



Robotics

Dynamics

*1D point mass, damping & oscillation, PID,
dynamics of mechanical systems,
Euler-Lagrange equation, Newton-Euler, joint
space control, reference trajectory following,
optimal operational space control*

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Kinematic

instantly change joint velocities \dot{q} :

$$\Delta q_t \stackrel{!}{=} J^\# (y^* - \phi(q_t))$$

accounts for kinematic coupling of joints but **ignores inertia, forces, torques**

gears, **stiff**, all of industrial robots



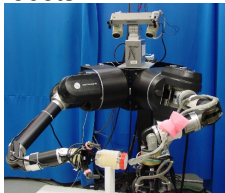
Dynamic

instantly change joint torques u :

$$u \stackrel{!}{=} ?$$

accounts for dynamic coupling of joints and full Newtonian physics

future robots, **compliant**, few research robots



When velocities cannot be changed/set arbitrarily

- Examples:
 - An air plane flying: You cannot command it to hold still in the air, or to move straight up.
 - A car: you cannot command it to move side-wards.
 - Your arm: you cannot command it to throw a ball with arbitrary speed (force limits).
 - A *torque controlled* robot: You cannot command it to instantly change velocity (infinite acceleration/torque).
- What all examples have in common:
 - One can set **controls** u_t (air plane's control stick, car's steering wheel, your muscles activations, torque/voltage/current send to a robot's motors)
 - But these controls only indirectly influence the **dynamics of state**

$$x_{t+1} = f(x_t, u_t)$$

Dynamics

- The dynamics of a system describes how the controls u_t influence the change-of-state of the system

$$x_{t+1} = f(x_t, u_t)$$

- The notation x_t refers to the *dynamic state* of the system: e.g., joint positions *and velocities* $x_t = (q_t, \dot{q}_t)$.
- f is an arbitrary function, often smooth

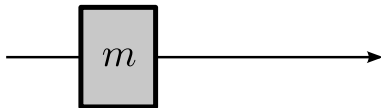
Outline

- We start by discussing a **1D point mass** for 3 reasons:
 - The most basic force-controlled system with inertia
 - We can introduce and understand **PID control**
 - The behavior of a point mass under PID control is a *reference* that we can also follow with arbitrary dynamic robots (if the dynamics are known)
- We discuss computing the dynamics of general robotic systems
 - Euler-Lagrange equations
 - Euler-Newton method
- We derive the dynamic equivalent of inverse kinematics:
 - operational space control

PID and a 1D point mass

The dynamics of a 1D point mass

- Start with simplest possible example: 1D point mass (no gravity, no friction, just a single mass)



- The state $x(t) = (q(t), \dot{q}(t))$ is described by:
 - position $q(t) \in \mathbb{R}$
 - velocity $\dot{q}(t) \in \mathbb{R}$
- The controls $u(t)$ is the force we apply on the mass point
- The system dynamics is:

$$\ddot{q}(t) = u(t)/m$$

1D point mass – proportional feedback

- Assume current position is q .
The goal is to move it to the position q^* .

What can we do?

1D point mass – proportional feedback

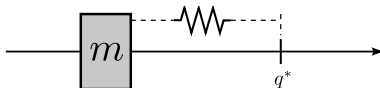
- Assume current position is q .
The goal is to move it to the position q^* .

What can we do?

- **Idea 1:**

“Always pull the mass towards the goal q^ :”*

$$u = K_p (q^* - q)$$



1D point mass – proportional feedback

- What's the effect of this control law?

$$m \ddot{q} = u = K_p (q^* - q)$$

$q = q(t)$ is a function of time, this is a second order differential equation

1D point mass – proportional feedback

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- Solution: **assume** $q(t) = a + b e^{\omega t}$
(a “non-imaginary” alternative would be $q(t) = a + b e^{-\lambda t} \cos(\omega t)$)

1D point mass – proportional feedback

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$$m b \omega^2 e^{\omega t} = K_p q^* - K_p a - K_p b e^{\omega t}$$

$$(m b \omega^2 + K_p b) e^{\omega t} = K_p (q^* - a)$$

$$\Rightarrow (m b \omega^2 + K_p b) = 0 \wedge (q^* - a) = 0$$

$$\Rightarrow \omega = i \sqrt{K_p/m}$$

$$q(t) = q^* + b e^{i \sqrt{K_p/m} t}$$

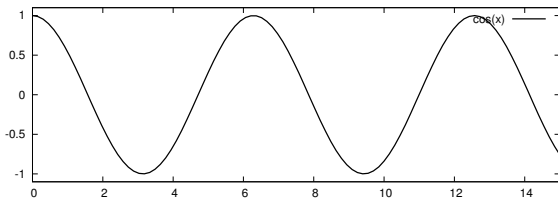
This is an oscillation around q^* with amplitude $b = q(0) - q^*$ and frequency $\sqrt{K_p/m}$!

1D point mass – proportional feedback

$$m \ddot{q} = u = K_p (q^* - q)$$

$$q(t) = q^* + b e^{i\sqrt{K_p/m} t}$$

Oscillation around q^* with amplitude $b = q(0) - q^*$ and frequency $\sqrt{K_p/m}$



1D point mass – derivative feedback

- **Idea 2**

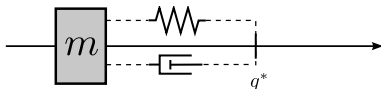
“Pull less, when we’re heading the right direction already:”

“Damp the system:”

$$u = K_p(q^* - q) + K_d(\dot{q}^* - \dot{q})$$

\dot{q}^* is a desired goal velocity

For simplicity we set $\dot{q}^* = 0$ in the following.



1D point mass – derivative feedback

- What's the effect of this control law?

$$m\ddot{q} = u = K_p(q^* - q) + K_d(0 - \dot{q})$$

- Solution: **again assume** $q(t) = a + be^{\omega t}$

$$m b \omega^2 e^{\omega t} = K_p q^* - K_p a - K_p b e^{\omega t} - K_d b \omega e^{\omega t}$$

$$(m b \omega^2 + K_d b \omega + K_p b) e^{\omega t} = K_p (q^* - a)$$

$$\Rightarrow (m \omega^2 + K_d \omega + K_p) = 0 \wedge (q^* - a) = 0$$

$$\Rightarrow \omega = \frac{-K_d \pm \sqrt{K_d^2 - 4mK_p}}{2m}$$

$$q(t) = q^* + b e^{\omega t}$$

The term $-\frac{K_d}{2m}$ in ω is real \leftrightarrow exponential decay (damping)

1D point mass – derivative feedback

$$q(t) = q^* + b e^{\omega t}, \quad \omega = \frac{-K_d \pm \sqrt{K_d^2 - 4mK_p}}{2m}$$

- Effect of the second term $\sqrt{K_d^2 - 4mK_p}/2m$ in ω :

$$K_d^2 < 4mK_p \Rightarrow \omega \text{ has imaginary part}$$

oscillating with frequency $\sqrt{K_p/m - K_d^2/4m^2}$

$$q(t) = q^* + b e^{-K_d/2m t} e^{i\sqrt{K_p/m - K_d^2/4m^2} t}$$

$$K_d^2 > 4mK_p \Rightarrow \omega \text{ real}$$

strongly damped

$$K_d^2 = 4mK_p \Rightarrow \text{second term zero}$$

only exponential decay

1D point mass – derivative feedback

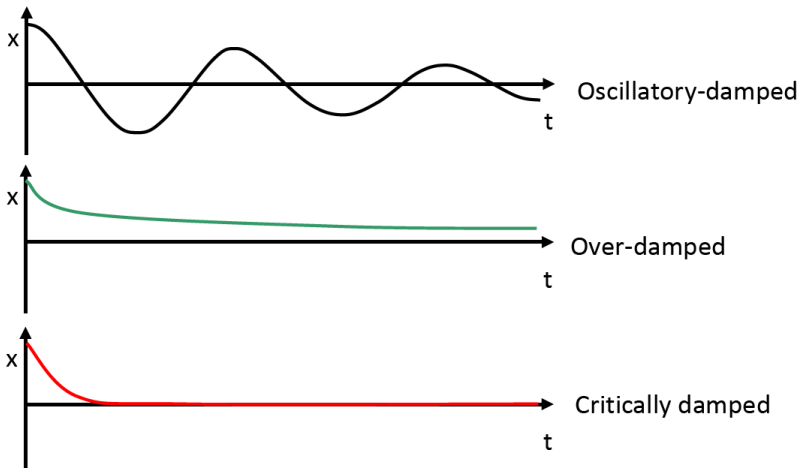


illustration from O. Brock's lecture

1D point mass – derivative feedback

Alternative parameterization:

Instead of the *gains* K_p and K_d it is sometimes more intuitive to set the

- wave length $\lambda = \frac{1}{\omega_0} = \frac{1}{\sqrt{K_p/m}}$, $K_p = m/\lambda^2$, $\omega_0 = T/(2\pi)$
- damping ratio $\xi = \frac{K_d}{\sqrt{4mK_p}} = \frac{\lambda K_d}{2m}$, $K_d = 2m\xi/\lambda$

$\xi > 1$: over-damped

$\xi = 1$: critically damped

$\xi < 1$: oscillatory-damped

$$q(t) = q^* + be^{-\xi t/\lambda} e^{i\sqrt{1-\xi^2} t/\lambda}$$

1D point mass – integral feedback

- **Idea 3**

“Pull if the position error accumulated large in the past:”

$$u = K_p(q^* - q) + K_d(\dot{q}^* - \dot{q}) + K_i \int_{s=0}^t (q^*(s) - q(s)) ds$$

- This is not a linear ODE w.r.t. $x = (q, \dot{q})$.

However, when we extend the state to $x = (q, \dot{q}, e)$ we have the ODE

$$\dot{q} = \dot{q}$$

$$\ddot{q} = u/m = K_p/m(q^* - q) + K_d/m(\dot{q}^* - \dot{q}) + K_i/m e$$

$$\dot{e} = q^* - q$$

(no explicit discussion here)

1D point mass – PID control

$$u = K_p(q^* - q) + K_d(\dot{q}^* - \dot{q}) + K_i \int_{s=0}^t (q^* - q(s)) ds$$

- **PID control**

- Proportional Control (“Position Control”)

$$u \propto K_p(q^* - q)$$

- Derivative Control (“Damping”)

$$u \propto K_d(\dot{q}^* - \dot{q}) \quad (\dot{x}^* = 0 \rightarrow \text{damping})$$

- Integral Control (“Steady State Error”)

$$u \propto K_i \int_{s=0}^t (q^*(s) - q(s)) ds$$

Controlling a 1D point mass – lessons learnt

- Proportional and derivative feedback (PD control) are like adding a spring and damper to the point mass
- PD control is a *linear control law*

$$(q, \dot{q}) \mapsto u = K_p(q^* - q) + K_d(\dot{q}^* - \dot{q})$$

(linear in the *dynamic system state* $x = (q, \dot{q})$)

- With such linear control laws we can design approach trajectories (by tuning the gains)
 - but no optimality principle behind such motions

Example: Learning PID Gains for Multivar. Control

Model Based Policy Search for Automatic Tuning of Multivariate PID Controllers

Andreas Doerr^{1,2}, Duy Nguyen-Tuong¹, Alonso Marco², Stefan Schaal^{2,3}, Sebastian Trimpe²

- How to choose the PID gains?
- Obtaining (i.e. optimizing) controller gains through trial-error-based learning. See ICRA 2017 paper for more details.

Dynamics of mechanical systems

Two ways to derive dynamics equations for mechanical systems

- The Euler-Lagrange equation, $L = L(t, q(t), \dot{q}(t))$,

$$\frac{d}{dt} \frac{\partial L}{\partial \dot{q}} - \frac{\partial L}{\partial q} = u$$

Used when you want to derive analytic equations of motion (“on paper”)

- The Newton-Euler recursion (and related algorithms)

$$f_i = m\dot{v}_i, \quad u_i = I_i\dot{w} + w \times Iw$$

Algorithms that “propagate” forces through a kinematic tree and numerically compute the *inverse* dynamics $u = \text{NE}(q, \dot{q}, \ddot{q})$ or *forward* dynamics $\ddot{q} = f(q, \dot{q}, u)$.

The Euler-Lagrange equation

$$\frac{d}{dt} \frac{\partial L}{\partial \dot{q}} - \frac{\partial L}{\partial q} = u$$

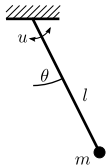
- $L(q, \dot{q})$ is called **Lagrangian** and defined as

$$L = T - U$$

where T =kinetic energy and U =potential energy.

- q is called generalized coordinate – any coordinates such that (q, \dot{q}) describes the state of the system. Joint angles in our case.
- u are external forces

Example: A pendulum



- Generalized coordinates: angle $q = (\theta)$
- Kinematics:
 - velocity of the mass: $v = (l\dot{\theta} \cos \theta, 0, l\dot{\theta} \sin \theta)$
 - angular velocity of the mass: $w = (0, -\dot{\theta}, 0)$
- Energies:

$$T = \frac{1}{2}mv^2 + \frac{1}{2}w^T I w = \frac{1}{2}(ml^2 + I_2)\dot{\theta}^2, \quad U = -mgl \cos \theta$$

- Euler-Lagrange equation:

$$\begin{aligned} u &= \frac{d}{dt} \frac{\partial L}{\partial \dot{q}} - \frac{\partial L}{\partial q} \\ &= \frac{d}{dt} (ml^2 + I_2)\dot{\theta} + mgl \sin \theta = (ml^2 + I_2)\ddot{\theta} + mgl \sin \theta \end{aligned}$$

The Euler-Lagrange equation

- How is this typically done?
- **First**, describe the *kinematics and Jacobians* for every link i :

$$(q, \dot{q}) \mapsto \{T_{W \rightarrow i}(q), v_i, w_i\}$$

Recall $T_{W \rightarrow i}(q) = T_{W \rightarrow A} T_{A \rightarrow A'}(q) T_{A' \rightarrow B} T_{B \rightarrow B'}(q) \dots$

Further, we know that a link's velocity $v_i = J_i \dot{q}$ can be described via its position Jacobian. Similarly we can describe the link's *angular velocity* $w_i = J_i^w \dot{q}$ as linear in \dot{q} .

- **Second**, formulate the kinetic energy

$$T = \sum_i \frac{1}{2} m_i v_i^2 + \frac{1}{2} w_i^\top I_i w_i = \sum_i \frac{1}{2} \dot{q}^\top M_i \dot{q}, \quad M_i = \begin{pmatrix} J_i \\ J_i^w \end{pmatrix}^\top \begin{pmatrix} m_i \mathbf{I}_3 & 0 \\ 0 & I_i \end{pmatrix} \begin{pmatrix} J_i \\ J_i^w \end{pmatrix}$$

where $I_i = R_i \bar{I}_i R_i^\top$ and \bar{I}_i the inertia tensor in link coordinates

- **Third**, formulate the potential energies (typically independent of \dot{q})

$$U = g m_i \text{height}(i)$$

- **Fourth**, compute the partial derivatives analytically to get something like

$$\underbrace{u}_{\text{control}} = \frac{d}{dt} \frac{\partial L}{\partial \dot{q}} - \frac{\partial L}{\partial q} = \underbrace{M}_{\text{inertia}} \ddot{q} + \underbrace{\dot{M} \dot{q}}_{\text{Coriolis}} - \underbrace{\frac{\partial T}{\partial q}}_{\text{gravity}} + \underbrace{\frac{\partial U}{\partial q}}_{\text{gravity}}$$

which relates accelerations \ddot{q} to the forces

Newton-Euler equation

- An algorithm that computes the *inverse dynamics*

$$u = \text{NE}(q, \dot{q}, \ddot{q})$$

by (recursively) computing force balance at each joint.

- **First**, expresses the force acting at the center of mass for an accelerated body using the **Newton's equation**:

$$f_i = m\dot{v}_i$$

- **Second**, expresses the torque (=control) acting on a rigid body (given an angular velocity and angular acceleration) using the **Euler's equation**

$$u_i = I_i \dot{w} + w \times I w$$

- There is a transformation between the Newton-Euler and Euler-Lagrange representation

Numeric algorithms for forward and inverse dynamics

- **Newton-Euler recursion:** very fast ($O(n)$) method to compute *inverse* dynamics

$$u = \text{NE}(q, \dot{q}, \ddot{q})$$

Note that we can use this algorithm to also compute

- gravity terms: $u = \text{NE}(q, 0, 0) = G(q)$
 - Coriolis terms: $u = \text{NE}(q, \dot{q}, 0) = C(q, \dot{q}) \dot{q} + G(q)$
 - column of Intertia matrix: $u = \text{NE}(q, 0, e_i) = M(q) e_i$
- **Articulated-Body-Dynamics:** fast method ($O(n)$) to compute *forward* dynamics $\ddot{q} = f(q, \dot{q}, u)$

Some last practical comments

- Use *energy conservation* to measure dynamic of physical simulation
- Physical simulation engines (developed for games):
 - ODE (Open Dynamics Engine)
 - Bullet (originally focussed on collision only)
 - Physx (Nvidia)

Differences of these engines to Lagrange, NE or ABD:

- Game engine can model much more: Contacts, tissues, particles, fog, etc
 - (The way they model contacts looks ok but is somewhat fictional)
 - On kinematic trees, NE or ABD are much more precise than game engines
 - Game engines do not provide *inverse* dynamics, $u = \text{NE}(q, \dot{q}, \ddot{q})$
-
- Proper modelling of contacts is really really hard

Controlling a dynamic robot

- We previously learnt the effect of PID control on a 1D point mass
- Robots are not a 1D point mass
 - Neither is each joint a 1D point mass
 - Applying separate PD control in each joint neglects force coupling
(Poor solution: Apply very high gains separately in each joint \leftrightarrow make joints stiff, as with gears.)
- However, knowing the robot dynamics we can transfer our understanding of PID control of a point mass to general systems

General robot dynamics

- Let (q, \dot{q}) be the dynamic state and $u \in \mathbb{R}^n$ the controls (typically joint torques in each motor) of a robot
- Robot dynamics can generally be written as:

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

$M(q) \in \mathbb{R}^{n \times n}$ is positive definite inertia matrix
(can be inverted \rightarrow forward simulation of dynamics)

$C(q, \dot{q}) \in \mathbb{R}^{n \times n}$ are the centripetal and coriolis forces

$G(q) \in \mathbb{R}^n$ are the gravitational forces

u are the joint torques

(cf. to the Euler-Lagrange equation on slide 22)

- We often write more compactly:

$$M(q) \ddot{q} + F(q, \dot{q}) = u$$

Controlling a general robot

- From now on we just assume that we have algorithms to efficiently compute $M(q)$ and $F(q, \dot{q})$ for any (q, \dot{q})
- **Inverse dynamics:** If we know the desired \ddot{q} for each joint,

$$u = M(q) \ddot{q} + F(q, \dot{q})$$

gives the necessary torques

- **Forward dynamics:** If we know which torques u we apply, use

$$\ddot{q} = M(q)^{-1}(u - F(q, \dot{q}))$$

to simulate the dynamics of the system (e.g., using Runge-Kutta)

Following a reference trajectory in joint space

- Given a twice-differentiable desired trajectory $q_{0:T}^{\text{ref}}$ (generated with some motion profile or alike), we can at each $t \in [0, T]$ numerically compute

$$q_t^{\text{ref}} \rightarrow \dot{q}_t^{\text{ref}}, \ddot{q}_t^{\text{ref}}$$

- Applying the inverse dynamics model, we can (theoretically) compute the exact torques u for the robot to follow the desired trajectory $(q_{0:T}^{\text{ref}}, \dot{q}_{0:T}^{\text{ref}}, \ddot{q}_{0:T}^{\text{ref}})$
- Why this approach would not work?

In practice ...

- Disturbances on the actuators, truncation errors on data, ...
- Inaccurate knowledge on robot parameters, e.g. link masses, inertias, center of mass, ...
- Carried payload might be unknown, changing masses, ...
- Unknown non-linearities, e.g. elasticity, complex friction, ...

Trajectory tracking controllers

- Introducing feedbacks (similar to the case of 1D point mass) to compensate the modelling errors results in a large set of tracking controllers
- Inverse dynamics feedforward control, feedback linearization, computed torque control, ...
- Example: Inverse dynamics feedforward control

$$u_t = u_t^{FF}(q_t^{\text{ref}}, \dot{q}_t^{\text{ref}}, \ddot{q}_t^{\text{ref}}) + K_p(q_t^{\text{ref}} - q_t) + K_d(\dot{q}_t^{\text{ref}} - \dot{q}_t)$$
$$u_t^{FF} = M(q_t^{\text{ref}}) \ddot{q}_t^{\text{ref}} + F(q_t^{\text{ref}}, \dot{q}_t^{\text{ref}})$$

Following a reference trajectory in task space

- Recall the inverse kinematics problem:
 - We know the desired step δy^* (or velocity \dot{y}^*) of the *endeffector*.
 - Which step δq (or velocities \dot{q}) should we make in the joints?
- Equivalent dynamic problem:
 - We know how the desired acceleration \ddot{y}^* of the *endeffector*.
 - What controls u should we apply?

Operational space control

- Inverse kinematics:

$$q^* = \operatorname{argmin}_q \|\phi(q) - y^*\|_C^2 + \|q - q_0\|_W^2$$

- Operational space control (one might call it “Inverse task space dynamics”):

$$u^* = \operatorname{argmin}_u \|\ddot{\phi}(q) - \ddot{y}^*\|_C^2 + \|u\|_H^2$$

Operational space control

- We can derive the optimum perfectly analogous to inverse kinematics
We identify the minimum of a locally squared potential, using the local linearization (and approx. $\ddot{J} = 0$)

$$\ddot{\phi}(q) = \frac{d}{dt} \dot{\phi}(q) \approx \frac{d}{dt} (J\dot{q} + \dot{J}q) \approx J\ddot{q} + 2\dot{J}\dot{q} = JM^{-1}(u - F) + 2\dot{J}\dot{q}$$

We get

$$u^* = T^\sharp(\ddot{y}^* - 2\dot{J}\dot{q} + TF)$$

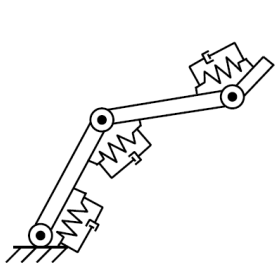
with $T = JM^{-1}$, $T^\sharp = (T^\top CT + H)^{-1}T^\top C$

$$(C \rightarrow \infty \Rightarrow T^\sharp = H^{-1}T^\top(TH^{-1}T^\top)^{-1})$$

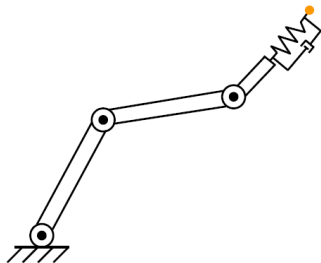
Controlling a robot – operational space approach

- Where could we get the desired \ddot{y}^* from?
 - **Reference trajectory** $y_{0:T}^{\text{ref}}$ in operational space
 - **PD-like behavior** in each operational space:

$$\ddot{y}_t^* = \ddot{y}_t^{\text{ref}} + K_p(y_t^{\text{ref}} - y_t) + K_d(\dot{y}_t^{\text{ref}} - \dot{y}_t)$$



Joint Space



Operational Space

illustration from O. Brock's lecture

- Operational space control: *Let the system behave as if we could directly “apply a 1D point mass behavior” to the endeffector*

Multiple tasks

- Recall trick last time: we defined a “big kinematic map” $\Phi(q)$ such that

$$q^* = \operatorname{argmin}_q \|q - q_0\|_W^2 + \|\Phi(q)\|^2$$

- Works analogously in the dynamic case:

$$u^* = \operatorname{argmin}_u \|u\|_H^2 + \|\Phi(q)\|^2$$

What have we learned? What not?

- More theory
 - Contacts \rightarrow Inequality constraints on the dynamics
 - Switching dynamics (e.g. for walking)
 - Controlling contact forces

- **Hardware limits**
 - I think: the current success stories on highly dynamic robots are all anchored in novel hardware approaches