 State Feedback

- Upon substitution,
- the new linear system is:

$$\dot{\underline{x}} = [F - GK]\underline{x} + GW\underline{v}$$

$$\underline{y} = [H - MK]\underline{x} + MW\underline{v}$$



- Can show:
  - Controllability is unaltered if  $W$  is full rank
  - Observability can be altered or even lost (i.e if  $H=MK$ ).

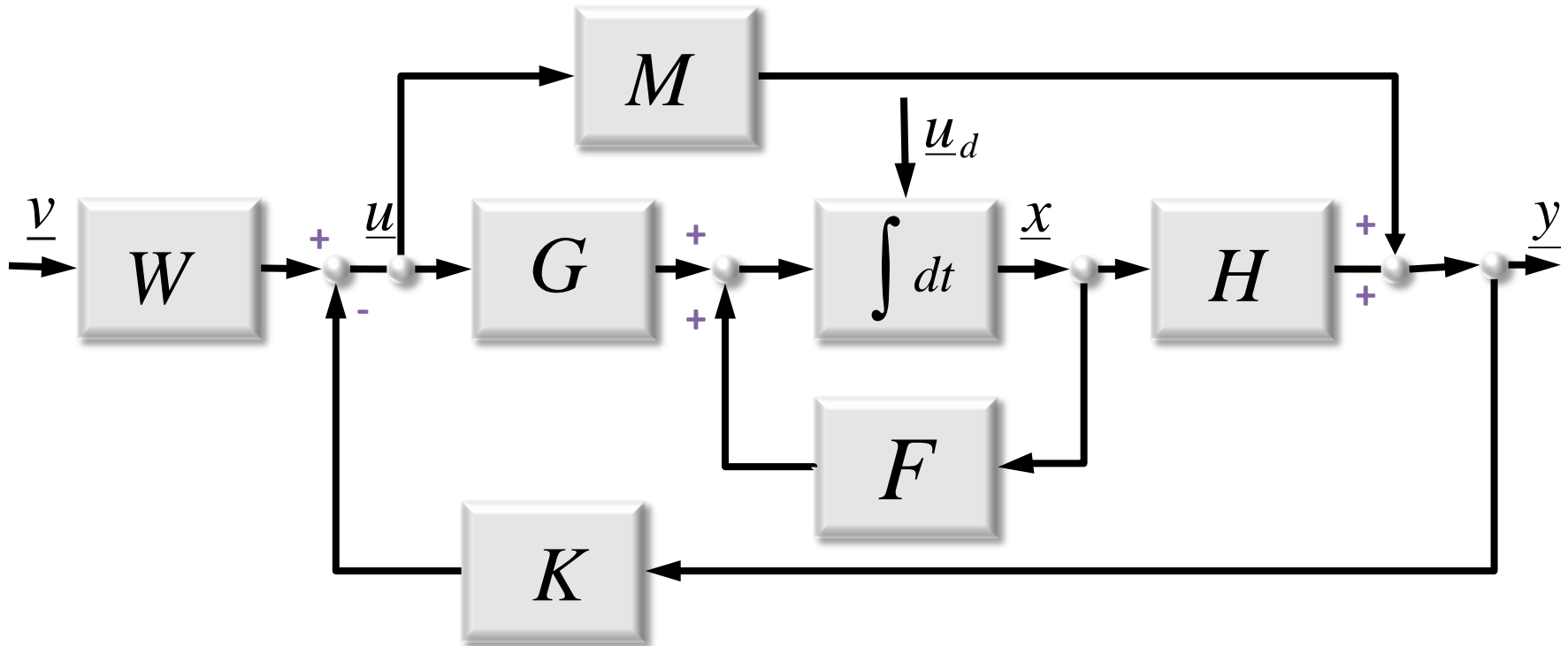
## 7.2.2.2 Eigenvalue Assignment

- Equivalent to pole placement.
- Consider time invariant case. Stability depends on eigenvalues of new dynamics matrix  $F-GK$ :

$$\det(\lambda I - F + GK) = 0$$

- If original system is controllable, these eigenvalues can be placed arbitrarily by suitable choice of the gain matrix  $K$ .

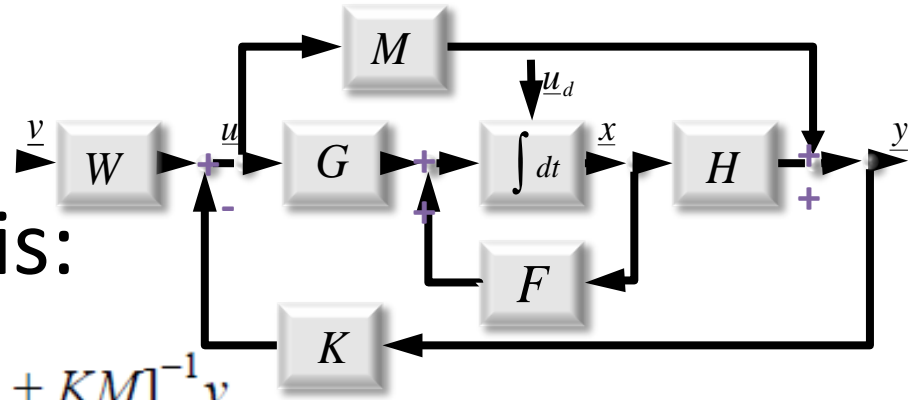
## 7.2.2.3 Output Feedback



$$\underline{u}(t) = W\underline{v}(t) - K\underline{y}(t)$$

## 7.2.2.3 Output Feedback

- Upon substitution,
- the new linear system is:



$$\dot{\underline{x}} = [F - GK[I_m + MK]^{-1}H]\underline{x} + GW[I_r + KM]^{-1}\underline{v}$$

$$\underline{y} = [I_m + MK]^{-1}[H\underline{x} + MW\underline{v}]$$

- Can show:
  - Controllability is unaltered if  $W$  and  $[I_r + KM]^{-1}$  are of full rank
  - Observability is preserved.



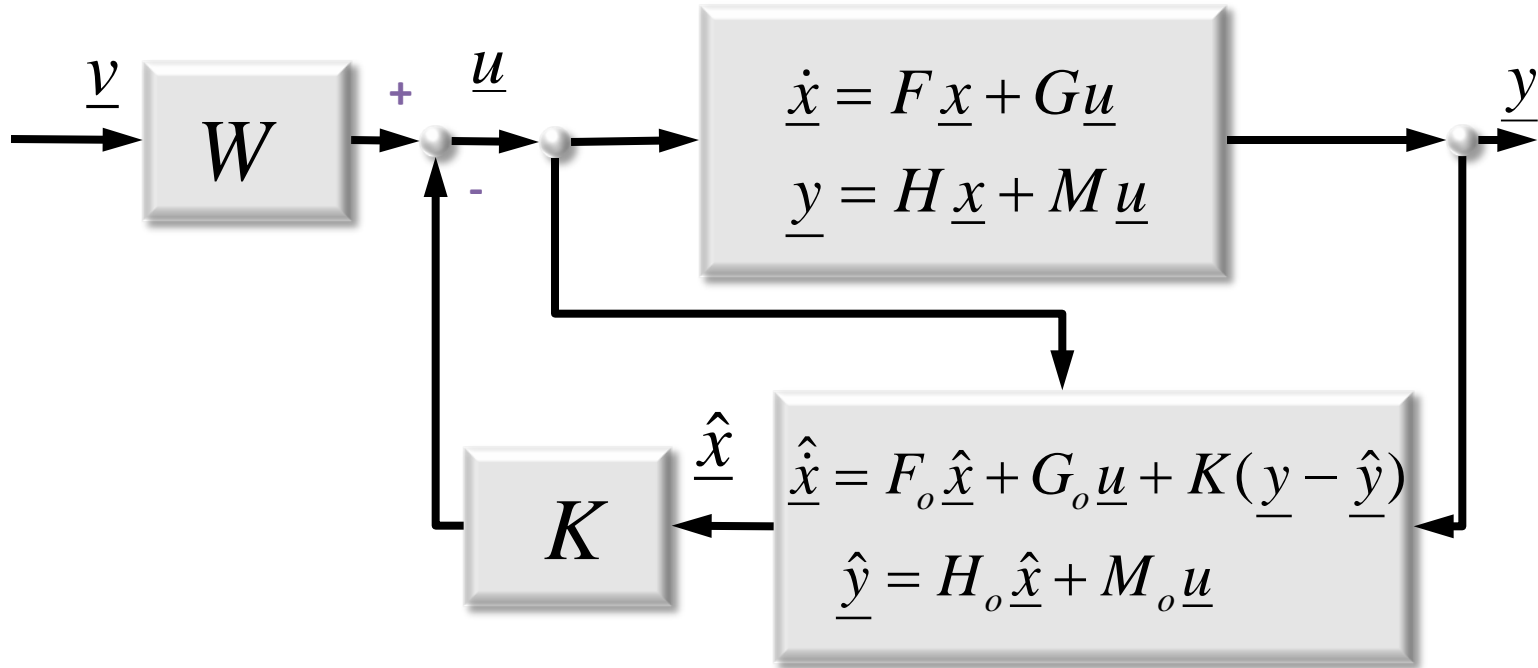
## 7.2.2.4 Eigenvalue Assignment

- If original system ...
  - is completely controllable
  - and  $H$  is full rank
- $m$  of these e-values can be placed arbitrarily by suitable choice of the gain matrix  $K$ .

## 7.2.2.5 Observers

- Clearly, output feedback is inferior.
- Can we:
  - reconstruct the state from the measurements?
  - Use the reconstructed state as state feedback.
- Surprisingly, yes.

## 7.2.2.5 Observers



- Almost every mobile robot looks like this.
- The observer is the state estimation system.
  - Hence, the Kalman filter.

## 7.2.2.5 Observers

- The predicted output is:

$$\hat{\underline{y}} = H_o \hat{\underline{x}} + M_o \underline{u}$$

- The observer dynamics have one extra input – the output prediction error:

$$\frac{d}{dt} \hat{\underline{x}} = F_o \hat{\underline{x}} + G_o \underline{u} + K_o (\underline{y} - \hat{\underline{y}}) \quad \text{Ko is TBD}$$

- Subtract this from real system dynamics (assuming matrices match)

$$\frac{d}{dt} (\underline{x} - \hat{\underline{x}}) = F(\underline{x} - \hat{\underline{x}}) - K_o (\underline{y} - \hat{\underline{y}})$$

Same form  
as a  
controller!

## 7.2.2.5 Observers

- If the error dynamics are controllable, we can drive the state estimate to agree with the state in an arbitrarily short period of time.

$$\frac{d}{dt}(\underline{x} - \hat{\underline{x}}) = F(\underline{x} - \hat{\underline{x}}) - K_o(\underline{y} - \hat{\underline{y}})$$

Same form  
as a  
controller!

- Assuming measurements and matrices are known perfectly.

## 7.2.2.6 Control of Nonlinear Systems

- All mobile robots are nonlinear
  - Because the sensors and actuators are on the robot.
- So.... Why study all this linear system stuff?

## 7.2.2.6 Control of Nonlinear Systems

- All mobile robots are nonlinear
  - Because the sensors and actuators are on the robot.
- So.... Why study all this linear system stuff?
  - Control the linearized (error) dynamics.

# 7.2.2.6 Control of Nonlinear Systems

(Two DOF Design)

- Aka Feedforward with feedback trim....
  - Feed forward the reference trajectory open loop control.
  - Use feedback to reject disturbances etc.

$$\begin{aligned}\dot{\underline{x}}(t) &= \underline{f}(\underline{x}(t), \underline{u}(t)) \\ \underline{y}(t) &= \underline{h}(\underline{x}(t), \underline{u}(t))\end{aligned}$$

Nonlinear System

$$\begin{aligned}\delta\dot{\underline{x}}(t) &= F(t)\delta\underline{x}(t) + G(t)\delta\underline{u}(t) \\ \delta\underline{y}(t) &= H(t)\delta\underline{x}(t) + M(t)\delta\underline{u}(t)\end{aligned}$$

Linearized Error Dynamics

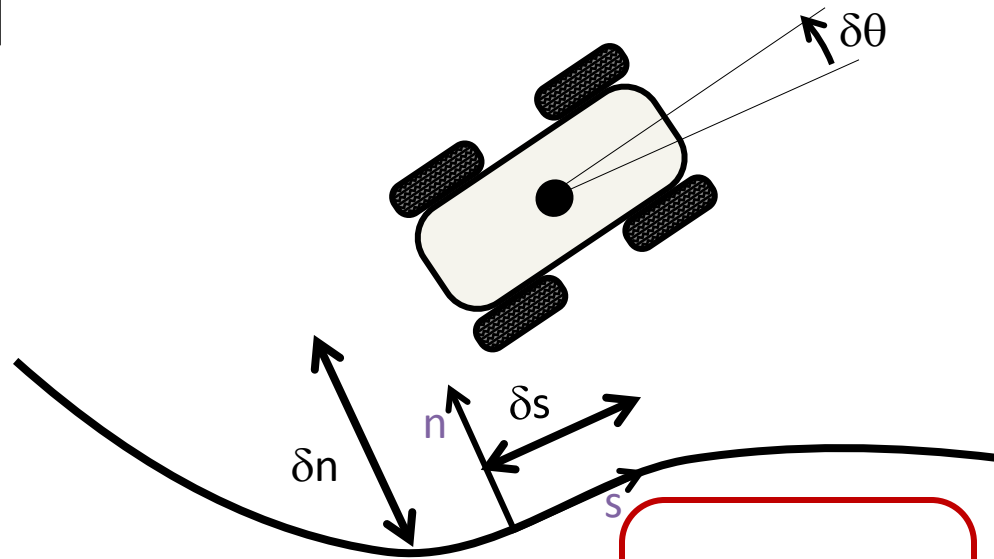


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## 7.2.3.1 Representing Trajectories

- Assume velocity is fwd along body x only
- States:  $\underline{x} = [x \ y \ \theta]^T$
- Inputs:  $\underline{u} = [\kappa \ V]^T$
- Nonlinear state space model in terms of time.



But notice speed  $V$  can be factored out.

$$\frac{d}{dt} \begin{bmatrix} x \\ y \\ \psi \end{bmatrix} = \begin{bmatrix} \cos \psi \\ \sin \psi \\ \kappa \end{bmatrix} v$$

$$\begin{bmatrix} x(t) \\ y(t) \\ \psi(t) \end{bmatrix} = \begin{bmatrix} x(0) \\ y(0) \\ \psi(0) \end{bmatrix} + \int_0^t \begin{bmatrix} \cos \psi \\ \sin \psi \\ \kappa \end{bmatrix} V dt$$

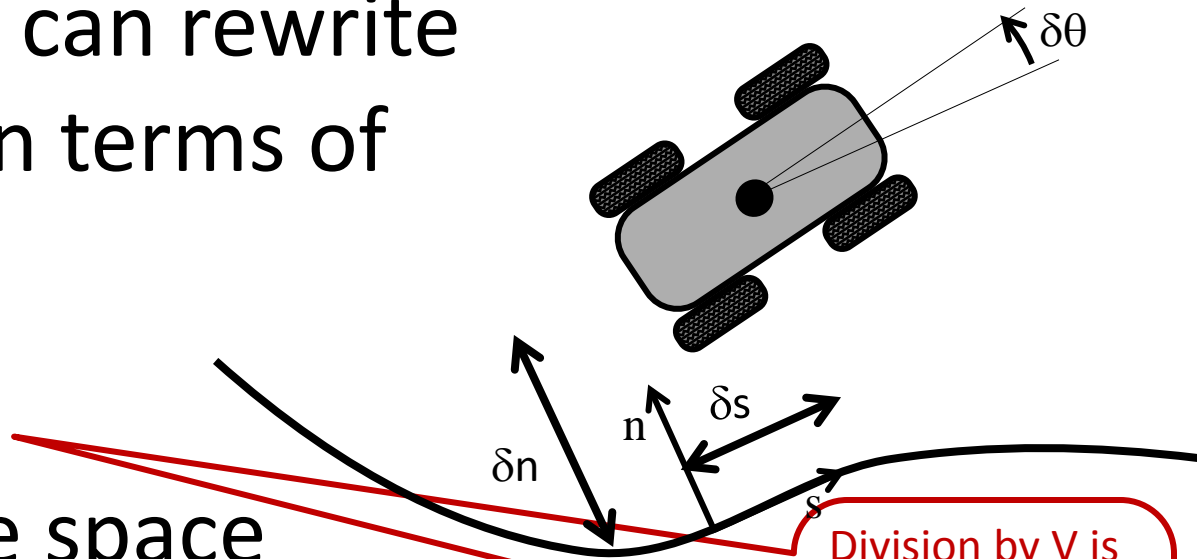
## 7.2.3.1 Representing Trajectories

- This means we can rewrite the dynamics in terms of distance

$$\frac{dx}{dt} / V = \frac{dx}{dt} / \frac{ds}{dt} = \frac{dx}{ds}$$

- Nonlinear state space model in terms of distance.

$$\frac{d}{ds} \begin{bmatrix} x \\ y \\ \psi \end{bmatrix} = \begin{bmatrix} \cos \psi \\ \sin \psi \\ \kappa \end{bmatrix} \quad \begin{bmatrix} x(s) \\ y(s) \\ \psi(s) \end{bmatrix} = \begin{bmatrix} x(0) \\ y(0) \\ \psi(0) \end{bmatrix} + \int_0^s \begin{bmatrix} \cos \psi \\ \sin \psi \\ \kappa \end{bmatrix} ds$$

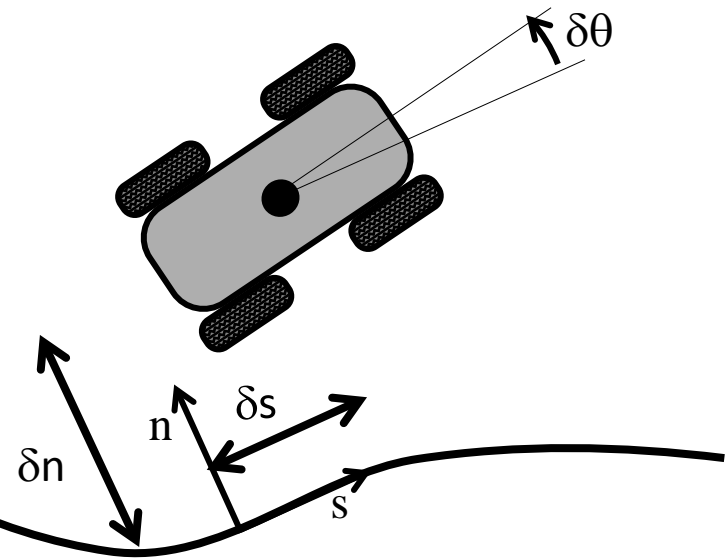


Division by  $V$  is only a problem if you insist on a curvature for every time.

## 7.2.3.2 Robot Trajectory Following

- States:  $\underline{x} = [x \ y \ \theta]^T$ .
- Inputs:  $\underline{u} = [\kappa \ V]^T$ .
- Nonlinear state space model:

$$\frac{d}{dt} \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} = \begin{bmatrix} \cos \theta \\ \sin \theta \\ \kappa \end{bmatrix} V$$



- Suppose a trajectory generator has produced a reference:

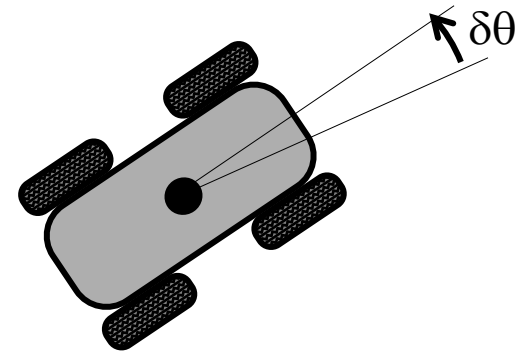
$$[\underline{u}_r(t), \underline{x}_r(t)]$$

- Assume full state feedback.

# 7.2.3.2.1 Linearization and Controllability

- Linearized Dynamics:

$$\frac{d}{dt} \begin{bmatrix} \delta x \\ \delta y \\ \delta \psi \end{bmatrix} = \begin{bmatrix} 0 & 0 & -vs\psi \\ 0 & 0 & vc\psi \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta x \\ \delta y \\ \delta \psi \end{bmatrix} + \begin{bmatrix} c\psi & 0 \\ s\psi & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta v \\ \delta \kappa \end{bmatrix}$$



- Convert coordinates to path tangent frame.

$$\begin{bmatrix} \delta \dot{s} \\ \delta \dot{n} \\ \delta \dot{\theta} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & V \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \delta s \\ \delta n \\ \delta \theta \end{bmatrix} + \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \delta V \\ \delta \kappa \end{bmatrix}$$

Very Simple System

Linear

Time Invariant for constant V

$$\underline{s} = \begin{bmatrix} s & n & \theta \end{bmatrix}^T$$

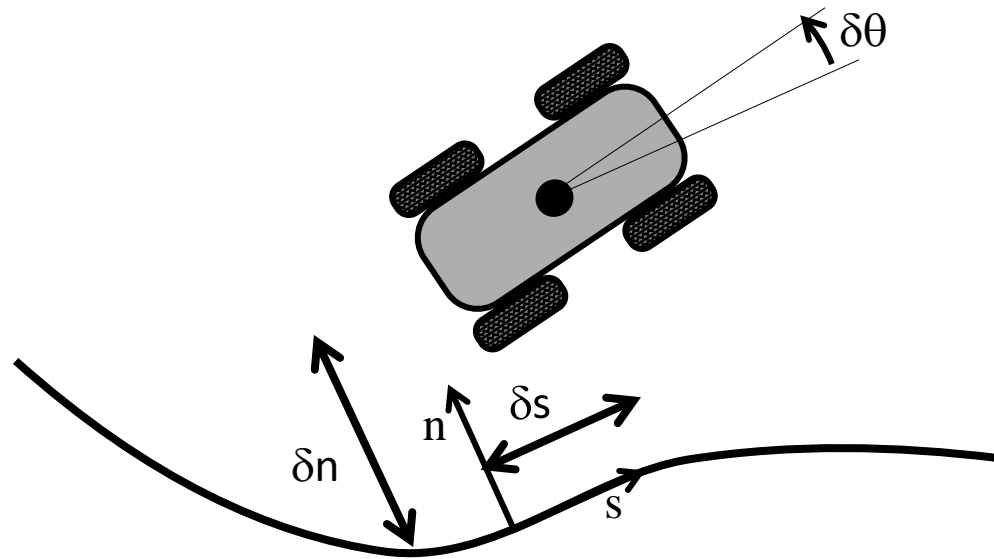
- Of the form:

$$\delta \dot{\underline{s}}(t) = F(t) \delta \underline{s}(t) + G(t) \delta \underline{u}(t)$$

# 7.2.3.2.1 Linearization and Controllability

- Controllable?

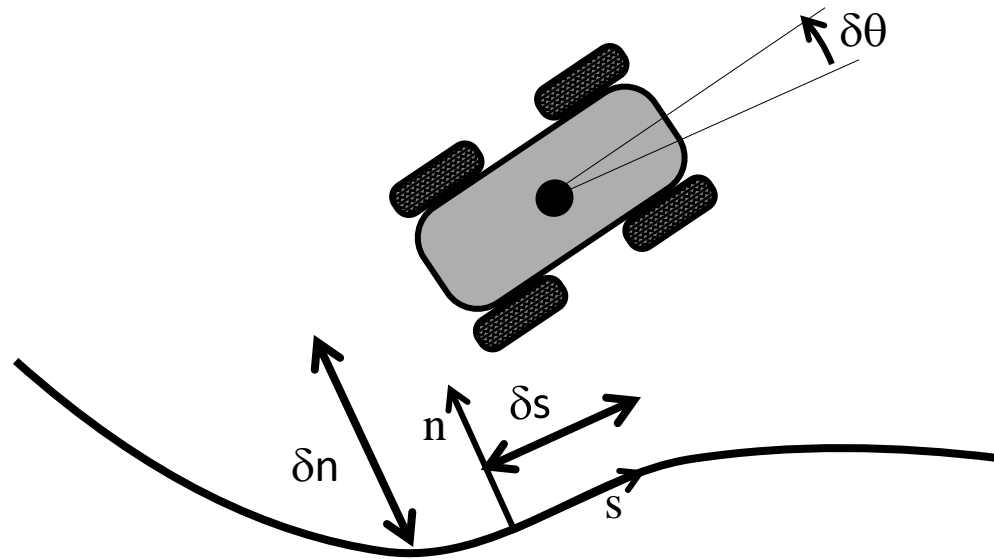
$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & V & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$



# 7.2.3.2.1 Linearization and Controllability

- Controllable?

$$Q = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & V & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$



## 7.2.3.2.2 State Feedback Control Law

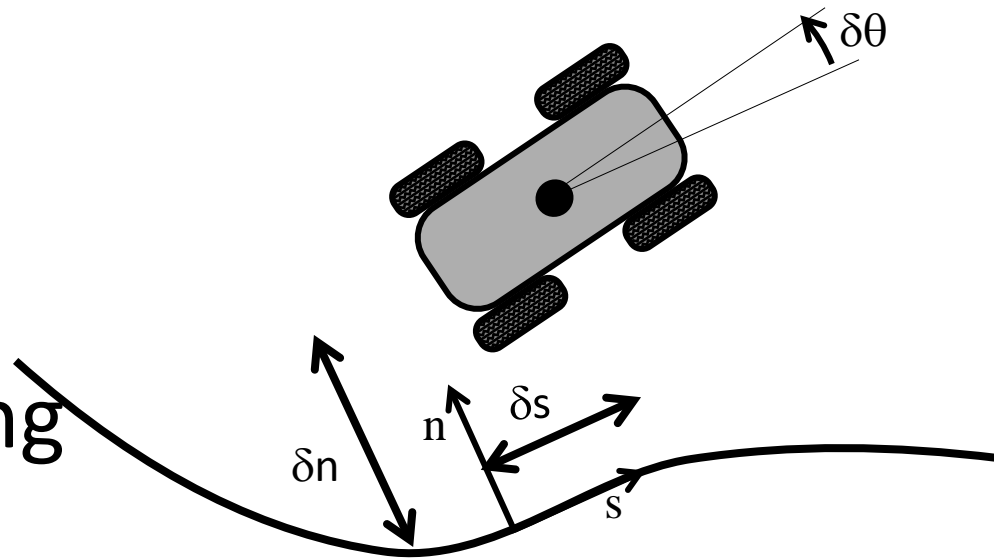
- State Feedback

$$\delta \underline{u}(t) = -K \delta \underline{s}(t)$$

- We know speed can control  $s$  and steering can control  $n$  and  $\theta$

so:

$$K = \begin{bmatrix} k_s & 0 & 0 \\ 0 & k_n & k_\theta \end{bmatrix}$$





# 7.2.3.2.2 State Feedback Control Law (Total Control Law)

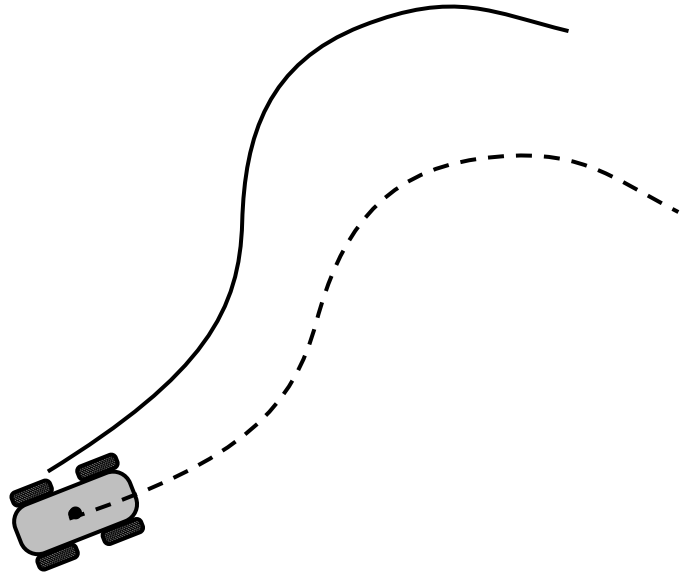
$$\underline{u}(t) = \underline{u}_r(t) + \delta \underline{u}(t) = \underline{u}_r(t) - \begin{bmatrix} k_s & 0 & 0 \\ 0 & k_n & k_\psi \end{bmatrix} \begin{bmatrix} \delta s \\ \delta n \\ \delta \psi \end{bmatrix}$$

Feedforward  
(path  
curvature and  
speed)

Feedback  
P and PD  
controllers

# 7.2.3.2.3 Behavior

(Open Loop Servo Execution)



$$\kappa_d(s) = \kappa(s_{\text{measured}})$$

- While simple in principle, open loop execution does not reject disturbances.
- Even a single initial error can grow forever if not compensated.

# 7.2.3.2.3 Behavior

(Distance Based Open Loop Control)

- Ignore speed by converting to distance as the independent variable.
- Recall, this implies a particular path through space because:

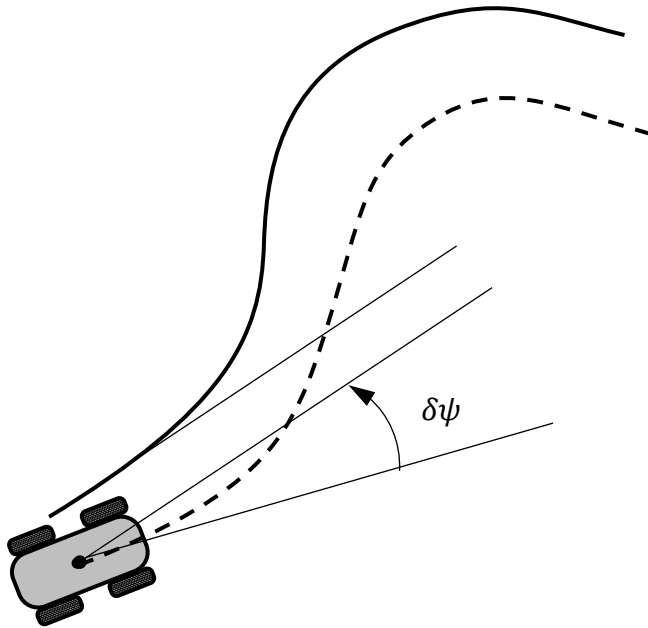
$$\psi(s) = \psi_0 + \int_0^s \kappa ds$$

$$x(s) = \int_0^s \cos[\theta(s)] ds$$

$$y(s) = \int_0^s \sin[\theta(s)] ds$$

# 7.2.3.2.3 Behavior

(Heading Error Compensation)



$$\Delta\kappa = \Delta\psi/L$$
$$\kappa_d(s) = \kappa(s_{\text{measured}}) + \Delta\kappa$$

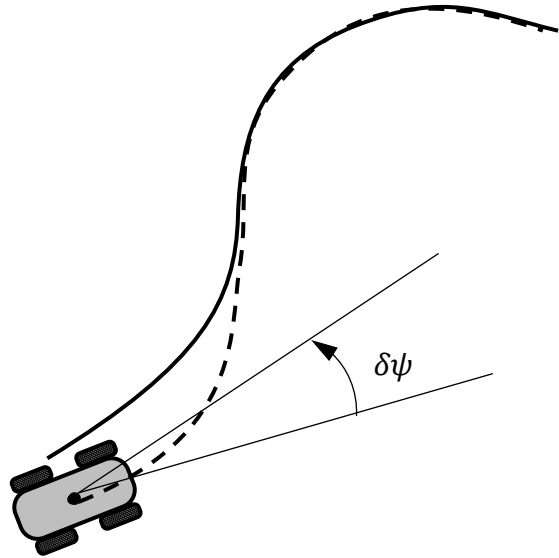
Pass original  
command to  
output

Plus a  
correction

- Passes original command directly to output.
- Bends the response path to be parallel to the desired.
- BUT: Does not move paths together.

# 7.2.3.2.3 Behavior

(Full Pose Error Compensation)



$$\Delta\kappa = \Delta\psi/L$$

$$\Delta\kappa = 2\Delta x/L^2$$

- Passes original command directly to output.
- $\Delta x$  is coordinate of closest point in body coords.
- Also adds two corrective amounts intended to remove present error.

## 7.2.3.2.4 Eigenvalue Placement

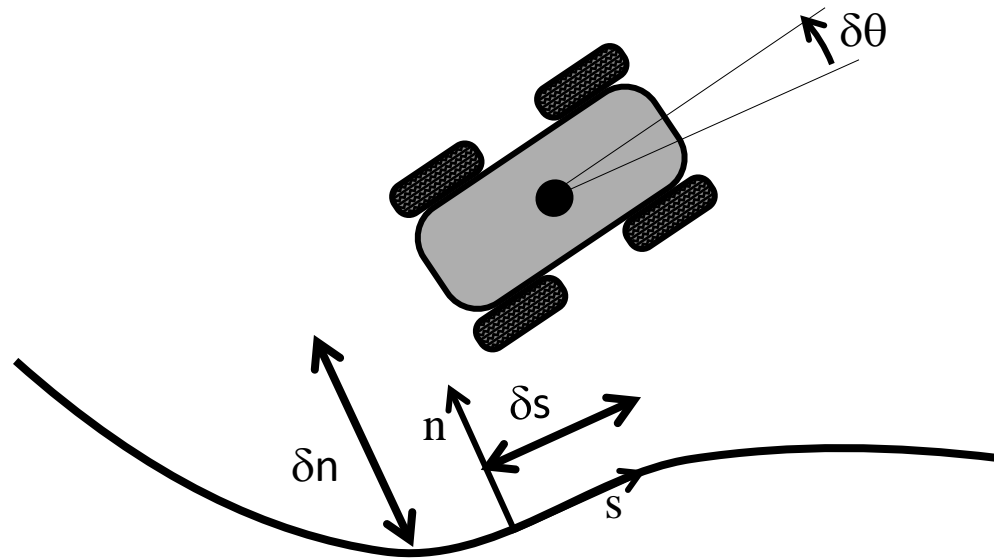
- New closed loop dynamics matrix:

$$F - GK = - \begin{bmatrix} k_s & 0 & 0 \\ 0 & 0 & -v \\ 0 & k_n & k_\psi \end{bmatrix}$$

- Characteristic poly:

$$\det(\lambda I - F + GK) = \begin{vmatrix} \lambda + k_s & 0 & 0 \\ 0 & \lambda & -v \\ 0 & k_n & \lambda + k_\psi \end{vmatrix}$$

$$(\lambda^3 + \lambda^2(k_\psi + k_s) + \lambda(k_n v + k_s k_\psi) + k_s k_n v)$$



Any coefficients are possible  
so.....  
Any roots are possible.

## 7.2.3.2.5 Gains

- Both curvature gains can be related to a characteristic length.

$$k_n = \frac{2}{L^2} \quad k_\psi = \frac{1}{L}$$

- Then  $\delta\kappa_\psi = \delta\psi/L$  removes heading error after moving a distance  $L$ .
- And  $\delta\kappa_n = 2\delta n/L^2$  removes crosstrack error after travelling a distance  $L$ .
- Also  $\tau_s = 1/k_s$  is the time constant of speed error response.

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# 7.2.4 Perception Based Control

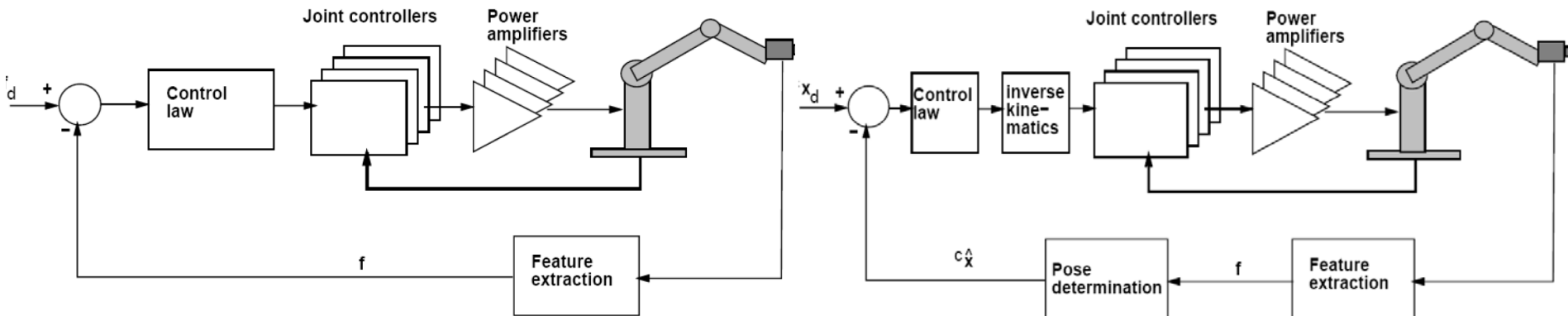
(Visual Servoing)

- Observed feature residuals can be generated by:
  - Perceived errors in pose estimates in a region of overlap (registration) or ...
  - Real errors in pose itself in a positioning task.
- In the latter case, it is natural to close a servo loop and drive the system to move to reduce the error. This is visual servoing.
- Must maintain feature correspondences during motion:
  - Embedded feature tracking problem.

# 7.2.4 Perception Based Control

(Visual Servoing : Architecture : Errors)

- Image-based control forms errors in image space.
  - Servoing done in image space
- Position-based control forms errors from object poses:
  - Poses derived from image features
  - Servoing done in pose space.

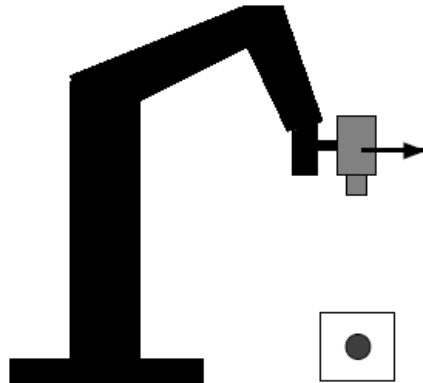


# 7.2.4 Perception Based Control

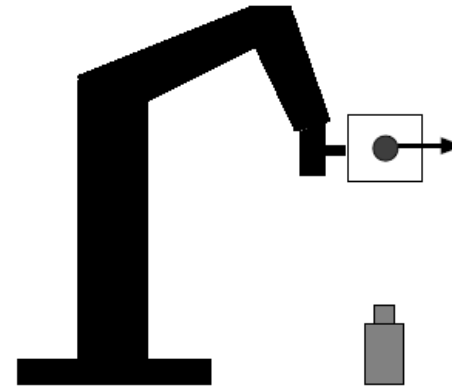
(Visual Servoing : Architecture : Camera Position)

- Camera may be moving or stationary.
- Required motions are reversed with respect to each other.

Eye-in-Hand system

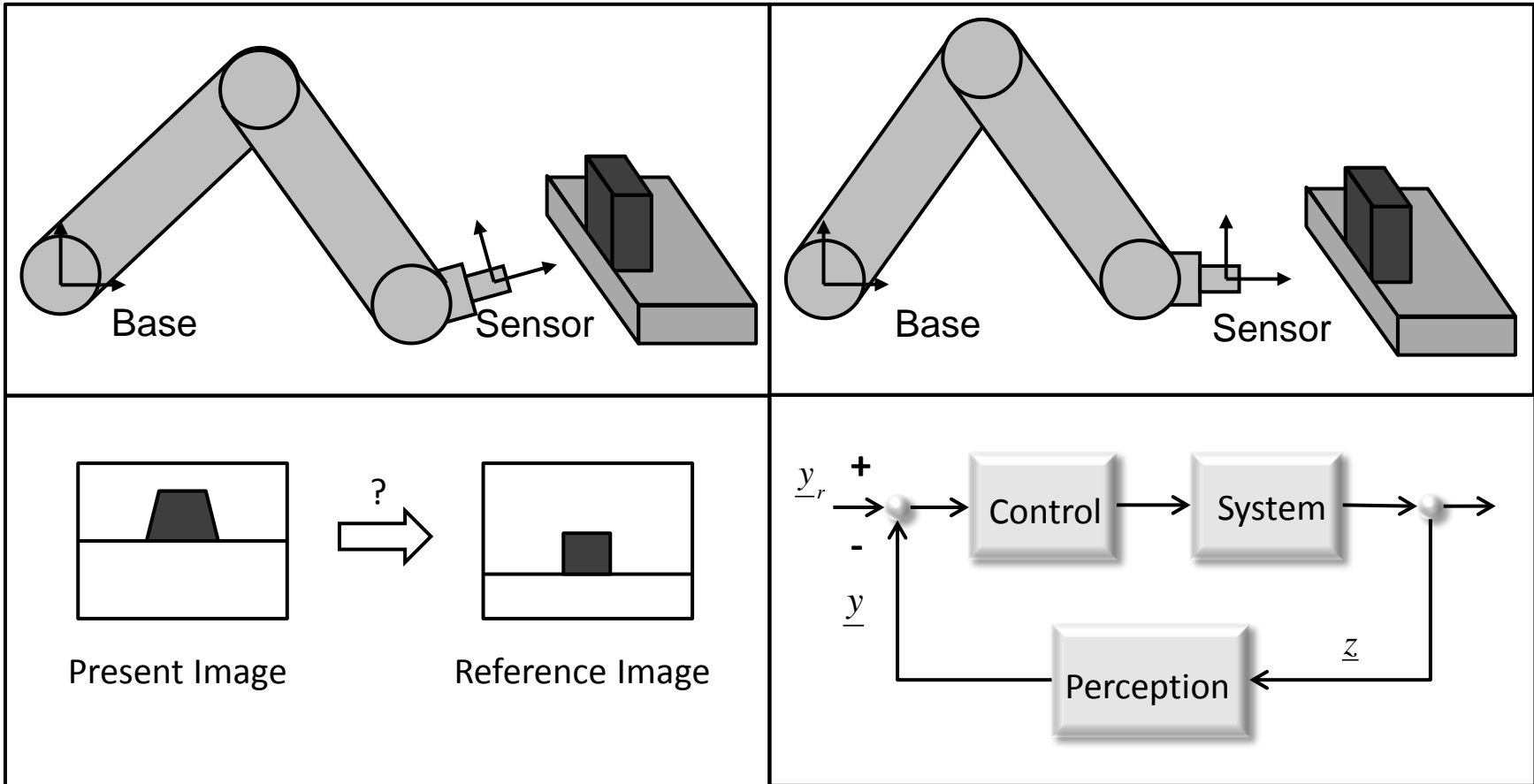


Eye-to-Hand system

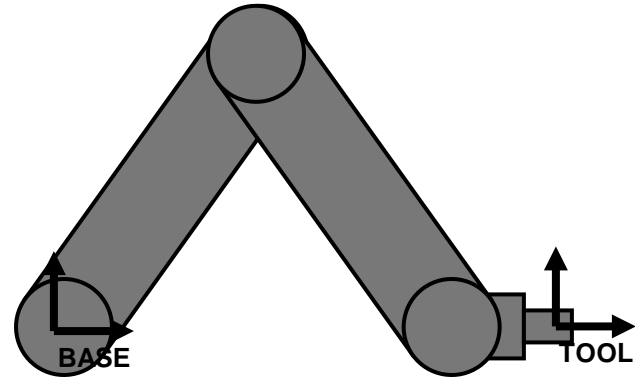
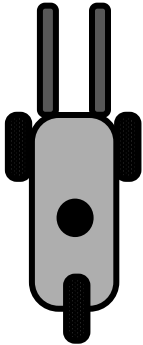
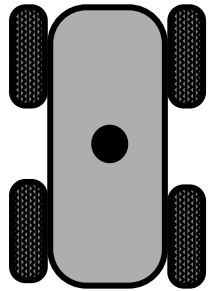


# 7.2.4.1 Error Coordinates

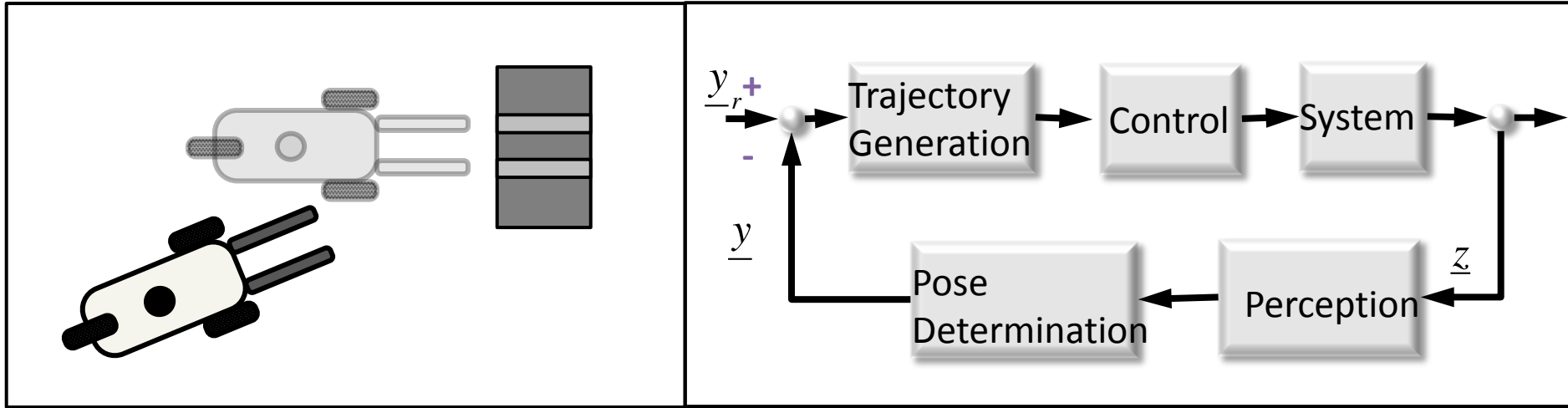
(Image Based Visual Servoing)



- Problem: drive the system (usually with a camera attached) to turn the present image into the desired image.
- An excellent way to drive up to something with a poor pose estimate.



# 7.2.4.1 Error Coordinates (Image Based Visual Servoing)



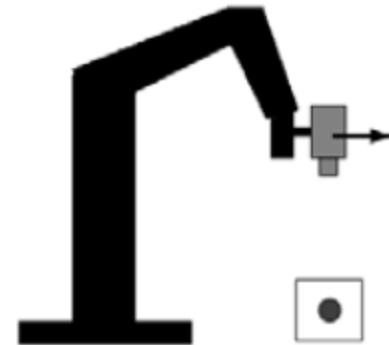
- Explicitly calculate the pose of the object relative to the camera.
- Compute the error in the pose.

# 7.2.4.2 Visual Servoing

(Image Formation Model)

- Observations / measurements  $z$  depend on the pose  $r$  of the camera w.r.t. the object.

$$\underline{z} = h(\underline{\rho}(t))$$



# 7.2.4.2 Visual Servoing

(Image Formation Model)

- $k$  adequate features in  $\underline{z}$  with which to control the  $m$  dof of the system.
- Usually:  
$$k \geq m \quad m \leq 6$$
- A goal image space configuration  $\underline{z}_r$ :
- Regulate the error:  $\underline{z}_r - \underline{z}$ :
- Typically track features at near video rate.



# 7.2.4.4 Controller Design

## (Basic Controller)

- Observable features  $z$  depend in a predictable way on the camera projection model  $h(\_)$  and the pose  $\underline{\rho}(t)$  of the target object wrt the camera:

$$\underline{z} = h(\underline{\rho}(t))$$

- $z$  could also be interpreted simply as the pose relative to the target in a position-based approach.

# 7.2.4.4 Controller Design

## (Basic Controller)

$$\underline{z} = h(\underline{\rho}(t))$$

- Taking the time derivative:

$$\text{Eqn A} \quad \dot{\underline{z}} = \frac{\partial h}{\partial \underline{\rho}} \frac{d\underline{\rho}}{dt} = \mathbf{L}_f \underline{v}(t)$$

Jacobian  $L_f$  is called the interaction matrix.

- Also, by definition:

$$\Delta \underline{z} = \mathbf{L}_f \Delta \underline{\rho}$$

- We might solve this with the LPI:  $\Delta \underline{\rho} = \mathbf{L}_f^+ \Delta \underline{z}$

- If  $\Delta z$  is the feature error, then:

$$\Delta \underline{\rho} = L_f^+ [\underline{z}_r - \underline{z}]$$

Pose error that explains the feature error to first order.

## 7.2.4.4 Controller Design (Basic Controller)

$$\Delta \underline{\rho} = L_f^+ [\underline{z}_r - \underline{z}]$$

- Divide by a small  $Dt$  to get:

Pose velocity

$$\underline{v} = L_f^+ \frac{d}{dt} [\underline{z}_r - \underline{z}]$$

Feature error rate

- Suppose we would like the feature rate to be consistent with nulling the error in  $t$  ( $1/l$ ) seconds.

$$\frac{d}{dt} [\underline{z}_r - \underline{z}] = - \frac{[\underline{z}_r - \underline{z}]}{\tau} = -\lambda [\underline{z}_r - \underline{z}]$$

- Substituting above:

$$\underline{v}_c = -\lambda L_f^+ [\underline{z}_r - \underline{z}]$$

## 7.2.4.4 Controller Design

(Basic Controller)

$$\underline{v}_c = -\lambda L_f^+ [\underline{z}_r - \underline{z}]$$

- This is a proportional controller with gain:

$$K_p = \lambda = 1/\tau$$

- Drives observed feature errors exponentially to zero.
- Substituting the control into the dynamics gives the closed loop error dynamics:

$$\dot{\underline{z}} = L_f \underline{v}_c(t) = -\lambda L_f L_f^+ [\underline{z}_r - \underline{z}]$$

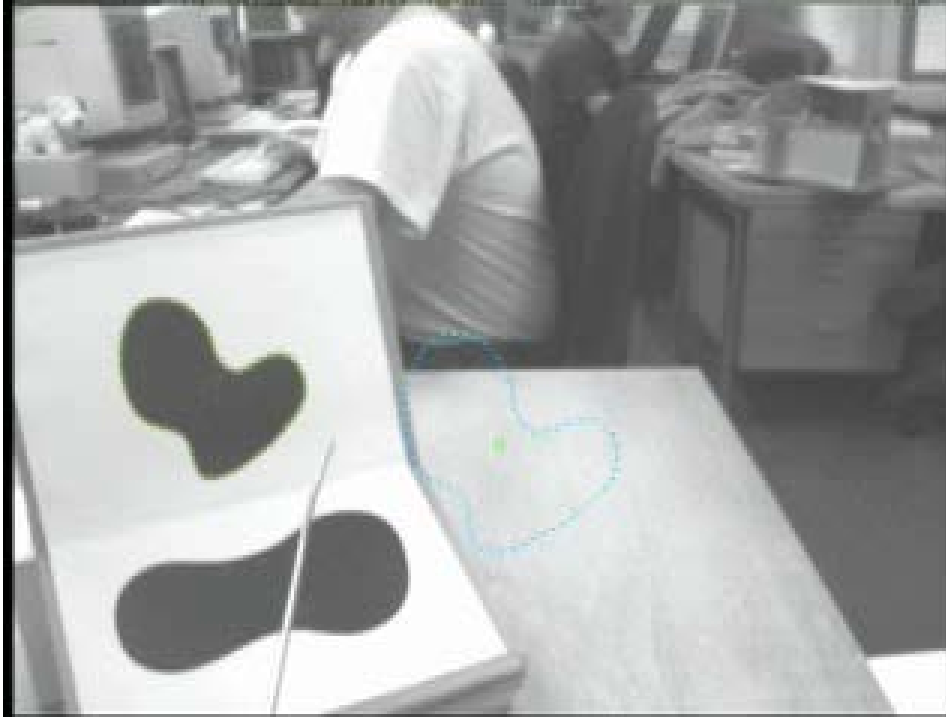
Eqn A

## 7.2.4.4 Controller Design

$$\dot{\bar{z}} = L_f v_c(t) \stackrel{\text{(Behavior)}^+}{=} -\lambda L_f L_f^+ [\bar{z}_r - \bar{z}]$$

- Case 1:  $L_f L_f^+ = \mathbf{I}$  perfect behavior
- Case 2:  $L_f L_f^+ > 0$  error decreases
- Case 3:  $L_f L_f^+ < 0$  error increases
- Ideally:
  - $L_f$  is not singular anywhere.
  - There are no non-optimum local minima.

# Videos



Moment Visual Servoing



Face Visual Servoing

# Outline

- 7.2 State Space Control
  - 7.2.1 Introduction
  - 7.2.2 State Space Feedback Control
  - 7.2.3 Example: Robot Trajectory Following
  - 7.2.4 Perception Based Control
  - 7.2.5 Steering Trajectory Generation
  - Summary

# 7.2.5 Steering Trajectory Generation

(Trajectory Generation)

- Trajectory generation is necessary for any kind of precision control of mobile robots.
- The problem occurs in various forms:
  - “Steering” (curvature generation) problem.
  - “Smooth stopping” (velocity profile) problem.
  - Both at once
    - Sometimes in terms of linear and angular velocity.



# 7.2.5 Steering Trajectory Generation

(Definitions)

- Let a trajectory be a specification of an entire motion.

- Could be explicitly in terms of state:

$$\{\underline{\mathbf{x}}(t) | (t_0 < t < t_f)\}$$

- Could be implicitly in terms of inputs:

$$\{\underline{\mathbf{u}}(t) | (t_0 < t < t_f)\}$$

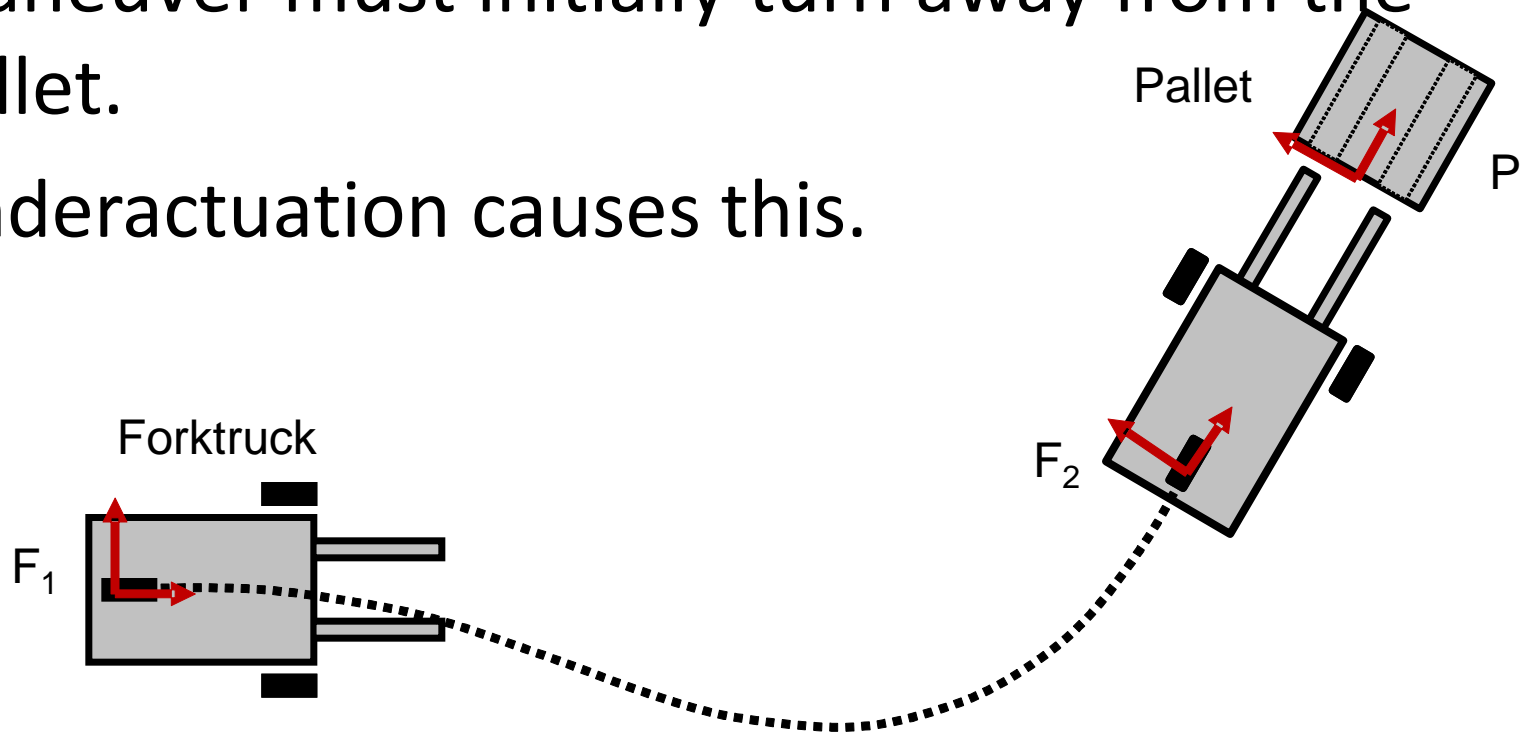
- Need both for 2 dof control

- Both can be visualized as the trajectory followed by the tip of a vector over time.

# 7.2.5 Steering Trajectory Generation

(Motivation)

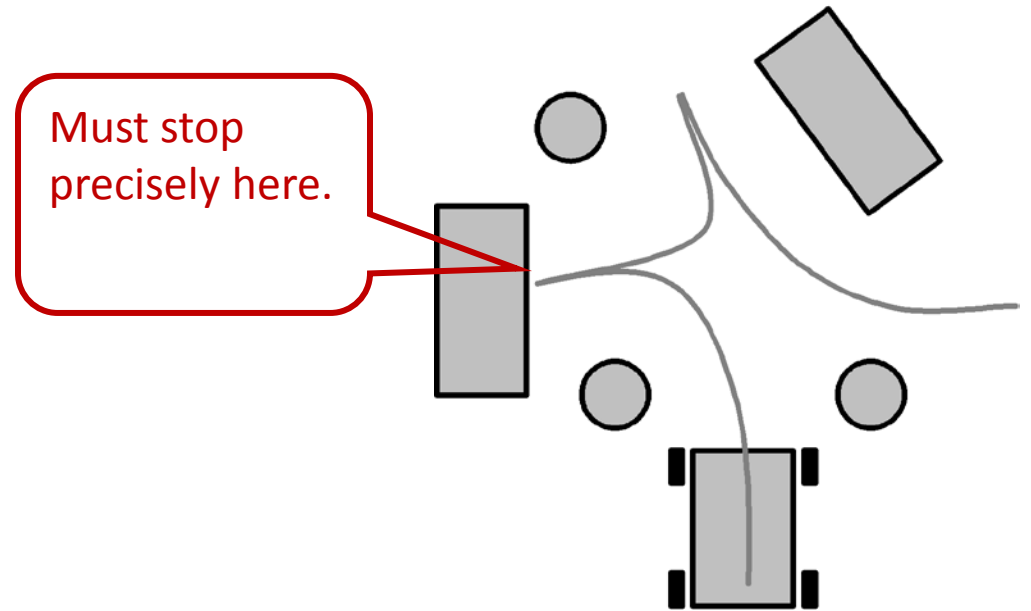
- Load cannot be approached sideways.
- Visualize driving backward from goal.
- Maneuver must initially turn away from the pallet.
- Underactuation causes this.



# 7.2.5 Steering Trajectory Generation

(Motivation : Precision Control)

- Precision control is necessary:
  - when goals states must be achieved precisely
  - when paths must be followed precisely.
- That happens in cluttered environments, for example.

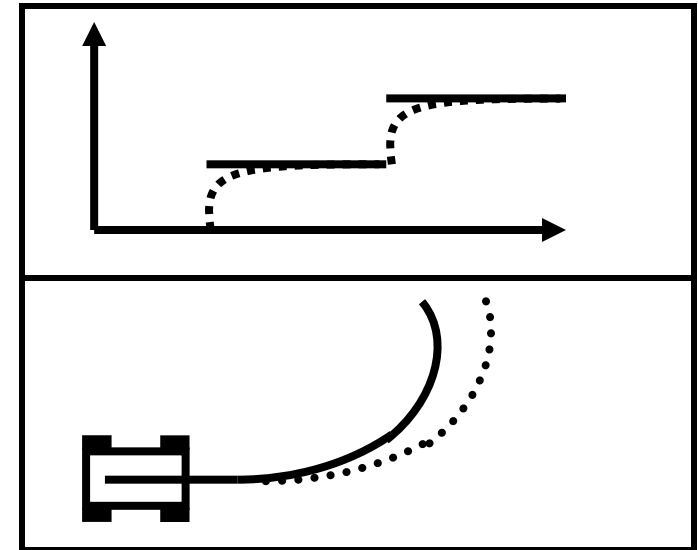


The robot must not only follow the intended curves but it must come to a stop neither too early (which would make achieving the next goal impossible) nor too late (which will cause a collision).

# 7.2.5 Steering Trajectory Generation

(Motivation : Reduced Following Error)

- Trajectory generation can compensate for the predictable causes of following error.
- Using trajectory generation, you can decide what to ask for, in order to get what you want.



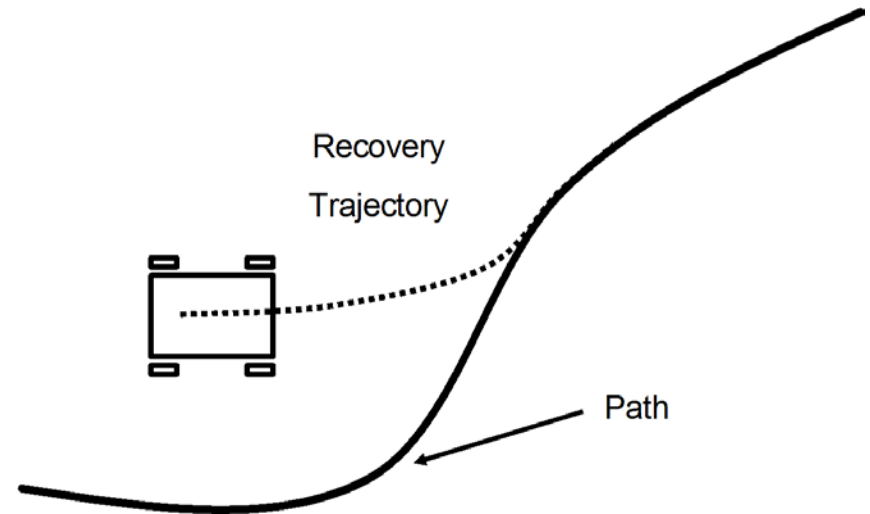
————— Command  
..... Response

The nonideal response to a discontinuous curvature control can be visualized in either input space or state space.

# 7.2.5 Steering Trajectory Generation

(Motivation : Corrective Trajectories)

- Control layers above the coordinated control layer....
  - Have easier jobs to do with a trajectory generator to talk to.



The best recovery trajectory is one which reacquires the path at the correct heading and curvature.

# 7.2.5.1 Problem Specification

- Dynamics:

$$\dot{\underline{x}} = f(\underline{x}, \underline{u})$$

- Physical constraints:  $|\underline{u}(t)| \leq \underline{u}_{\max}(t)$   $|\dot{\underline{u}}(t)| \leq \dot{\underline{u}}_{\max}(t)$

- Turn radius bounded from below

- Curvature is bounded by mechanisms and terrain friction.

- Boundary conditions:

$$\underline{x}(t_0) = \underline{x}_0$$

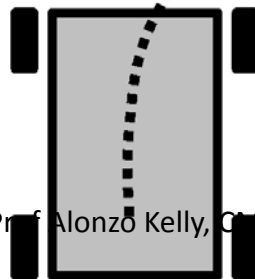
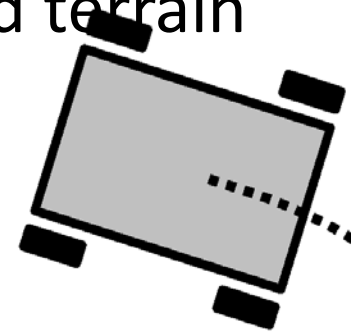
$$\underline{x}(t_f) = \underline{x}_f$$

Goal State

$$(\underline{x}, \underline{y}, \theta, \kappa, V)_f$$

Start State

$$(\underline{x}, \underline{y}, \theta, \kappa, V)_0$$



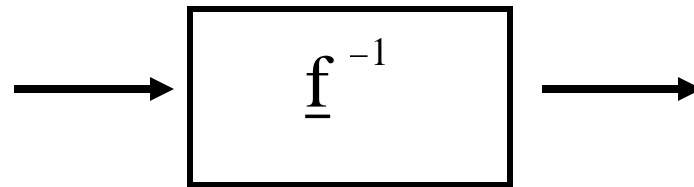
# 7.2.5.1 Problem Specification

(Constraint : Dynamics)

- For a system:

$$\dot{\underline{x}} = f(\underline{x}, \underline{u})$$

- Problem: determine an entire control function  $\underline{u}(t)$  which generates some desired state trajectory  $\underline{x}(t)$ .



- It's the problem of inverting a differential equation.

# 7.2.5.2 Formulation as a Rootfinding Problem

(Existence)

- Every  $u(t)$  generates some  $x(t)$ ...

$$\mathbf{x}(t) = \mathbf{x}(0) + \int_0^t \mathbf{f}(\underline{\mathbf{x}}, \underline{\mathbf{u}}, t) dt$$

- However, many arbitrary  $x(t)$ 's represent infeasible motions.
  - Mathematical reasons – underactuation
  - Physics reasons - friction
  - Power related reasons - horsepower



## 7.2.5.2 Formulation as a Rootfinding Problem (Parameterization)

- Function space of all  $\underline{u}(t)$  is too large to search.
- Parameterize inputs:  $\underline{u}(t) \rightarrow \underline{\tilde{u}}(\underline{p}, t)$
- Easy to see by Taylor series that  $\underline{p}$  spans all possible  $\underline{u}(t)$ 
  - Pick any  $\underline{u}_k(t)$  you like.
  - Write its Taylor series
  - Coefficients  $\underline{p}_k$  approximate  $\underline{u}_k(t)$  arbitrarily well.
  - But  $\underline{u}_k(t)$  was arbitrary too  $\rightarrow$  so  $\underline{p}_k$  spans everything!

## 7.2.5.2 Formulation as a Rootfinding Problem

(Parameterization)

- Now  $\underline{p}$  determines  $\underline{u}(t)$  which determines  $\underline{x}(t)$ , so dynamics become:

$$\dot{\underline{x}}(t) = \underline{f}[\underline{x}(\underline{p}, t), \underline{u}(\underline{p}, t), t] = \tilde{\underline{f}}(\underline{p}, t)$$

- The boundary conditions become:

Integrals are suppressed notationally – but they are still there.

$$\underline{g}(\underline{p}, t_0, t_f) = \underline{x}(t_0) + \int_{t_0}^{t_f} \tilde{\underline{f}}(\underline{p}, t) dt = \underline{x}_b$$

- This is conventionally written as:

$$\underline{c}(\underline{p}, t_0, t_f) = \underline{h}(\underline{p}, t_0, t_f) - \underline{x}_b = 0$$

## 7.2.5.2 Formulation as a Rootfinding Problem (Parameterization)

- Wait a minute!:

$$\underline{c}(\underline{p}, t_0, t_f) = 0$$

- That is a rootfinding problem!
- Conclusion:
  - the problem of inverting a nonlinear vector differential equation
  - can be converted to a rootfinding problem
  - using parameterization.

## 7.2.5.3 Steering Trajectory Generation

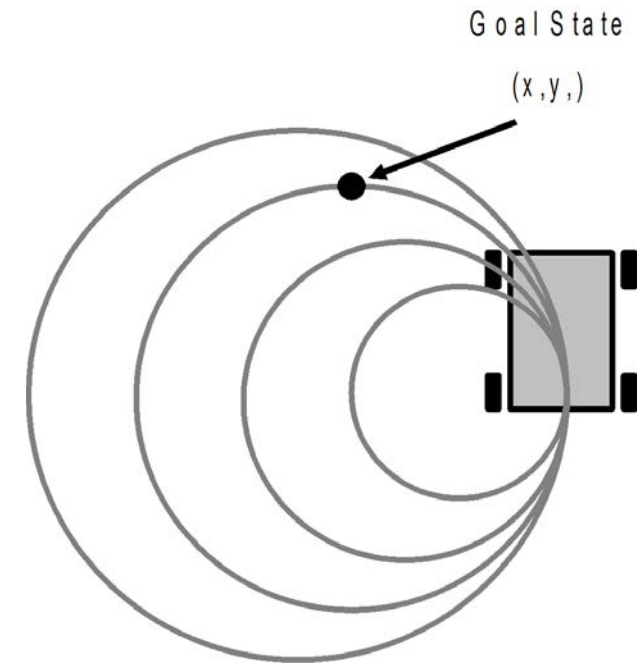
- Switch to steering problem and ignore velocity.
- Often it is convenient to change the independent variable from time to distance.  $\underline{q} = [\underline{p}^T, s_f]^T$
- Let the initial distance  $s_0$  be zero and absorb the final distance into the parameter vector, thus:

$\underline{p}$  became longer but  $t_0$  and  $t_f$  have been eliminated.

# 7.2.5.3 Steering Trajectory Generation

(Degrees of Freedom)

- If  $u(p, sf)$  has  $n$  parameters, these can be used to satisfy  $n$  constraints.
- For example, an arc trajectory really has two parameters – radius and length.
- Imagine the circles moving outward until they hit the point.
- Its not too hard to find the radius and distance which hit the point.
- Terminal heading and curvature are beyond your control.

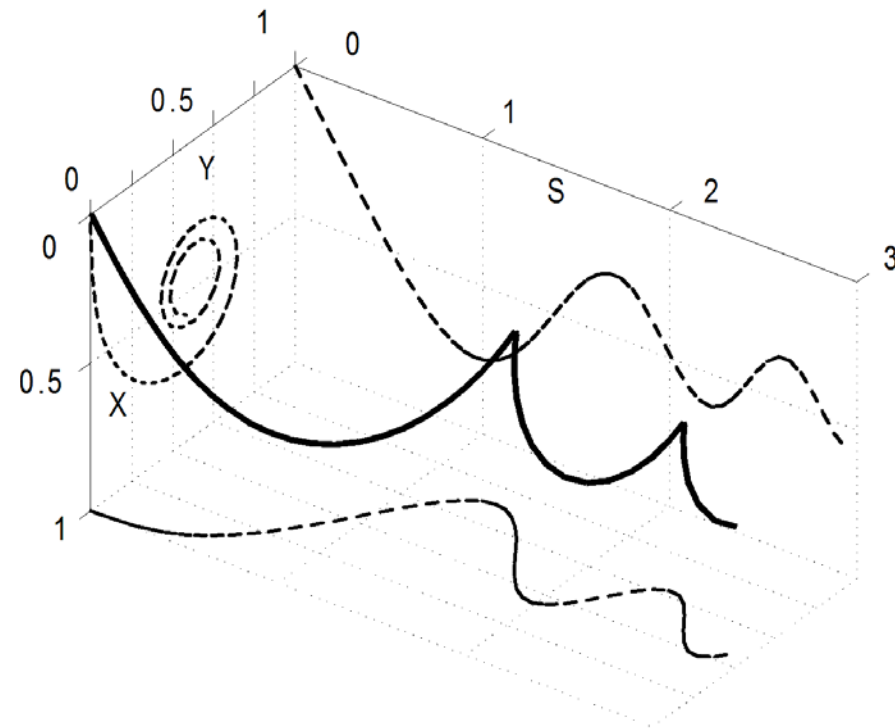


# 7.2.5.3 Steering Trajectory Generation (Clothoids)

- Another historically popular curve is the clothoid. It's a linear curvature polynomial:

$$\kappa(s) = a + bs$$

- This has 3 degrees of freedom but its still not enough for some problems.



# 7.2.5.3 Steering Trajectory Generation

(Polynomial Spirals)

- We can without loss of generality consider the initial pose to be at the origin.
- If initial and final curvature matter, that leaves FIVE constraints:

$$x(s_f) = x_f$$

$$y(s_f) = y_f$$

$$\theta(s_f) = \theta_f$$

$$\kappa(0) = \kappa_0$$

$$\kappa(s_f) = \kappa_f$$

- A curve with 5 dof is a cubic spiral:

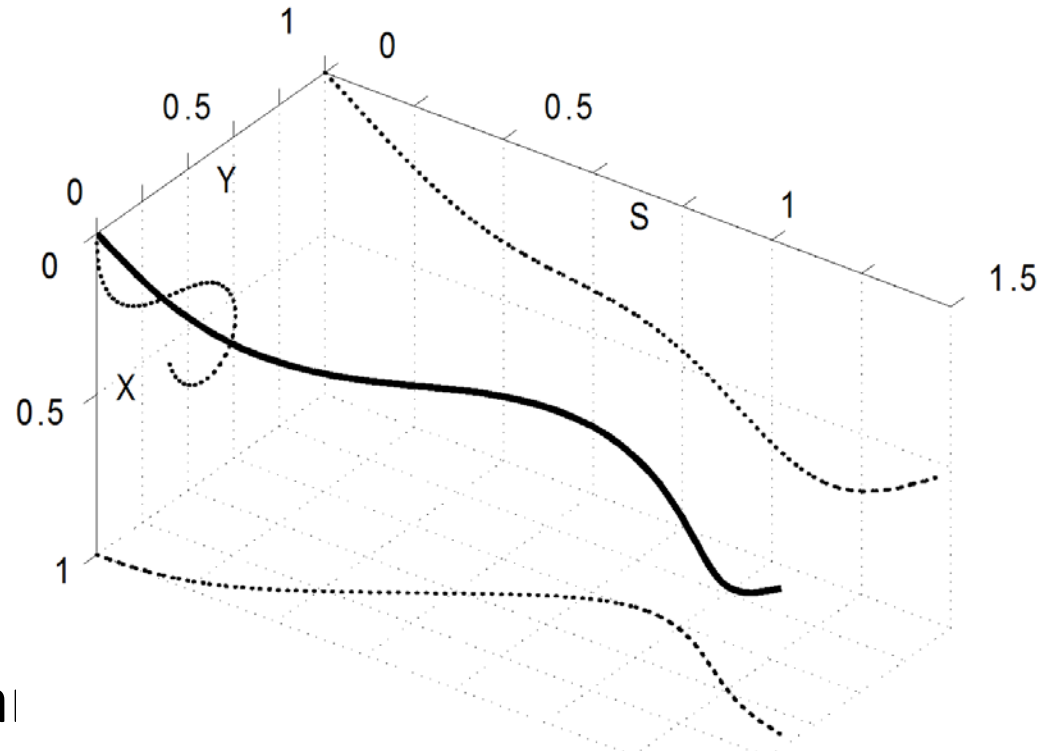
$$\kappa(s) = a + bs + cs^2 + ds^3$$

The parameter  $s_f$  must be distinguished from the variable  $s$ . The 5<sup>th</sup> parameter  $s_f$  does not appear.

# 7.2.5.3 Steering Trajectory Generation

## (Polynomial Spirals)

- All cases mentioned so far are special cases of polynomials.
- This form of representation has several advantages:
  - Compact, just store coefficients
  - General, any function can be approximated.
  - Heading can be computed in closed form.

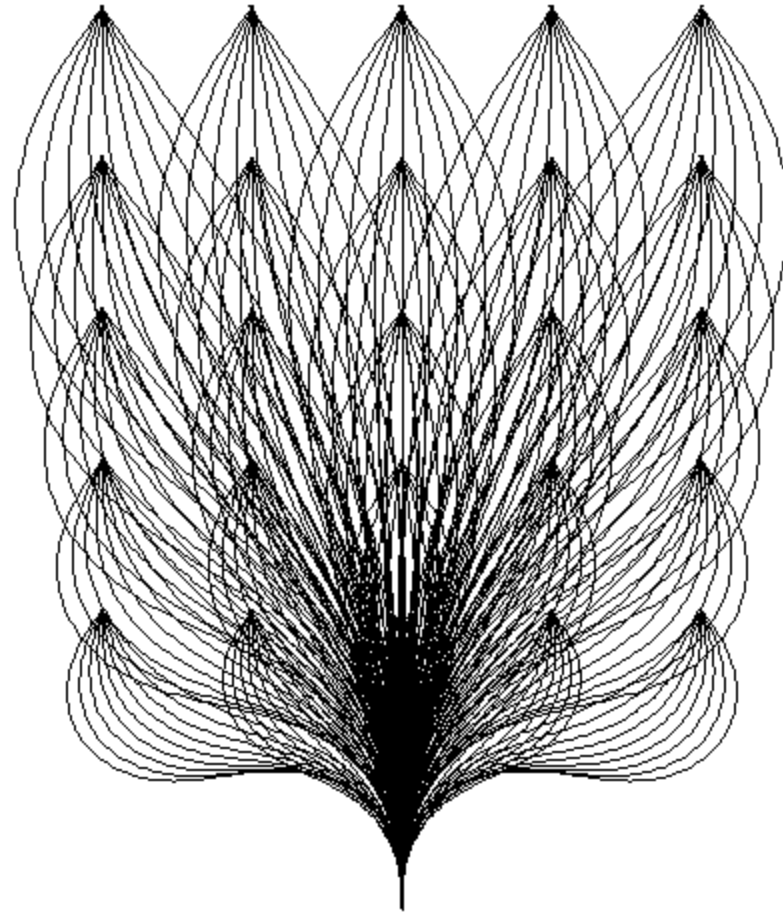


A Cubic Polynomial Spiral

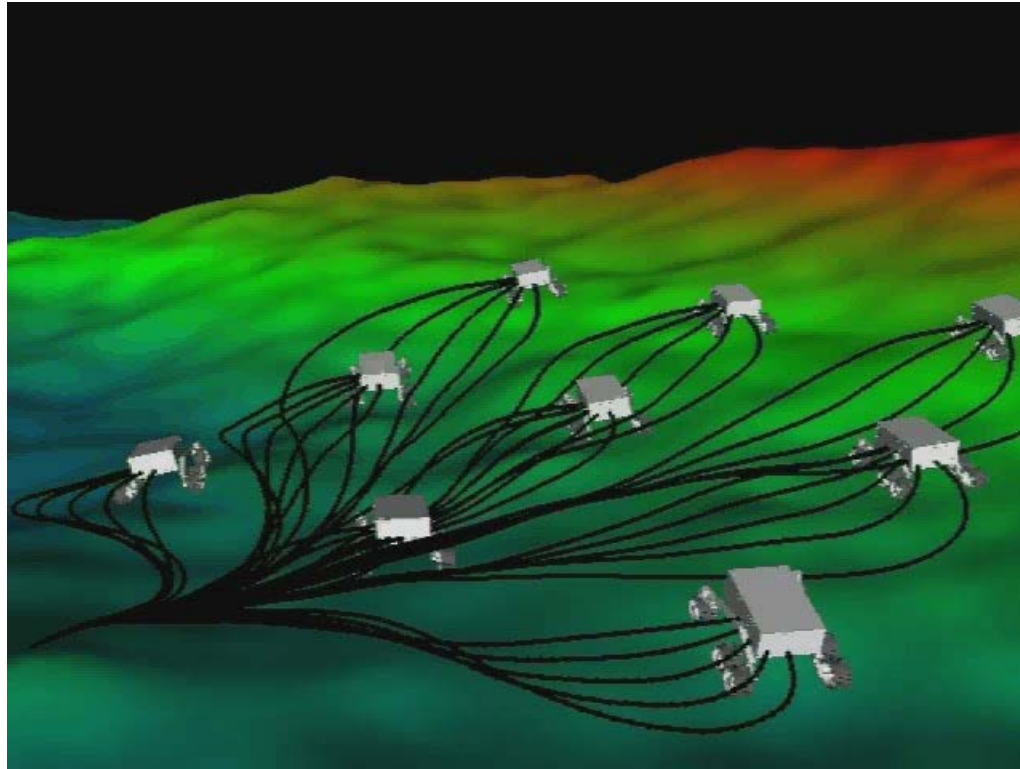


# 7.2.5.3 Steering Trajectory Generation (Polynomial Spirals)

- These curves can achieve any terminal posture.



# Video



# 7.2.5.4 Numerical Formulation

(Terminal Posture Acquisition)

- There are 5 constraints:

$$(\kappa_0, x_f, y_f, \theta_f, \kappa_f)$$

- The initial curvature constraint is trivial to satisfy:

$$a = \kappa_0$$

- Denote the remaining 4 parameters by:

$$\underline{q} = [b \ c \ d \ s_f]^T$$

# 7.2.5.4 Numerical Formulation

(Terminal Posture Acquisition)

- Now there are 4 complicated constraints on the 4 parameters:

$$\kappa(\underline{q}) = \kappa_0 + bs_f + cs_f^2 + ds_f^3 = \kappa_f$$

$$\theta(\underline{q}) = \kappa_0 s_f + \frac{b}{2}s_f^2 + \frac{c}{3}s_f^3 + \frac{d}{4}s_f^4 = \theta_f$$

$$x(\underline{q}) = \int_0^{s_f} \cos \left[ \kappa_0 s + \frac{b}{2}s^2 + \frac{c}{3}s^3 + \frac{d}{4}s^4 \right] ds = x_f$$

$$y(\underline{q}) = \int_0^{s_f} \sin \left[ \kappa_0 s + \frac{b}{2}s^2 + \frac{c}{3}s^3 + \frac{d}{4}s^4 \right] ds = y_f$$

# 7.2.5.4 Numerical Formulation

(Linearization)

- Despite the integrals, these are just 4 nonlinear equations of the form:

$$\underline{c}(\underline{q}) = \underline{g}(\underline{q}) - \underline{x}_b = 0$$

- Solve with a rootfinding technique like Newton's method:

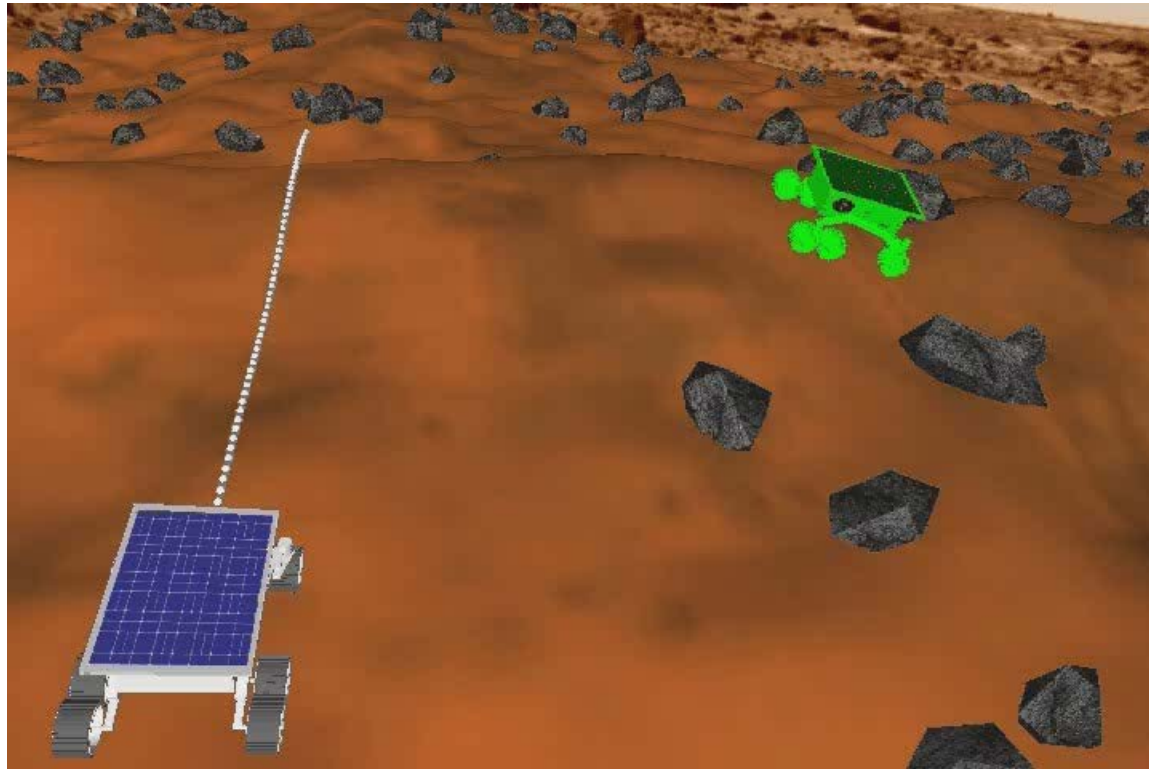
$$\Delta \underline{q} = -\underline{c}_{\underline{q}}^{-1} \underline{c}(\underline{q}) = -\underline{c}_{\underline{q}}^{-1} [\underline{g}(\underline{q}) - \underline{x}_b]$$

# Demo

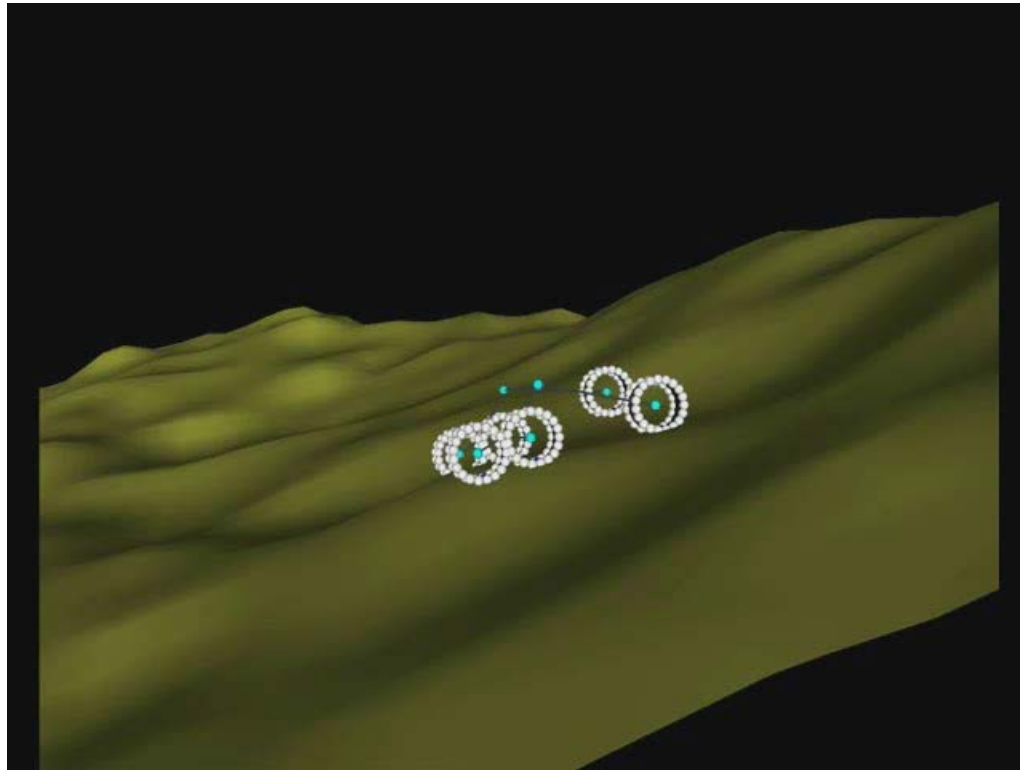
- [CuboidDemonstrator1.exe](#)

Right click and open hyperink

# Video



# Video





# Outline

- 7.2 State Space Control
  - 7.2.1 Introduction
  - 7.2.2 State Space Feedback Control
  - 7.2.3 Example: Robot Trajectory Following
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# Summary

- State Space control is more powerful than classical.
  - Theorems provide conditions for arbitrary controllability.
- Observer theory reveals duality of controls and estimation.
- 2 dof control is a good way to follow trajectories.
- Parameterization is a good way to generate them for open loop control.
- Linearization is effective for nonlinear control.

# Summary

- Visual servoing implements a closed loop using vision as the feedback sensor.
- A basic version tries to drive an image into coincidence with some reference image by:
  - forming errors in image space.
  - deriving corrective velocity commands from the errors.