

# Joint-Space Control

## Optimization-based Robot Control

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Very active research topic between 2004 and 2015 [10, 6, 7, 9, 4, 3].

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Very active research topic between 2004 and 2015 [10, 6, 7, 9, 4, 3].

Now not so active anymore (i.e. problem solved), but widely used.

1. Theory of Joint Space Control ( $\approx$  1:15 hour)
2. Implementation ( $\approx$  1 hour)
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4. Implementation ( $\approx$  1 hour)

## Notation & Definitions

The **state** of the system is denoted  $x \triangleq (q, v)$ .

**Configuration** vector  $q \in \mathbb{R}^{n_q}$  of (relative) joint angles.

**Velocity** vector  $v = \dot{q} \in \mathbb{R}^{n_v}$  of (relative) joint velocities.

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The identity matrix is denoted  $I$ .

The zero matrix is denoted  $0$ .

When needed, the size of the matrix is written as index, e.g.,  $I_3$ .



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2. Inverse Dynamics Control as Optimization Problem

# Joint-Space Inverse Dynamics Control

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# Robot Manipulator

Given (nonlinear) manipulator dynamics:

$$M(q)\dot{v} + h(q, v) = \tau \quad (1)$$

## Problem

Find  $\tau(t)$  so that  $q(t)$  follows reference  $q^r(t)$ .

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$$\dot{v}^d = \dot{v}^r - K_d(v - v^r) - K_p(q - q^r) \quad (2)$$

where  $K_p, K_d$  are diagonal positive-definite gain matrices.



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$$\underbrace{\begin{bmatrix} \dot{e} \\ \ddot{e} \end{bmatrix}}_{\dot{x}} = \underbrace{\begin{bmatrix} 0 & I \\ -K_p & -K_d \end{bmatrix}}_A \underbrace{\begin{bmatrix} e \\ \dot{e} \end{bmatrix}}_x$$

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$A$  is Hurwitz if  $K_p$  and  $K_d$  are diagonal and positive-definite  $\rightarrow$   
 $\lim_{t \rightarrow \infty} x(t) = 0 \rightarrow \lim_{t \rightarrow \infty} q(t) = q^r(t)$

# Many names for the same approach

This control law:

$$\tau = M(\dot{v}^r - K_d \dot{e} - K_p e) + h \quad (3)$$

is known as:

- **Inverse-Dynamics (ID) Control**: because based on inverse dynamics computation.
- **Computed Torque**: because it computes torques needed to get desired accelerations.
- **Feedback Linearization** (from control theory): because it uses state feedback to linearize closed-loop dynamics.

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Another variant (with similar properties) exists:

$$\tau = M\dot{v}^r - K_d \dot{e} - K_p e + h \quad (4)$$

## Other Control Laws for Manipulators

Simpler control laws often used for manipulators.

A common option is **PD+gravity compensation**:

$$\tau = \underbrace{-K_d \dot{e} - K_p e}_{PD} + \underbrace{g(q)}_{\text{gravity compensation}} \quad (5)$$



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In theory “ID control” outperforms “PD+gravity”, which outperforms “PID”.

In practice the opposite could occur because of model errors.

# Inverse Dynamics Control as Optimization Problem

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# Inverse Dynamics (ID) Control as Least-Squares Problem

Solution of optimization problem:

$$\begin{aligned} (\tau^*, \dot{v}^*) = & \underset{\tau, \dot{v}}{\operatorname{argmin}} && \|\dot{v} - \dot{v}^d\|^2 \\ & \text{subject to} && M\dot{v} + h = \tau \end{aligned} \quad (7)$$

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Problem (7) is Least-Squares Program/Problem (LSP).

# Taxonomy of Convex Optimization Problems

Least-Squares Programs (LSP) have:

- linear equality/inequality constraints ( $Ax \leq b$ , or  $Ax = b$ )
- 2-norm of linear cost function ( $\|Ax - b\|^2$ )

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LSPs are subclass of convex Quadratic Programs (QPs), which have:

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→ We can solve LSP/QPs inside 1 kHz control loops!

## Adding Torque Limits to ID Control

Take the ID control LSP:

$$\begin{aligned} & \underset{\tau, \dot{v}}{\text{minimize}} && \|\dot{v} - \dot{v}^d\|^2 \\ & \text{subject to} && M\dot{v} + h = \tau \end{aligned} \tag{9}$$

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LSPs allow for **linear inequality constraints** → we can add torque limits:

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Main advantage of optimization: inequality constraints.



## Adding Current Limits for Electric Motors

In electric motors current  $i$  is proportional to torque  $\tau$ :

$$i = k_{\tau}\tau \quad (11)$$

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## Adding Joint Velocity Limits

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$$v(t + \Delta t) = v(t) + \Delta t \dot{v} \quad (13)$$

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## Adding Joint Position Limits

Could use same trick for position limits:

$$q(t + \Delta t) = q(t) + \Delta t v(t) + \frac{1}{2} \Delta t^2 \dot{v} \quad (15)$$

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However, this can result in **high accelerations**, typically **incompatible** with torque/current limits  $\rightarrow$  unfeasible LSP.

Better approaches exist [1, 8, 2], but we don't discuss them here.

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 $\tau, \dot{v}$

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