

# Lecture notes: Trajectory tracking control for robot manipulators

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This lecture note is based on

- Chapter 8 in M. Spong **Robot modeling and control**.
- Chapter ~~5~~<sup>4.5</sup>: Position Control and Trajectory Tracking of Murray et. al. **A Mathematical Introduction to Robotic Manipulation**

# Inverse dynamics control

Consider the dynamic model

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q) = \tau.$$

Question: How to design trajectory tracking control?

- Recall: Trajectory tracking control for

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

- Consider use it for nonlinear trajectory tracking control: What is the linear system now?

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q) = \tau.$$

Let  $\tau = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q)$ .

Since the inertia matrix is invertible, the system dynamical model reduces to

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q) = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q)$$

$$\because M(q) \text{ invertible} \Rightarrow M(q)\ddot{q} = M(q)\ddot{q}$$

$$M^{-1}(q) \text{ exists}$$

$$\therefore \ddot{q} = \ddot{q}$$

# Inverse dynamic control

Given

$$\ddot{q} = a_q$$

decoupled joint dynamics.

Write into the state space form:

$$\begin{aligned} x_1 &= q \\ x_2 &= \dot{q} \end{aligned} \Rightarrow \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \begin{bmatrix} x_2 \\ a_q \end{bmatrix}$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}}_{\text{state}} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \underbrace{a_q}_{\substack{\text{input} \\ \rightarrow u}}$$

$$\begin{aligned} \dot{x} &= Ax + Bu \\ x^d &= Ax^d + Bu^d \end{aligned}$$

← traj. generation

# Inverse dynamic control

Let  $q^d(t)$  be the desired trajectory (cont. differentiable at least twice)  
the control input  $a_q$  should be

$$M(q^d) \ddot{q}^d + C(q^d, \dot{q}^d) \dot{q}^d + N(q^d) = \tau^d$$

$$x^d = \begin{bmatrix} x_1^d \\ x_2^d \end{bmatrix}$$

$$x_1^d = q^d$$

$$x_2^d = \dot{q}^d$$

$$\dot{x}_2^d = \ddot{q}^d$$

$$u^d = a_q^d$$

$$\tau^d = M(q^d) a_q^d + C(q^d, \dot{q}^d) \dot{q}^d + N(q^d)$$

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$$\dot{x} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ 1 \end{bmatrix} a_q \quad ; \quad \dot{x}^d = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} x^d + \begin{bmatrix} 0 \\ 1 \end{bmatrix} a_q^d$$

$$a_q = -K(x - x^d) + a_q^d$$

$$a_q = - \begin{bmatrix} \underline{K_1} & \underline{K_2} \end{bmatrix} \begin{bmatrix} x_1 - x_1^d \\ x_2 - x_2^d \end{bmatrix} + a_q^d$$

$$= - \begin{bmatrix} K_p & K_d \end{bmatrix} \begin{bmatrix} q - q^d \\ \dot{q} - \dot{q}^d \end{bmatrix} + a_q^d$$

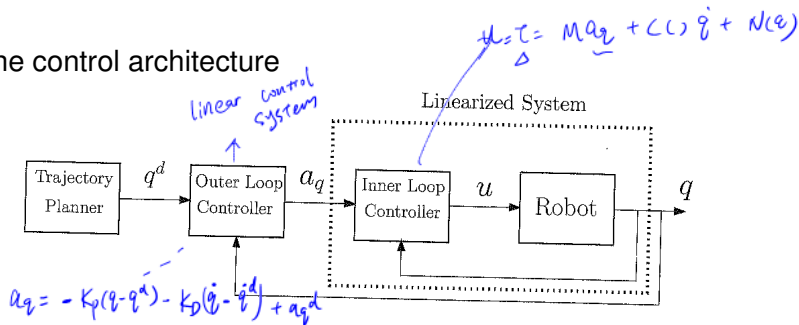
$$a_q = \underbrace{-K_p(q - q^d)}_{\substack{\uparrow \\ \text{position} \\ \text{error}}} - \underbrace{K_d(\dot{q} - \dot{q}^d)}_{\substack{\uparrow \\ \text{vel. error}}} + \underbrace{a_q^d}$$

PD control

$$\tau = M a_q + C(\cdot) \dot{q} + N(q)$$

# Inverse dynamic control

the control architecture



- Outer: input  $q^d, \dot{q}^d, q, \dot{q}$ , output  $a_q$
- Inner: input  $q, \dot{q}, a_q$ , and output  $u$  (or  $\tau$ ).

Flat output:

$$\begin{aligned} z &\rightarrow x, \dot{x}, \underline{u} \\ q &\rightarrow \eta, \dot{\eta}, a_q = \ddot{\eta} \end{aligned}$$



# Computed Torque control: idea

Inverse dynamic control is also known as computed torque control, as it can be written as:

Since  $q$  and  $\dot{q}$  are measured, we modify the input(torques) to be

$$\tau = M(q)\ddot{q}_d + C(q, \dot{q})\dot{q} + N(q, \dot{q})$$

And thus if our model is accurate.

$$M(q)\ddot{q}_d + C(q, \dot{q})\dot{q} + N(q, \dot{q}) = M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q, \dot{q})$$

i.e.

$$\ddot{q} = \ddot{q}_d$$

Again, with accurate initial state and model,  $q(t) = q_d(t)$  for all time  $t \geq 0$ .

# Computed Torque control

With inaccurate initial state and models, the **mismatch** between our current state  $q$  and the desired state  $q_d$  is

$$\underline{e} = q - q_d$$

The control objective is to achieve asymptotical stability:  
 $\lim_{t \rightarrow \infty} e(t) = 0$ .

$$\begin{aligned}\dot{e} &= \dot{q} - \dot{q}^d \\ \ddot{e} &= \ddot{q} - \ddot{q}^d\end{aligned}$$

$$M\ddot{e} + C(q, \dot{q})\dot{q} + N(q) = \tau - M\ddot{q}^d \quad \star$$

$$M(\ddot{q} - \ddot{q}^d) + C\dot{q} + N = \tau - M\ddot{q}^d$$

$$\begin{aligned}\star: \quad \ddot{e} &= M^{-1}(q)(\tau - C(q, \dot{q})\dot{q} - N(q) - M\ddot{q}^d) \quad \dots \textcircled{1} \\ &= \underline{v}\end{aligned}$$

$$\ddot{e} = v$$

$$\underline{v} = -K_p e - K_d \dot{e}$$

using ① =  $\underline{v}$  ↓

$$\tau = \underbrace{M(q)(-K_p e - K_d \dot{e})}_{\text{Feedback}} + \underbrace{M\ddot{q}^d + c(q, \dot{q})\dot{q} + N(q)}_{\text{Feed forward term}}$$

# Computed Torque control

With inaccurate initial state and models, the **mismatch** between our current state  $q$  and the desired state  $q_d$  is

$$e = q - q_d$$

The control objective is to achieve asymptotical stability:  
 $\lim_{t \rightarrow \infty} e(t) = 0$ .

- What is the dynamics of the error state?

$$\dot{e} = \dot{q} - \dot{q}_d$$

$$\ddot{e} = \ddot{q} - \ddot{q}_d$$

- What is the relation between input torques and the error states?  
Since by the dynamic model,

$$M(q)\ddot{q} = \tau - C(q, \dot{q})\dot{q} - N(q, \dot{q})$$

we have  $M(q)\ddot{e} = \tau - C(q, \dot{q})\dot{q} - N(q, \dot{q}) - M(q)\ddot{q}_d$ .

# Computed Torque control via feedback linearization

$$M(q)\ddot{e} = \tau - C(q, \dot{q})\dot{q} - N(q, \dot{q}) - M(q)\ddot{q}_d.$$

Consider the input  $v = M(q)^{-1}(\tau - C(q, \dot{q})\dot{q} - N(q, \dot{q}) - M(q)\ddot{q}_d)$ .

Let  $x_1 = e$  and  $x_2 = \dot{e}$ , reduce to a linear system

# Overview

Inverse dynamic control is also known as computed torque control, as it can be written as:

- Computed Torque Control.

$$\tau = \underbrace{M(q)(-K_P e - K_D \dot{e})}_{\text{Feedback control}} + \underbrace{C(q, \dot{q})\dot{q} + N(q, \dot{q}) + M(q)\ddot{q}_d}_{\text{Feedforward compensation}}$$

*if  $e = \dot{e} = 0 \Rightarrow \tau \Rightarrow \ddot{q} = \ddot{q}_d$*

- Inverse dynamic control:

$$\tau = M(q)a_q + C(q, \dot{q})\dot{q} + N(q, \dot{q})$$

and

$$a_q = -K_P e - K_D \dot{e} + \ddot{q}_d$$

and  $\ddot{q}_d = \ddot{q}^d$

$$\tau = M(q)(-K_P e - K_D \dot{e}) + M(q) \ddot{q}_d + C(q, \dot{q})\dot{q} + N(q, \dot{q})$$

*$\ddot{q} = \ddot{q}_d$*

# Exponential tracking with PD control

- Less demanding PD with gravity compensation realizes asymptotic stability for a setpoint control.

$$\tau = N(q, \dot{q}) - K_D \dot{e} - K_P e.$$

# Exponential tracking with PD control

- Less demanding PD with gravity compensation realizes **asymptotic stability** for a **setpoint control**.

$$\tau = N(q, \dot{q}) - \underbrace{K_D \dot{e} - K_P e}_{\text{Feedback control}}.$$

- Whileas computed Torque control

$$\tau = \underbrace{M(q)(-K_P e - K_D \dot{e})}_{\text{Feedback control}} + \underbrace{C(q, \dot{q})\dot{q} + N(q, \dot{q}) + M(q)\ddot{q}_d}_{\text{Feedforward compensation}}$$

realizes exponential trajectory tracking.



# Exponential tracking with PD control

- Less demanding PD with gravity compensation realizes **asymptotic stability** for a **setpoint control**.

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realizes exponential trajectory tracking.

Remove  $M(q)$   $\Rightarrow (-K_P e - K_D \dot{e}) + C(q, \dot{q})\dot{q} + N(q, \dot{q}) + M(q)\ddot{q}_d$

Augmented PD control law

$$\tau = \underbrace{(-K_P e - K_D \dot{e} + N(q, \dot{q}))}_{\text{PD control w gravity compensation}} + \underbrace{M(q)\ddot{q}_d + C(q, \dot{q})\dot{q}_d}_{\text{Partial feedforward}}$$

Realizes **exponential** trajectory tracking (when  $\dot{q}_d = 0$ , setpoint stabilization).

# Proof

The error dynamics with the control input:

$$\tau = \underbrace{(-K_P e - K_D \dot{e} + N(q, \dot{q}))}_{\text{PD control w gravity compensation}} + \underbrace{M(q)\ddot{q}_d + C(q, \dot{q})\dot{q}_d}_{\text{Partial feedforward}} \triangle$$

$$M\ddot{q} + C\dot{q} + N(q) = \tau$$

$$M(q)\ddot{q} + C\dot{q} + N(q) = -K_P e - K_D \dot{e} + N(q) + M\ddot{q}_d + C\dot{q}_d$$

$$M(\ddot{q} - \ddot{q}^d) + C(\dot{q} - \dot{q}^d) = -K_P e - K_D \dot{e}$$

$$M\ddot{e} + C\dot{e} = -K_P e - K_D \dot{e}$$

Asy. stability :  $\lim_{t \rightarrow \infty} e = 0$

# Exponential stability of augmented PD

Proof: Hint:

$$V = \underbrace{\frac{1}{2} \dot{e}^T M(q) \dot{e} + \frac{1}{2} e^T K_P e}_{\text{set point tracking.}} + \underbrace{\varepsilon e^T M(q) \dot{e}}_{\varepsilon > 0}$$

①  $V$  is Lyapunov candidate

②  $\dot{V}$  neg. def.

idea:  $\varepsilon$  is arbitrarily small.

$$\|M(q)\| < \lambda$$

To show that:  $\dot{V} \geq 0$  by a choice of  $\varepsilon$   
and using the upper bound  $\|M(q)\|$ .

# Workspace control

Suppose given a path  $x_d(t) \in SE(3)$ : desirable end-effector configuration as a function of time.

To apply joint space control (centralized or decentralized)

① Solve  $q_d(t)$  from  $x_d(t)$  using inverse kinematics.

② Design joint space controller.

# Workspace control

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- ① Solve  $q_d(t)$  from  $x_d(t)$  using inverse kinematics.
  - time consuming.
  - hard to reason about the trajectory of end-effector with the trajectory of  $q$  — may cause undesirable behavior.
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- ② Design joint space controller.

To overcome these,

Direct workspace control.

# Recap

Forward kinematics: A smooth and invertible mapping  $f$  from the joint variables to the workspace variables

$$x = f(q)$$

The Jacobian

$$\dot{x} = J(q)\dot{q}, \quad J(q) = \frac{\partial f}{\partial q}$$

# Recap

Forward kinematics: A smooth and invertible mapping  $f$  from the joint variables to the workspace variables

$$x = f(q)$$

The Jacobian

$$\dot{x} = J(q)\dot{q}, \quad J(q) = \frac{\partial f}{\partial q}$$

Given  $f$  is smooth and invertible,

$$\dot{q} = J^{-1}\dot{x}, \quad \ddot{q} = J^{-1}\ddot{x} + \frac{d}{dt}(J^{-1})\dot{x}.$$

The dynamic of robot in the joint space

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + N(q, \dot{q}) = \tau$$



# Taskspace control

Suppose given a path  $X_d(t) \in \mathbb{R}^6$ : desirable end-effector configuration as a function of time using any minimal representation of  $SO(3)$ .

To apply joint space control (centralized or decentralized)

- ① Solve  $q^d(t)$  from  $X^d(t)$  using inverse kinematics.
  - time consuming.
  - hard to reason about the trajectory of end-effector with the trajectory of  $q$  — may cause undesirable behavior.
- ② Design joint space controller.

**To overcome these,** Direct task space control.

# From joint space to task space

State variables in

- Joint space:  $q$
- Work space:  $X$ .

$X$  is a function of  $q$ , we have

$$\dot{X} = J(q)\dot{q}$$

where  $J(q)$  is the **analytical** Jacobian. Using inverse dynamics control:

# Summary

- Show Lyapunov stability of decentralized PD control for planar manipulators.
- PD+Gravity compensation for set-point tracking.
- Inverse dynamics control for trajectory tracking.
- Inverse dynamics control in task space.

Cons:

- Inverse dynamics requires exact knowledge of model dynamics.
- PERFORMANCE is **NOT GUARANTEED** when
  - parameter becomes uncertain.
  - robot picking up an unknown load.

Next: Robust and adaptive control.