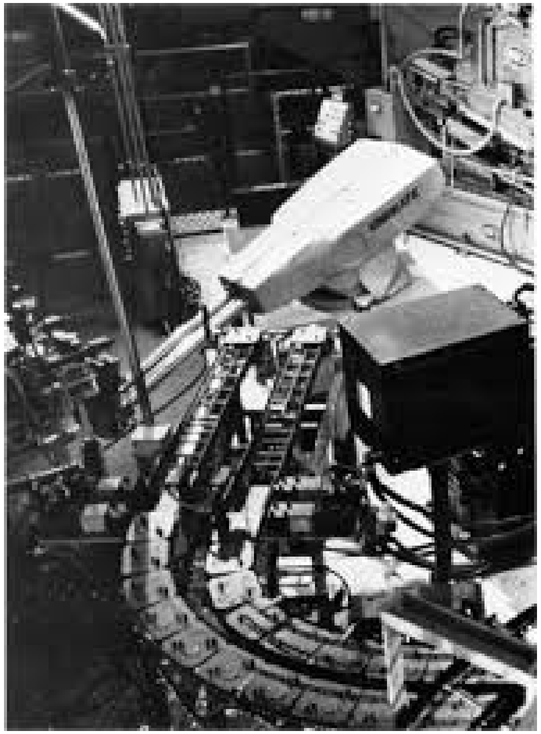
Intrinsically Elastic Actuation: A Novel Paradigm for High-Performance Torque Controlled Robots

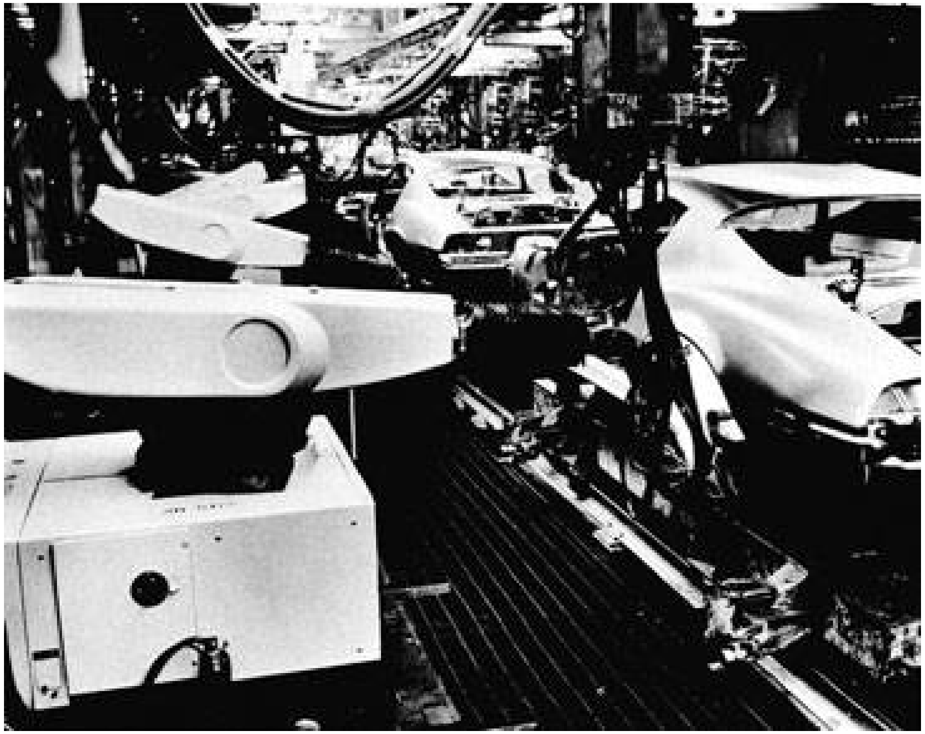
Sami Haddadin

Robotics and Mechatronics Center

German Aerospace Center

Unimate (Unimation)



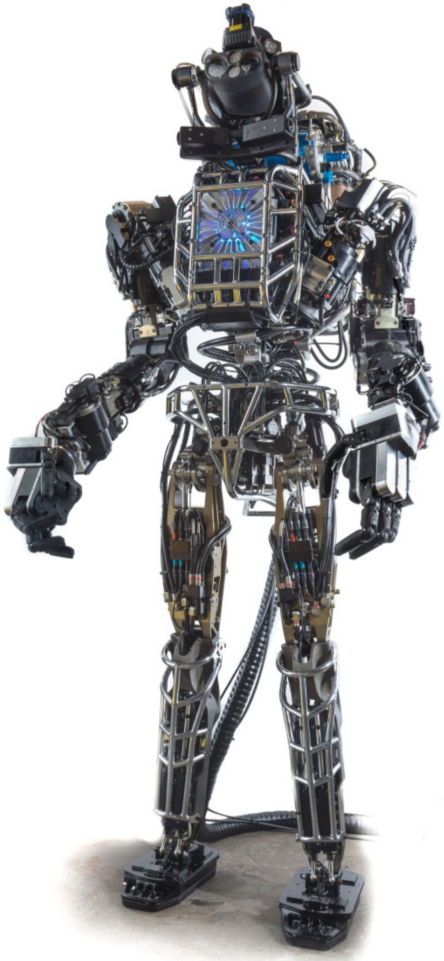


- First industrial robot in first robot company (Unimation)
- Developed by George Devol and Joseph Engelberger in the 1950s using his original patent filed in 1954 and granted in 1961

Humanoids

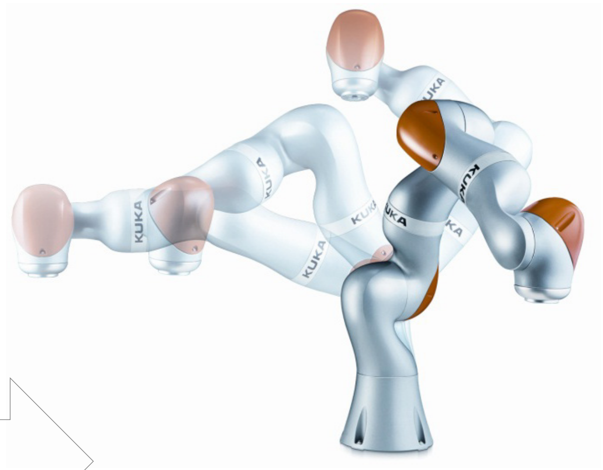

DLR, Germany

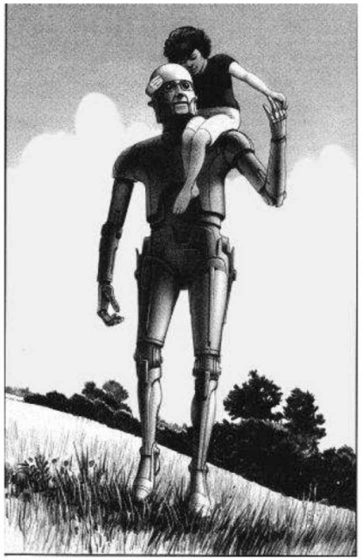

AIST, Japan


DARPA, USA

DLR

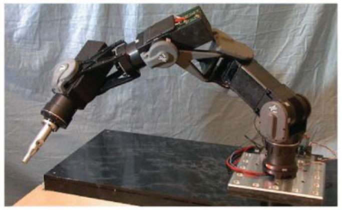
Paradigm Shift: New Generation of Robots



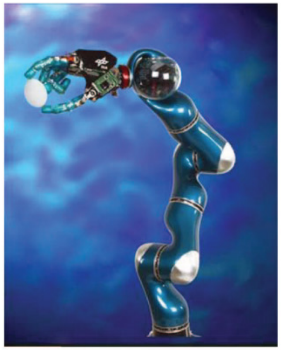


Enabler Technologies for Interaction: Lightweight Robots

LWR I (1992)



LWR II real (1999)



LWR III real (2002)

KINEMEDIC (2005)

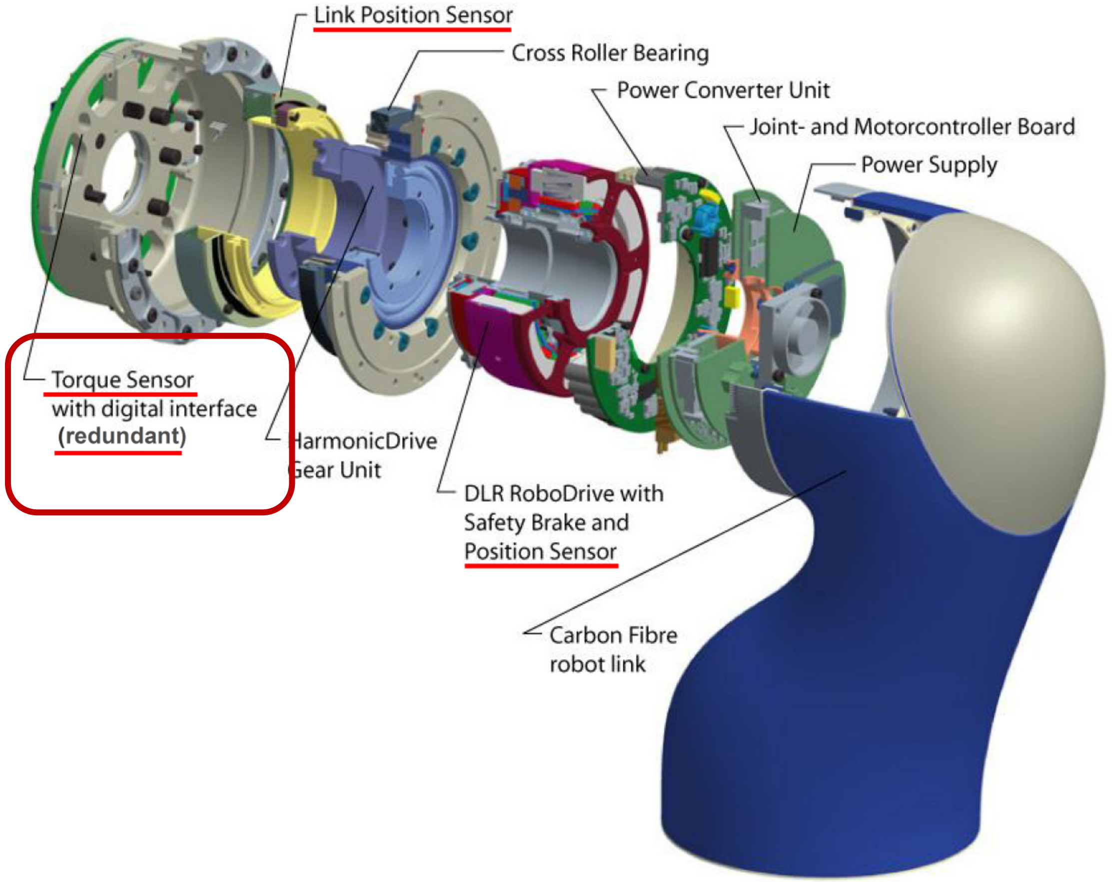
Hand I (1998)

Hand II (2001)

DLR‘s Lightweight Robots

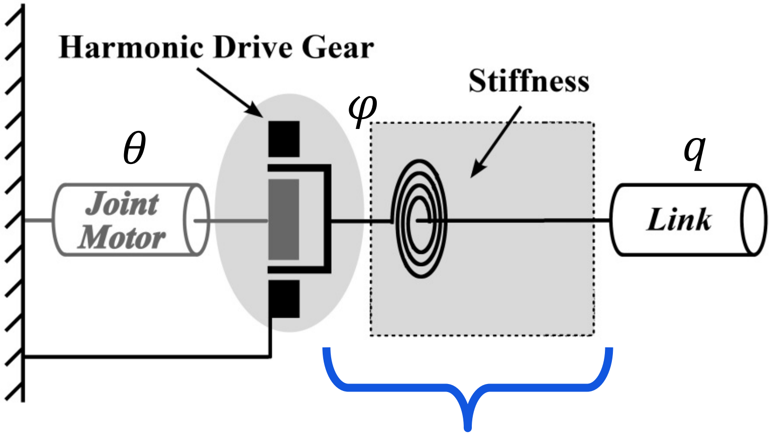
Barrett‘s WAM Arm

The Mechatronic Joint Design



Flexible joints

Joint model:



Strain gauge based torque sensor

Key Enabler: Joint Torque Sensor

Joint torque sensor	Movement accuracy	*Active vibration damping*
	Safe HRI	*Compliance control*
		Collision detection
		Collision reaction
		Self-collision avoidance
		Robust task execution

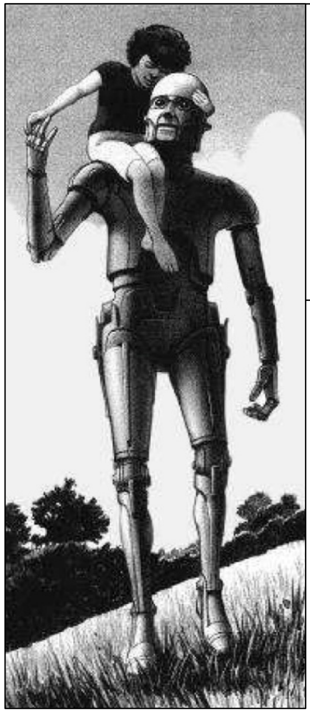
DLR

Possibilities

Performance Limitations of Rigid Robots

The Optimal Robot

Dynamic



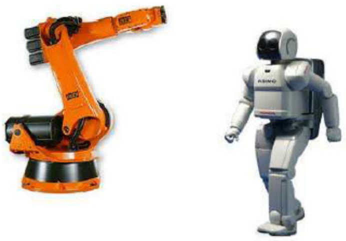
Sensitive

Safe

Newest Robot Generation

rigid and heavy

passively compliant & light



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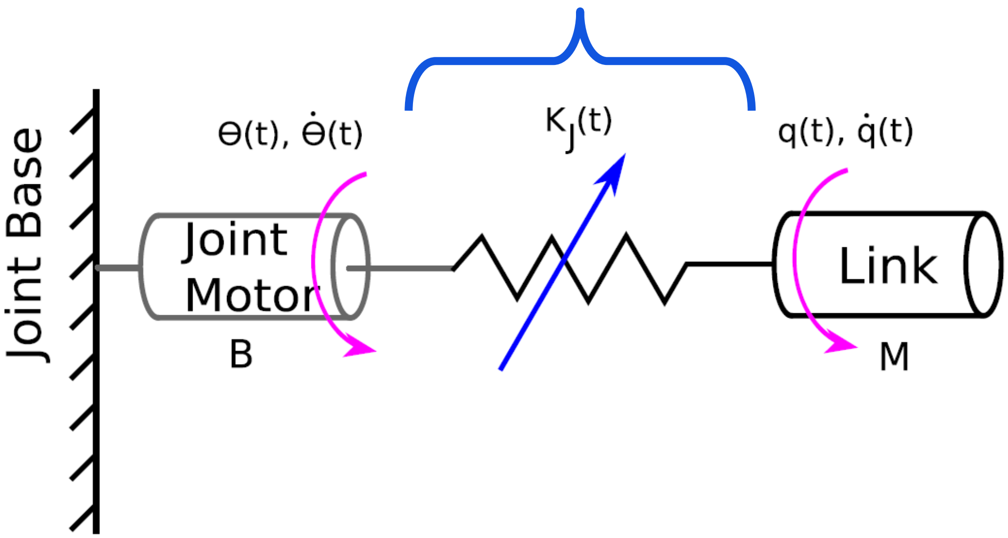
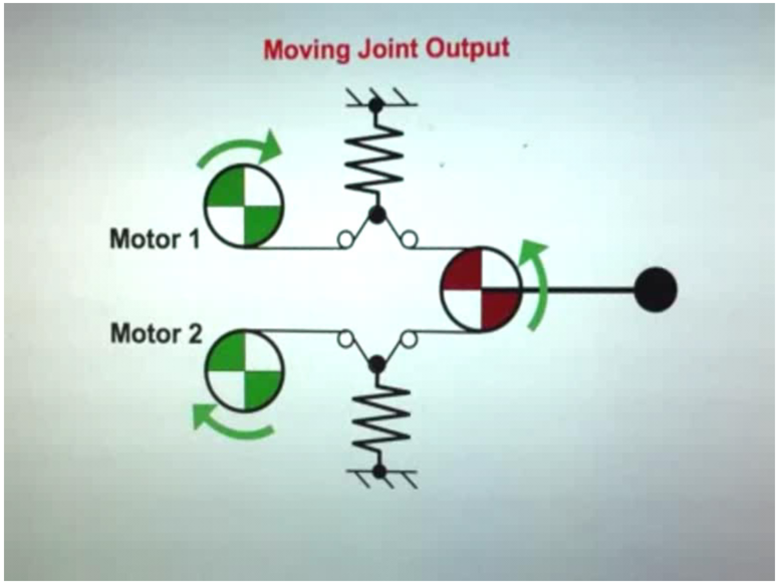
→

actively compliant & light

Elastic Robot Design

Torque Sensor implemented with two position sensors!





DLR Hand-Arm System

Problem Statement

Robots capable of high-performance safe interaction

AND

are able to achieve human like performance at the same time?

↓

It is possible to store energy!

↓

Can we transform this into kinetic energy?

In principle one should be able to move with the link considerably faster than maximum motor velocity!!

Exploiting Joint Elasticity

Key capabilities

- Elastic Joints:
  - Robustness
  - Performance

- Performance:
  - Maximize System Energy
  - Minimize Link Velocity
  - Time-Optimal Tracking
  - etc.

} Optimal Control(OC) Problems

↓

Pontryagin's Minimum Principle

$$\mathbb{H}(\boldsymbol{x}^*, \boldsymbol{\lambda}^*, u^*) \leq \mathbb{H}(\boldsymbol{x}^*, \boldsymbol{\lambda}^*, u)$$

↓

Description with Physical Quantities

Optimal Control

- First-Order Differential Equations:

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

- Inequality and End Constraints:

$$\boldsymbol{h}(\boldsymbol{x}(t), \boldsymbol{u}(t), t) \leq \boldsymbol{0} \qquad \boldsymbol{g}(\boldsymbol{x}(t_f), t_f) = \boldsymbol{0}$$

and

- Cost Functional: $J(\boldsymbol{u}) = \underbrace{\vartheta(\boldsymbol{x}(t_f), t_f))}_{\text{Terminal Cost}} + \underbrace{\int_{t_0}^{t_f} L(\xi, \boldsymbol{x}(t), \boldsymbol{u}(t))\mathrm{d}t}_{\text{Running Cost}}$

$$J(\boldsymbol{u}^*) = \min_{\boldsymbol{u} \in \mathbb{U}} J(\boldsymbol{u})$$

Problem: Find the piecesewise continuous Control: $\boldsymbol{u}^* \in \mathbb{U}$

Pontryagin's Minimum Principle (Unconstr. System)

- Hamiltonian:

$$\mathbb{H} = L(t, \boldsymbol{x}, \boldsymbol{u}) + \boldsymbol{\lambda}^T \boldsymbol{f}(t, \boldsymbol{x}, \boldsymbol{u})$$

- System Dynamics:

$$\dot{\boldsymbol{x}}^* = \frac{\partial \mathbb{H}}{\partial \boldsymbol{\lambda}}\Big|^* = \boldsymbol{f}((t, \boldsymbol{x}^*, \boldsymbol{u}^*)), \quad \boldsymbol{x}(t_0) = \boldsymbol{x}_0$$

- Costates Dynamics:

$$\dot{\boldsymbol{\lambda}}^* = -\frac{\partial \mathbb{H}}{\partial \boldsymbol{x}}\Big|^*, \quad \boldsymbol{\lambda}^*(t_f) = \frac{\partial \vartheta}{\partial \boldsymbol{x}}(\boldsymbol{x}(t_f), t_f))$$

- Minimum Principle:

$$\mathbb{H}(t, \boldsymbol{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{u}^*) \leq \mathbb{H}(t, \boldsymbol{x}^*, \boldsymbol{\lambda}^*, \boldsymbol{u}), \quad \forall \boldsymbol{u} \in \mathbb{U}$$

DLR

Considered Problems

Focus: Problems with no Running Costs

$$J(u) = \vartheta(\boldsymbol{x}(t_f), t_f) \longrightarrow$$ Fully Exploiting System Dynamics

Variety of Problems

1-DoF Systems

SEA

- **Velocity Input** $\dot{\theta} \in [\dot{\theta}_{min}, \dot{\theta}_{max}]$
  - Unconstrained System Sec.III.A
  - Limited Deflection ϕ Sec.III.F
- **Acceleration Input** $\ddot{\theta} \in [\ddot{\theta}_{min}, \ddot{\theta}_{max}]$
  - Unconstrained System Sec.III.B
  - Limited Motor Vel. $\dot{\theta}$ Sec.III.E
- **Torque Input** $\tau_m \in [\tau_{min}, \tau_{max}]$
  - Unconstrained System Sec.III.C
  - Limited Motor Vel. $\dot{\theta}$ Sec.III.E
- **Controller Input** $\dot{\theta}_d \in [\dot{\theta}_{min}, \dot{\theta}_{max}]$
  - QA-Joint with Real-World Constraints Sec.III.G
  - Motor Models PT_1,PT_2 Appx. A

VSA

- **Velocity and Stiffness Inputs** $\dot{\theta} \in [\dot{\theta}_{min}, \dot{\theta}_{max}]$, $k \in [k_{min}, k_{max}]$
  - Unconstrained System Sec.IV

***N*-DoF Systems**

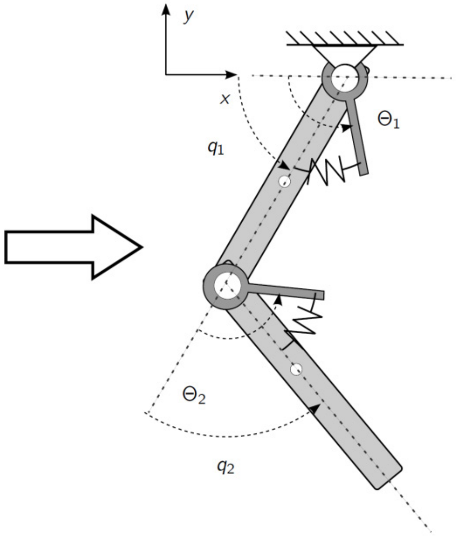
VSA

- **Velocity and Stiffness Inputs** $\dot{\boldsymbol{\theta}} \in [\dot{\boldsymbol{\theta}}_{min}, \dot{\boldsymbol{\theta}}_{max}]$, $\boldsymbol{k} \in [\boldsymbol{k}_{min}, \boldsymbol{k}_{max}]$
  - Unconstrained Double Pendulum Sec.V.A
  - Full Dynamics Sec.V.B.3

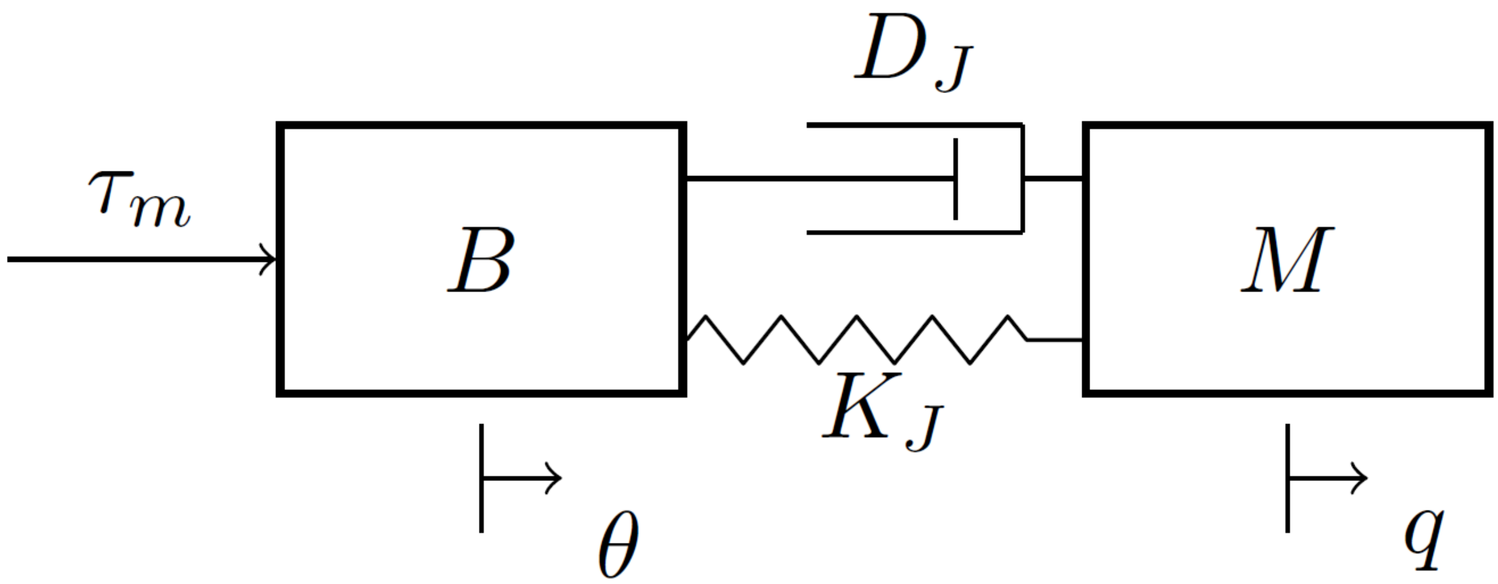
SEA

- **Velocity Inputs** $\dot{\boldsymbol{\theta}} \in [\dot{\boldsymbol{\theta}}_{min}, \dot{\boldsymbol{\theta}}_{max}]$
  - Unconstrained Double Pendulum Sec.V.A
  - Linearized Dynamics Sec.V.B.1
  - Full Dynamics Sec.V.B.2

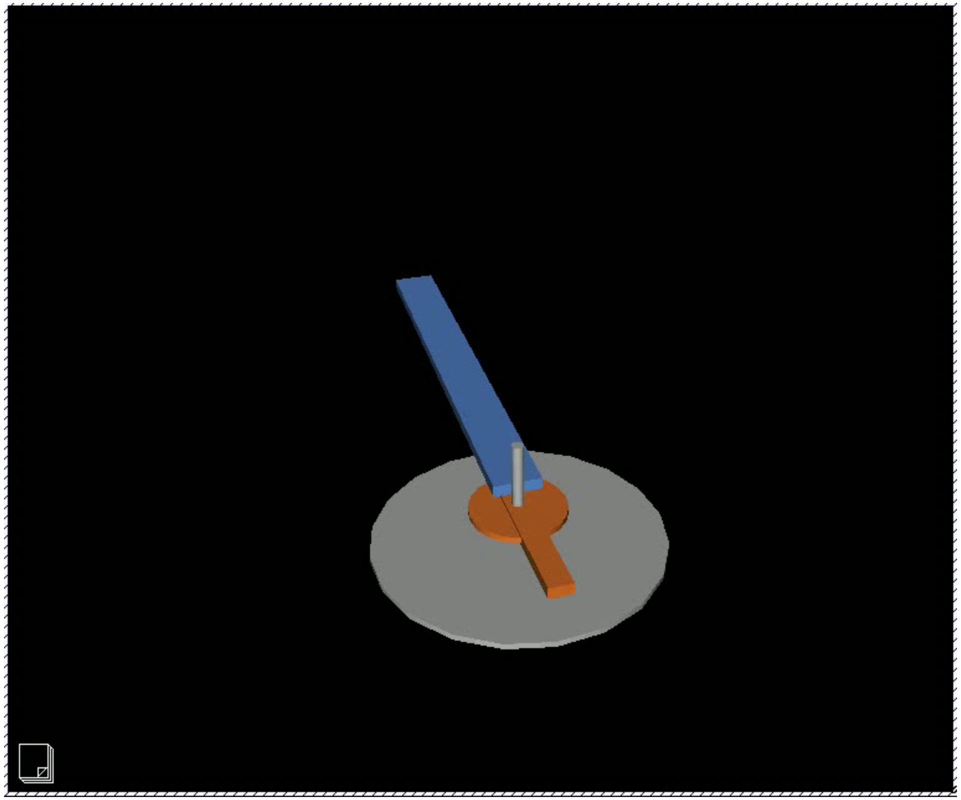
- **Velocity and Stiffness Motor Inputs** $\dot{\boldsymbol{\theta}} \in [\dot{\boldsymbol{\theta}}_{min}, \dot{\boldsymbol{\theta}}_{max}]$, $\boldsymbol{k} = \boldsymbol{k}(\boldsymbol{\sigma})$
  - DLR Hand-Arm System with Real-World Constrains Sec.V.C.1
  - Experiments: SEA,VSA Sec.V.C.2
  - Simulations: SEA,VSA Sec.V.C.2

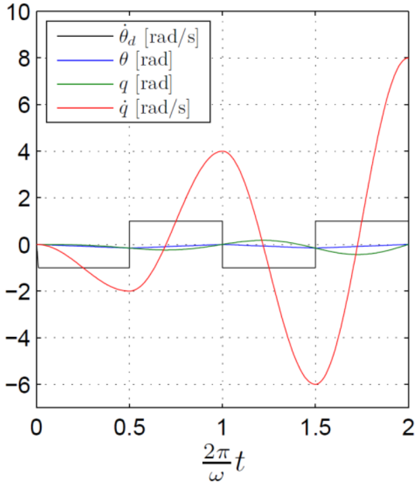


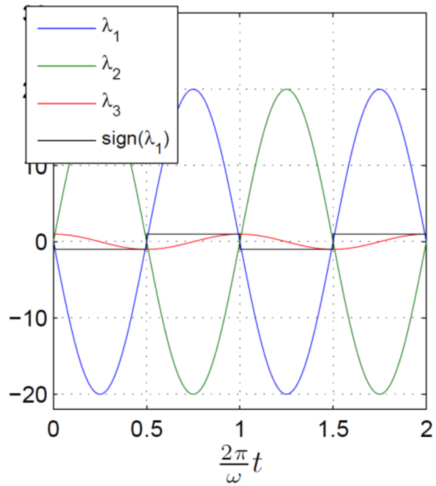
1DoF Case



Simple 1DoF case



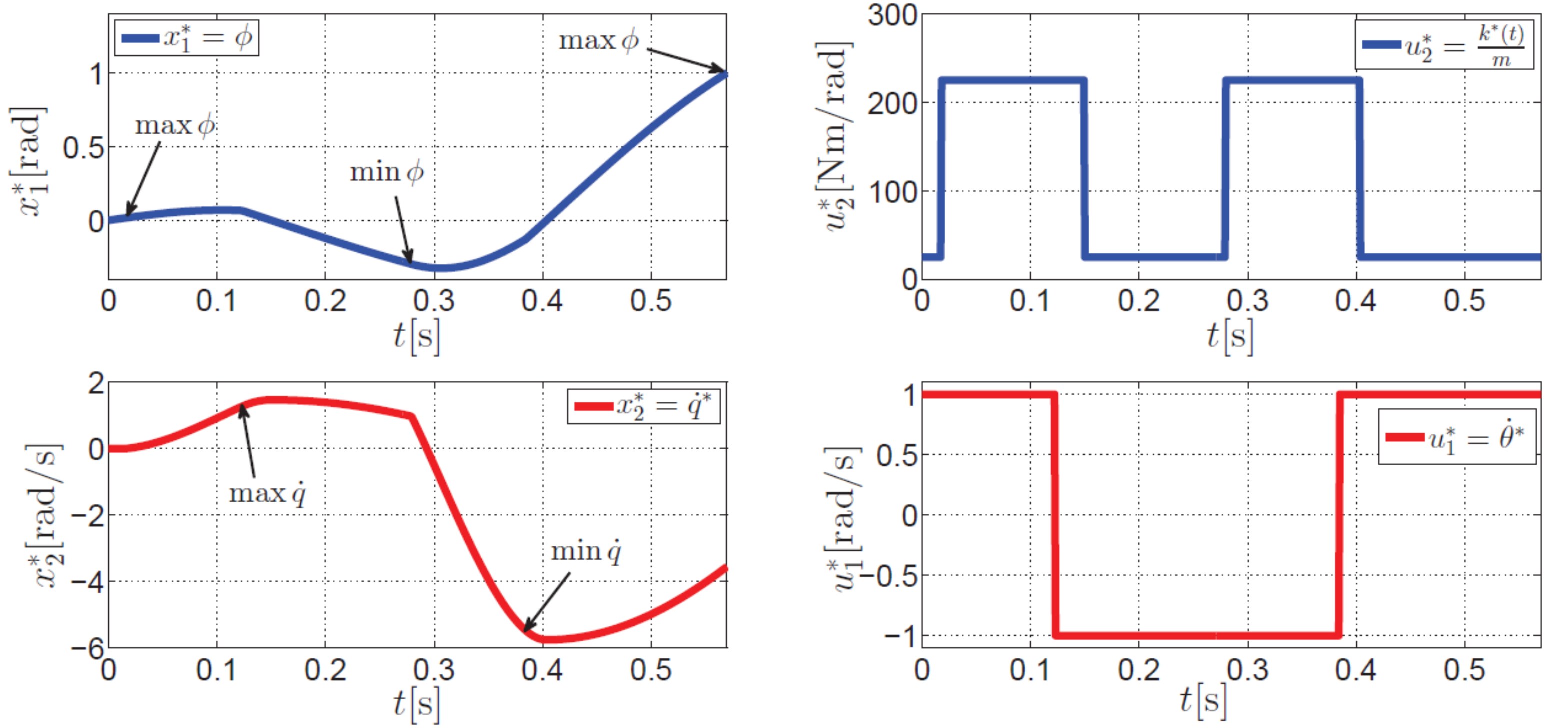




$$\dot{\theta}_d^* = \dot{\theta}_{\max} \operatorname{sgn}(\sin(\omega(t - t_f)))$$

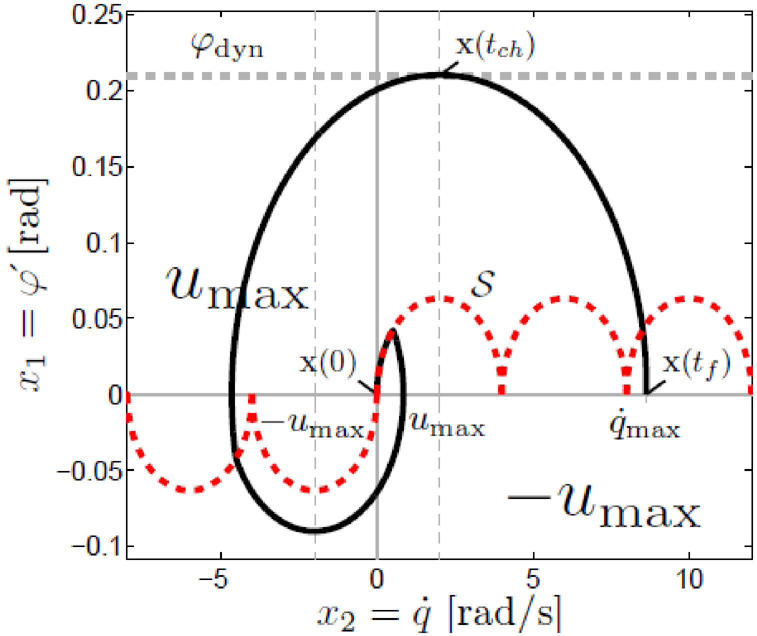
DLR

Example 1: $u_1 = \dot{\theta}, u_2 = k(t)$

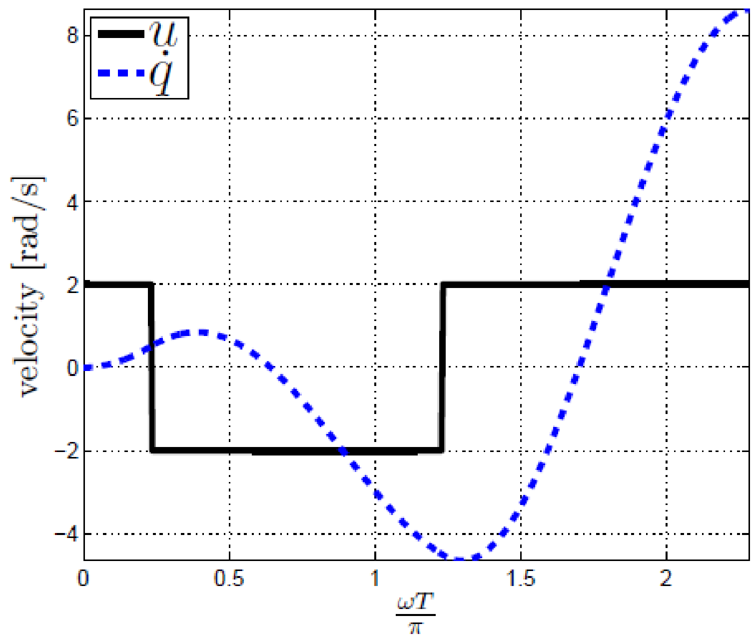


Example 2 (high spring energy): $u_1 = \dot{\theta}, \varphi \leq \varphi_{max}$

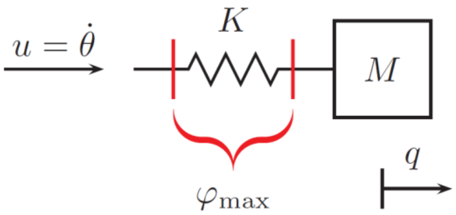
Phase plot:



Motor and link velocity:

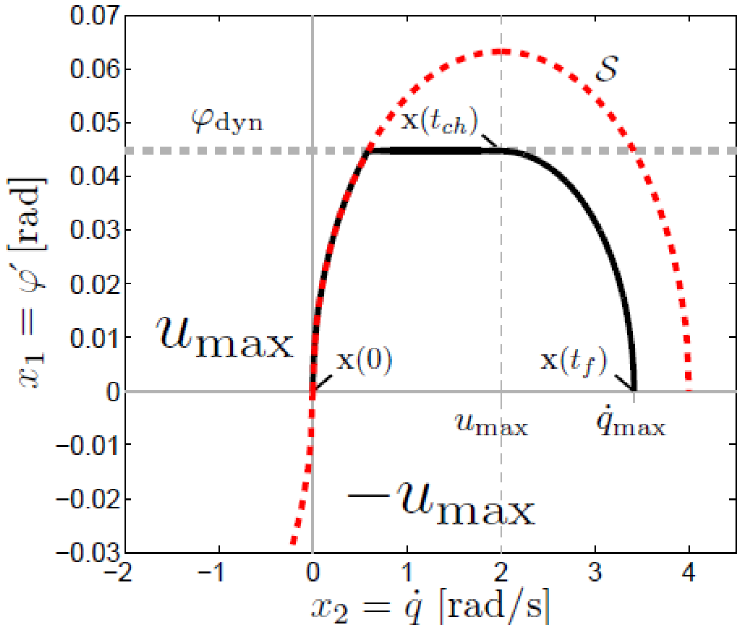


- Eigenfrequency excitation → multiple bang-bang cylces

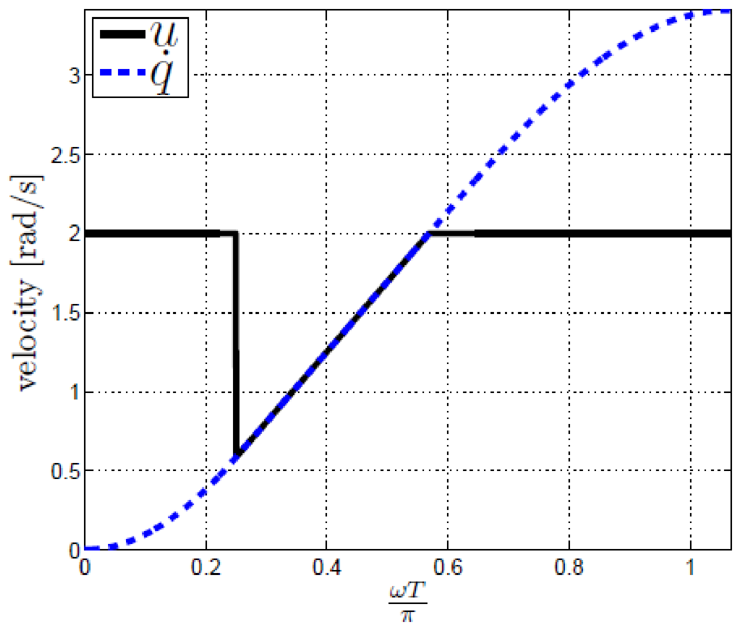


Example 2 (*low spring energy*): $u_1 = \dot{\theta}, \varphi \le \varphi_{max}$

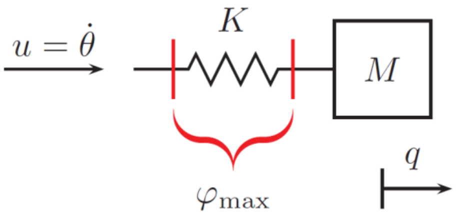
Phase plot:



Motor and link velocity:

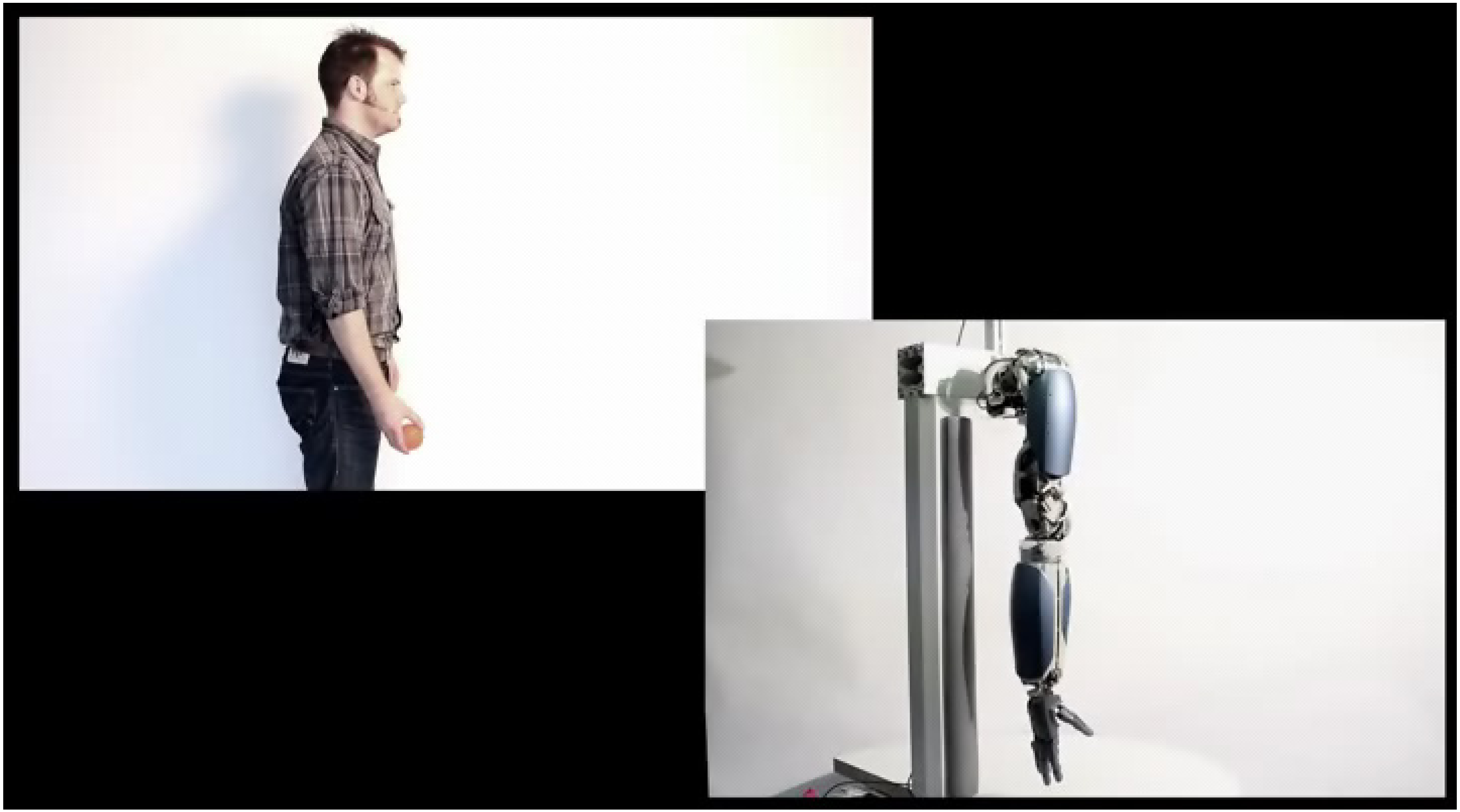


- Singular arc: max. deflection used for link acceleration

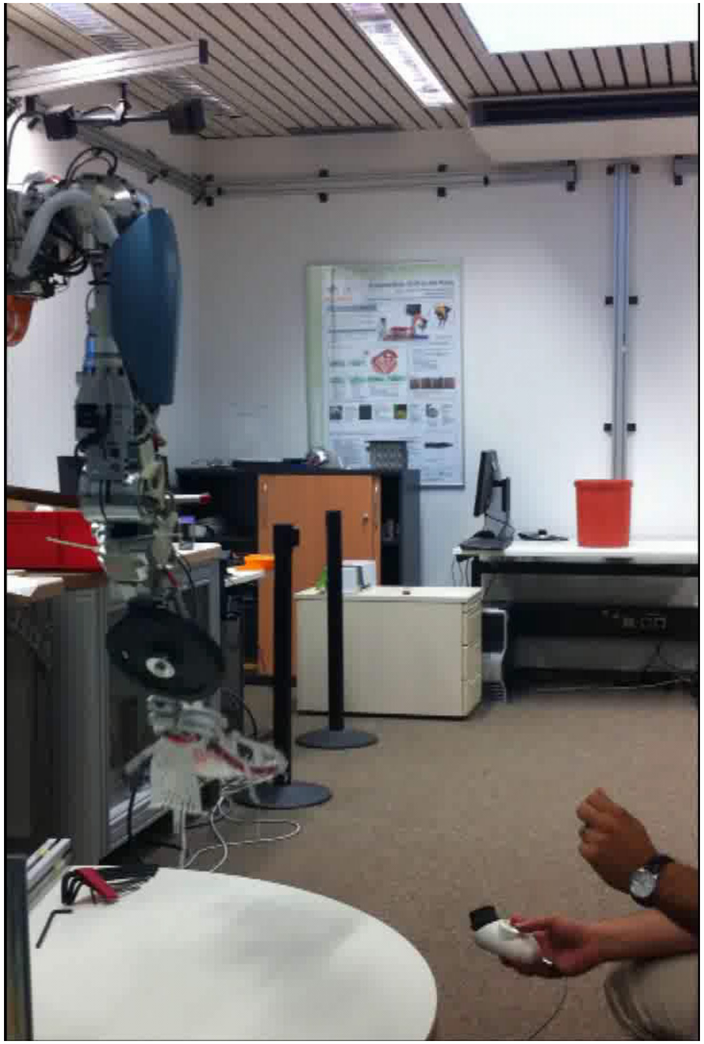


DLR

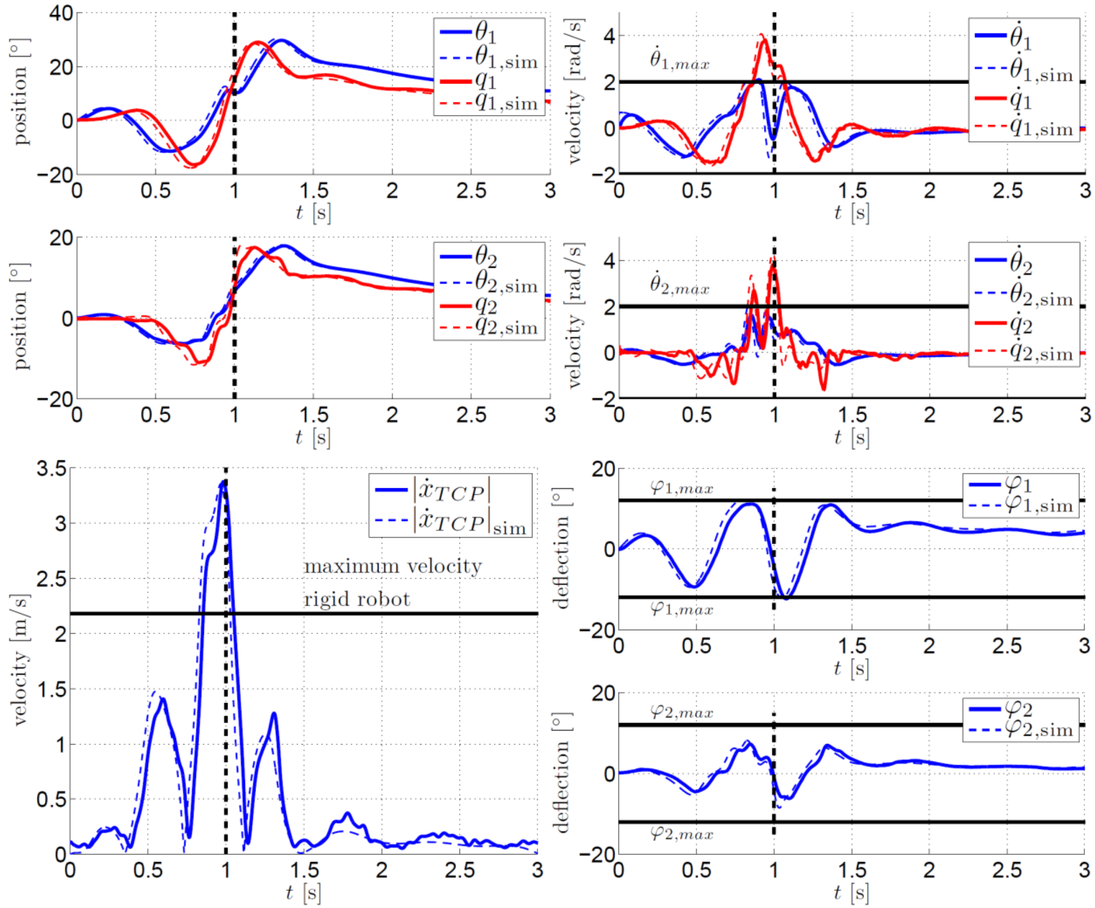
Full arm



Full arm



Experimental Data



Inherent Problem & Approach

Optimal control problems with full dynamics not analytically solvable

Robots are sought for dynamic environments and interaction, therefore, online is necessary!

$$M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau}_J$$

$$B\ddot{\boldsymbol{\Theta}} + \boldsymbol{\tau}_J = \boldsymbol{\tau}_m$$

$$\boldsymbol{\tau}_J = \boldsymbol{\tau}_J(\boldsymbol{\Theta}, \mathbf{q}, \boldsymbol{\sigma}),$$

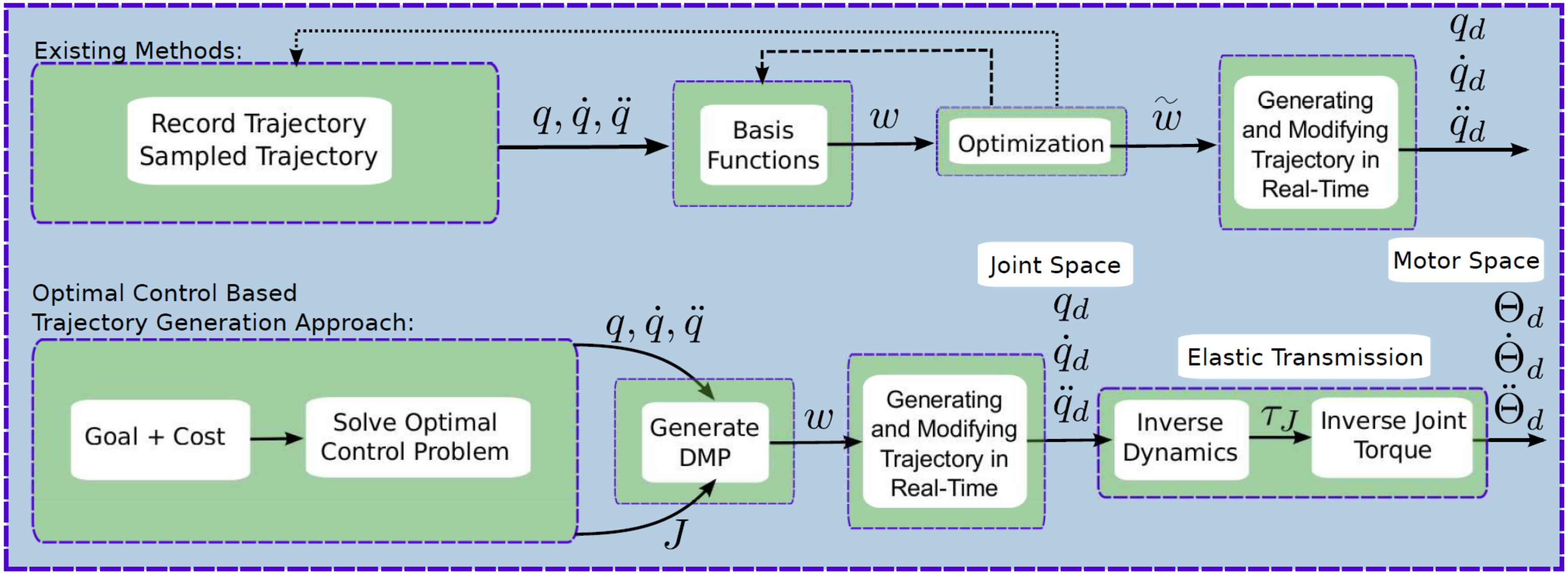
Idea:

1. Learn **optimal** motions
2. Generalize with dynamical systems and a cost based neighborhood metric

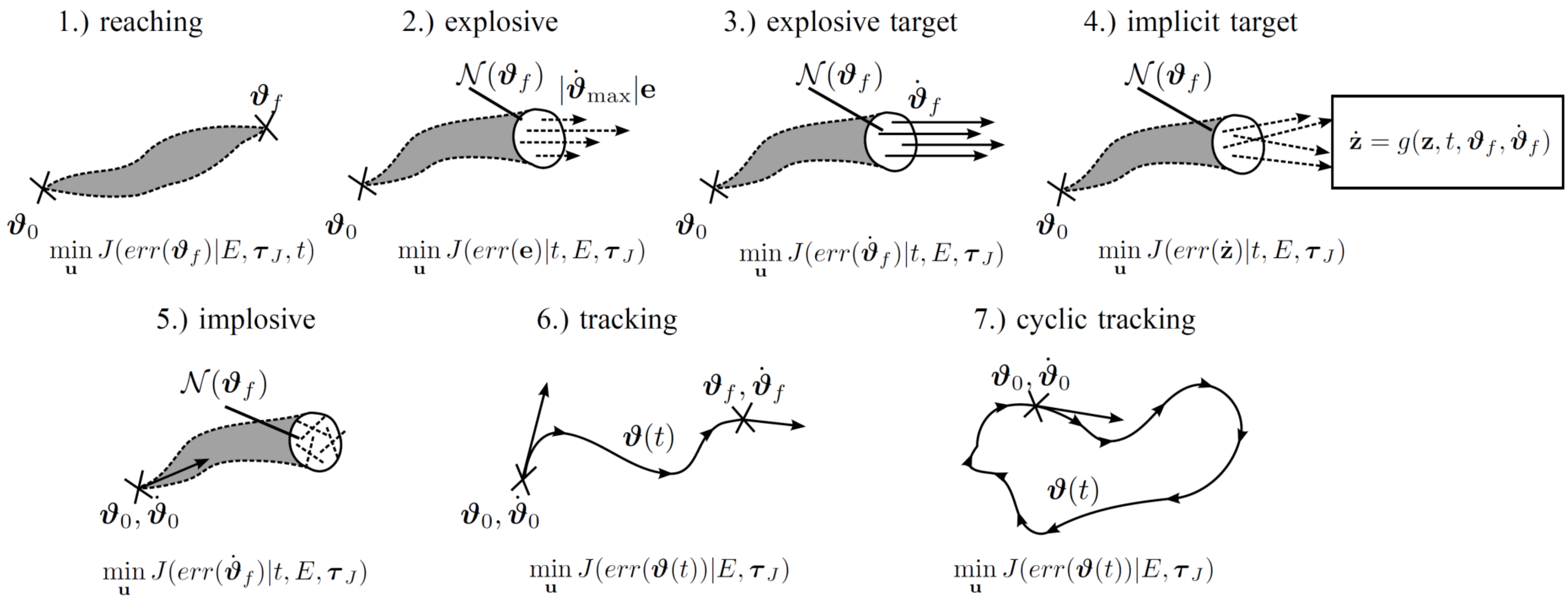
Remark:

Decoupling property: Learn **joint torques** and ignore motor dynamics

Optimal Learning and Generalisation Framework



Prototypical OC Problems



Learning

input : motion type, $\mathbf{c}(\mathbf{q})$, parameters $\{\boldsymbol{\xi}_k\}$
output: $\mathbf{w}^*, \boldsymbol{\Phi}^*$

for $k \leftarrow 1$ **to** m **do**

$$[\mathbf{q}_k^*, \dot{\mathbf{q}}_k^*, \ddot{\mathbf{q}}_k^*] = \min_{\mathbf{u}} J(\text{motion type}, \mathbf{c}(\mathbf{q}), \boldsymbol{\xi}_k) \;;$$

for $i \leftarrow 1$ **to** n **do**

$$\mathbf{f}_i^*(t_i) = -\tau^2 \ddot{\mathbf{q}}^*(t_i) + \kappa(t_i)(\mathbf{q}^*(\tau) - \mathbf{q}^*(t_i)) - D\tau\dot{\mathbf{q}}^*(t_i) \;;$$

$$x_i = \exp\left\{-\frac{\alpha_x}{\tau} t_i\right\} \;;$$

$$\mathbf{x}_i = [x_i; \cdots; x_i]_{dim=M\times 1} \;;$$

$$\mathbf{F}_k^* = [\mathbf{F}_k^*;\ \mathbf{f}_i^{*T}(t_i)] \;;$$

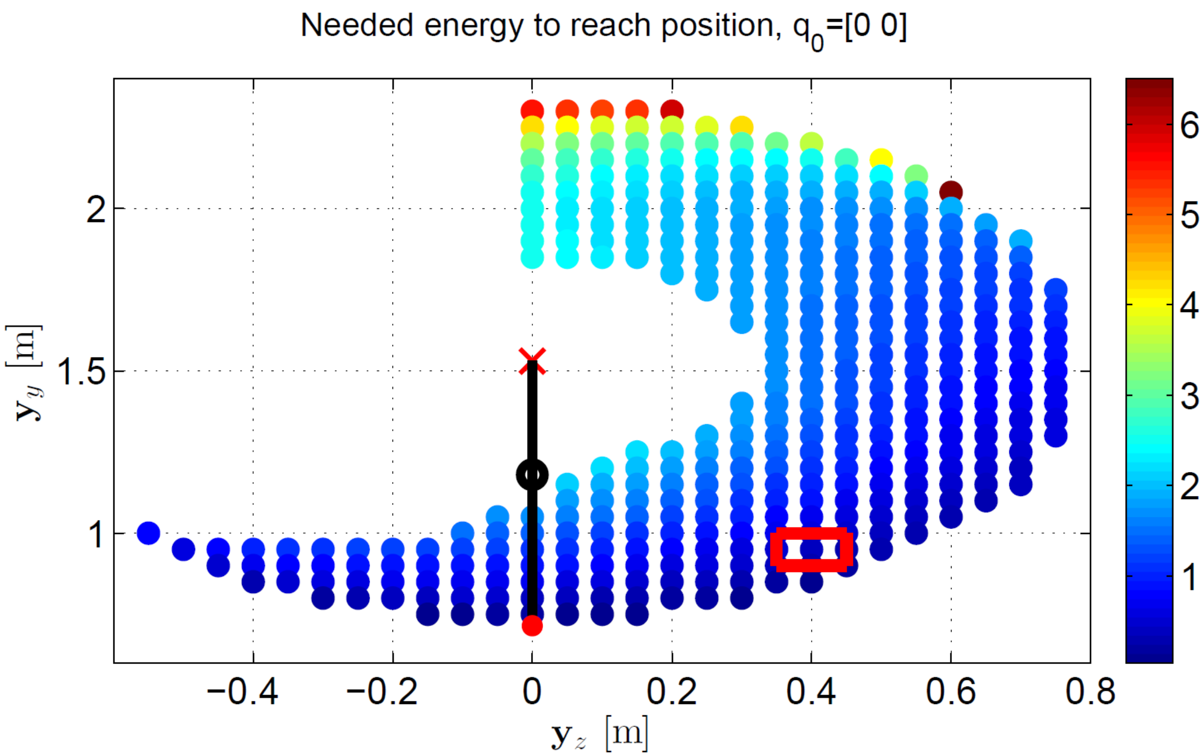
$$\mathbf{X} = [\mathbf{X};\ \mathbf{x}_i^T] \;;$$

end

$$[\mathbf{w}_k^*, \boldsymbol{\Phi}^*] = \min \Gamma[(\boldsymbol{\Phi}^j, \mathbf{F}_k^*, \mathbf{X}) \rightarrow \mathbf{w}^j \rightarrow \mathbf{f}_{\approx}^j]$$

end

Example cost manifold



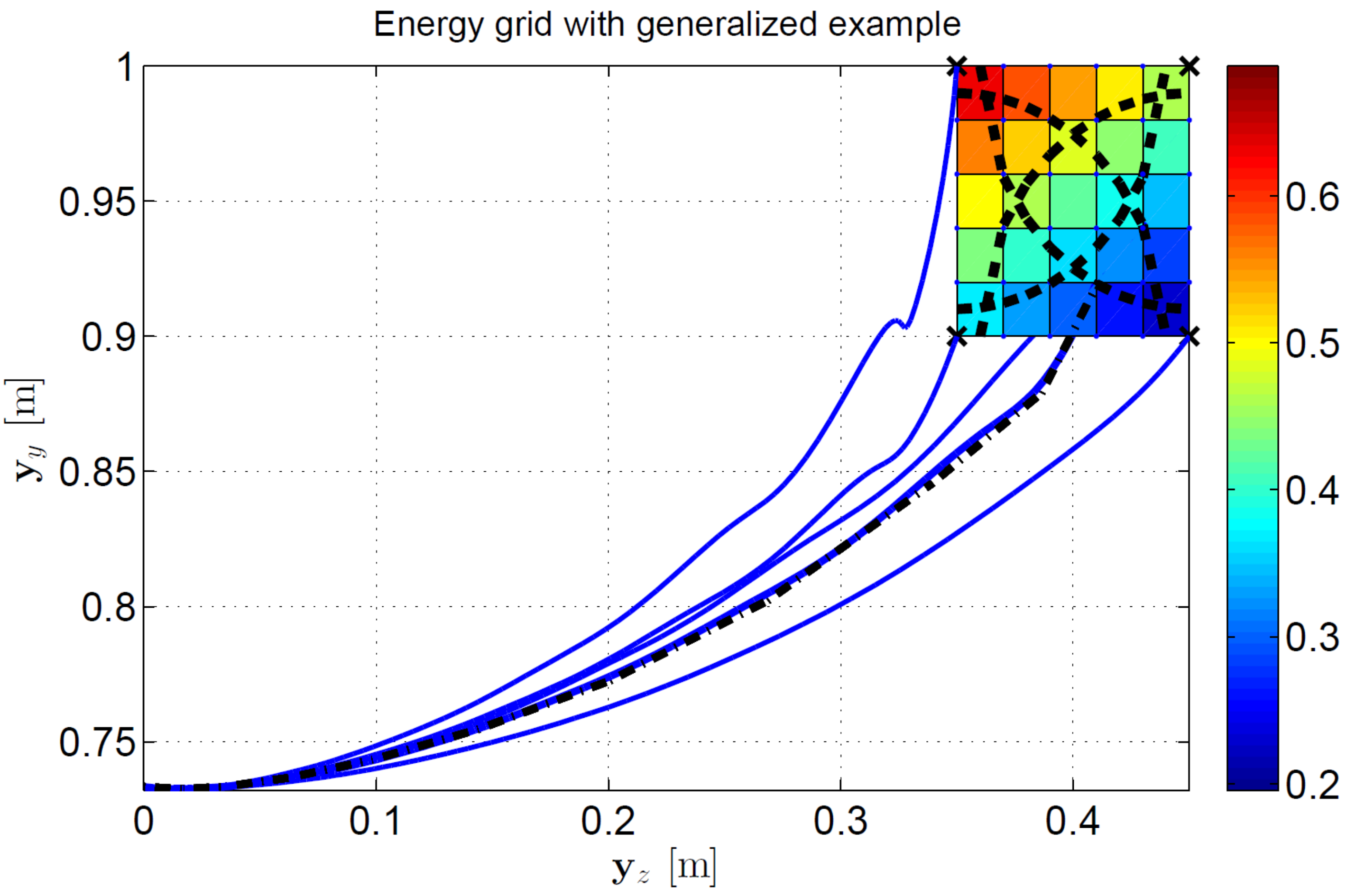
$$\min_{\dot{\boldsymbol{\Theta}}(t)} J = \int_{t_0}^{t_f} \left(\frac{1}{2} w_{\Theta_1} \dot{\Theta}_1^2 + \frac{1}{2} w_{\Theta_4} \dot{\Theta}_4^2 \right) \, dt$$

Generalization

$$\mathbf{w}_l^*(\mathbf{y}_g) = \frac{\sum_{\forall k:\sigma_k \leq \delta} \mathbf{w}_l^*(\mathbf{y}_k)\sigma_k^{-1}}{\sum_{\forall k:\sigma_k \leq \delta} \sigma_k^{-1}}$$

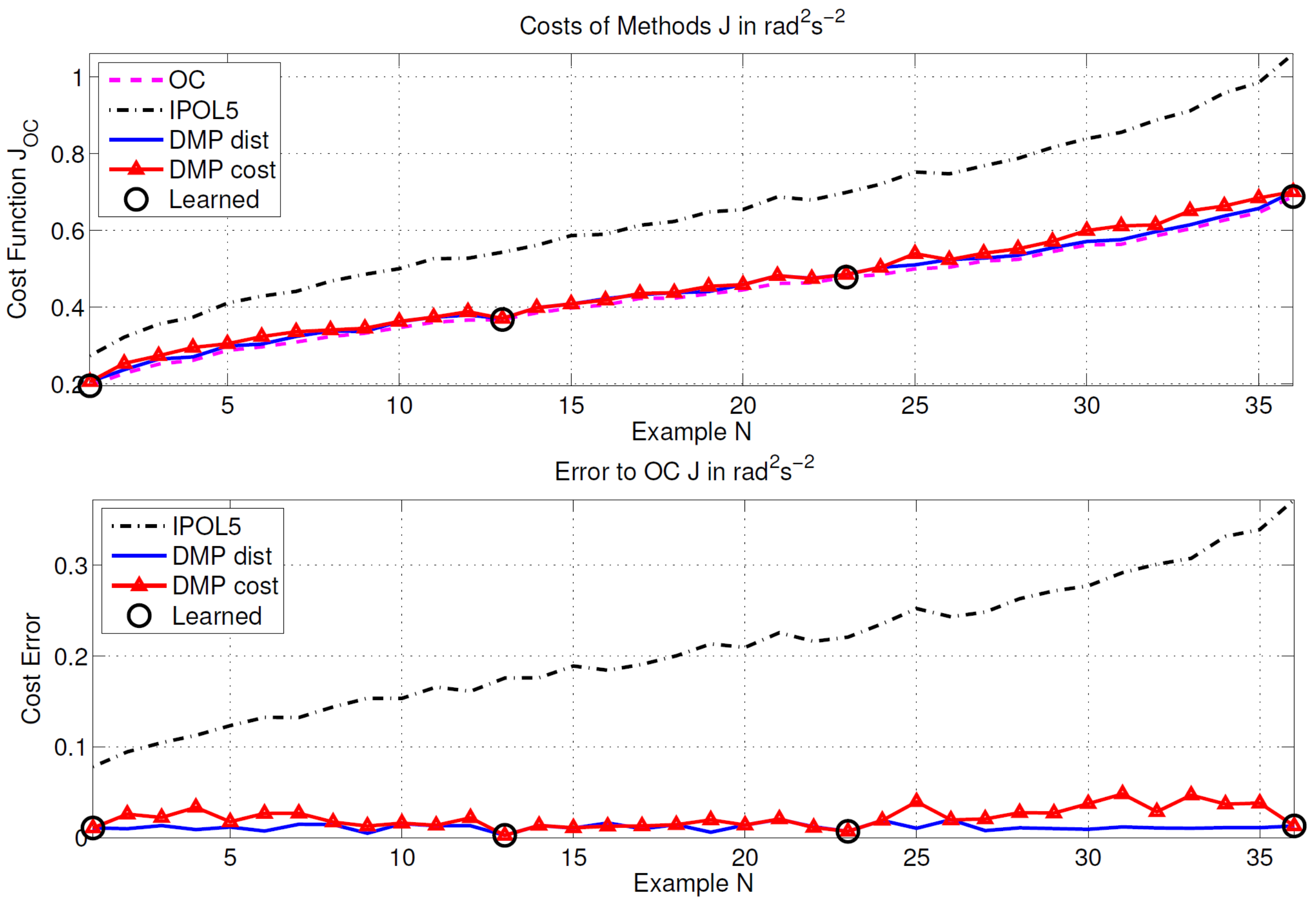
$$\sigma_k = \begin{cases} ||\mathbf{y}_g - \mathbf{y}_k|| + \epsilon, & ||\mathbf{y}_g - \mathbf{y}_k|| + \epsilon < \delta \\ \epsilon & ||\mathbf{y}_g - \mathbf{y}_k|| + \epsilon \geq \delta. \end{cases}$$

Generalization

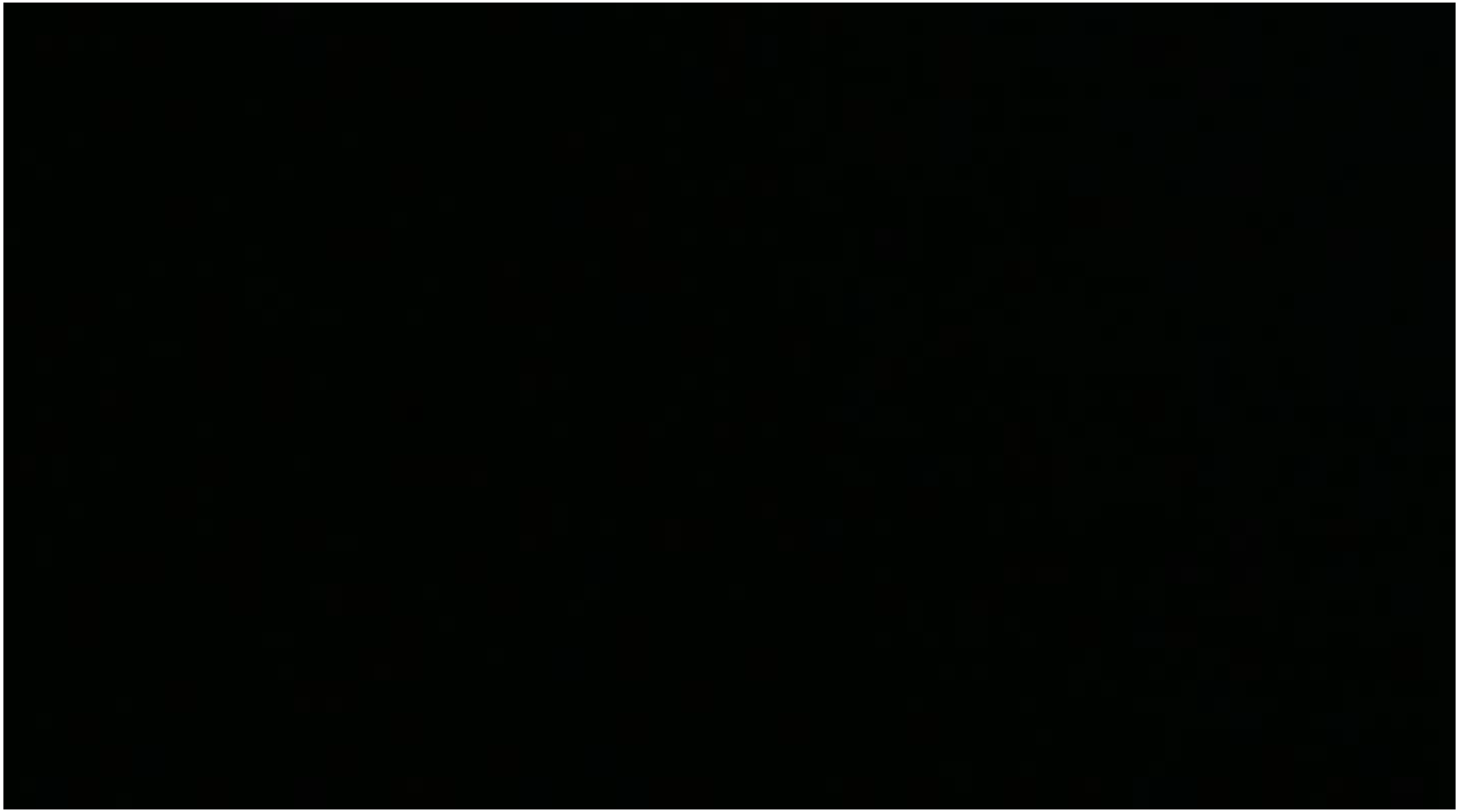


DLR

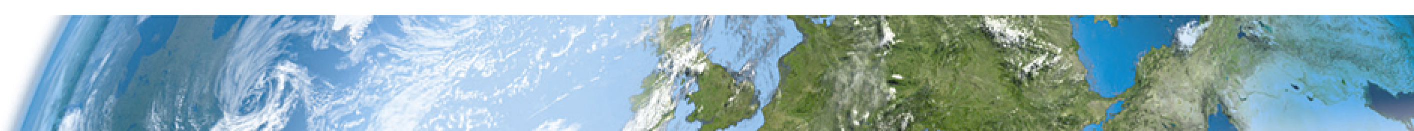
Example: Point-2-Point Motion



Intrinsic Elasticity

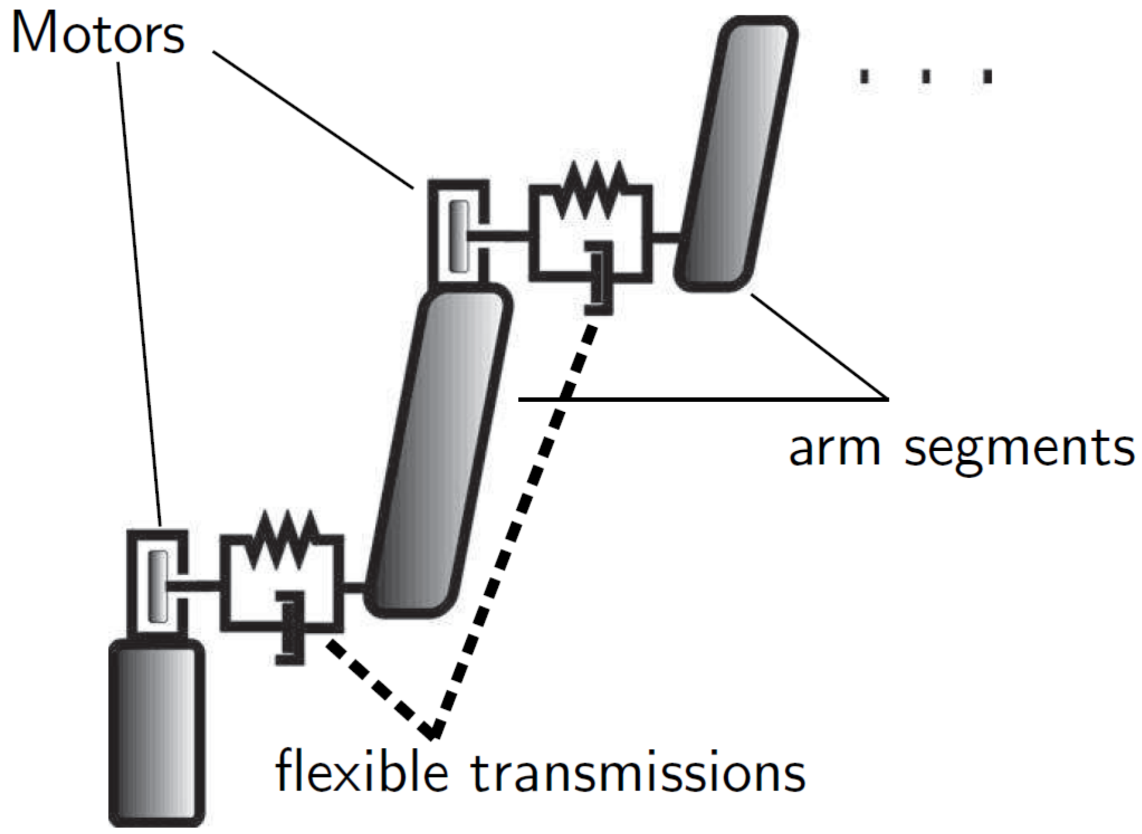


Thanks!

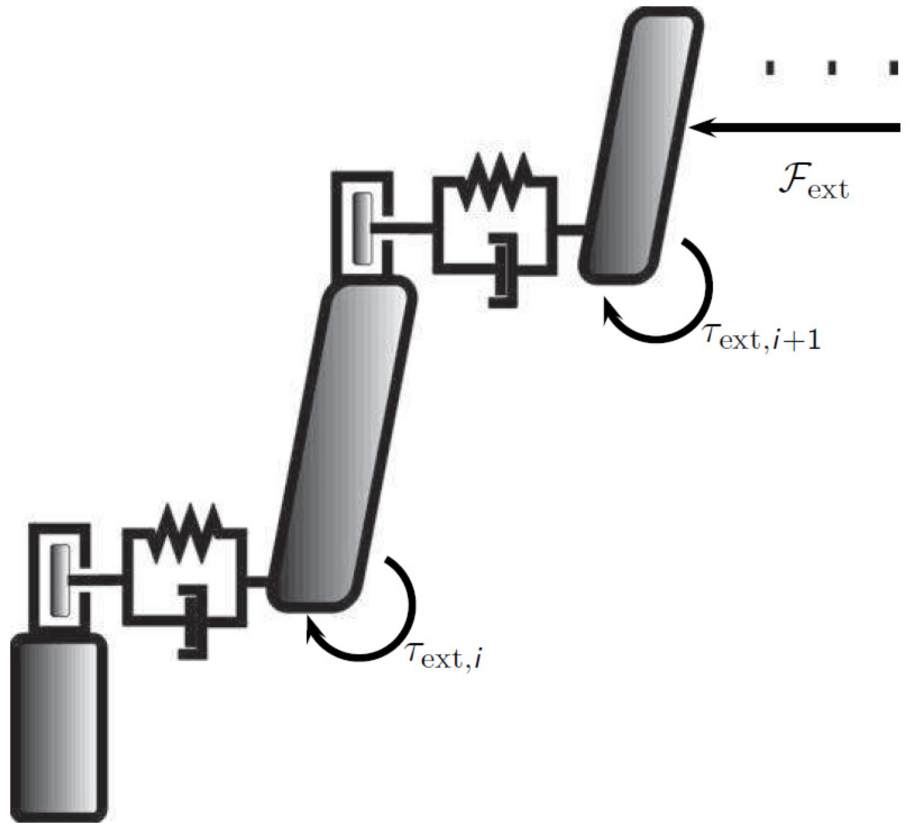


Collision detection & reflex reaction

Flexible Robots



Flexible Robots

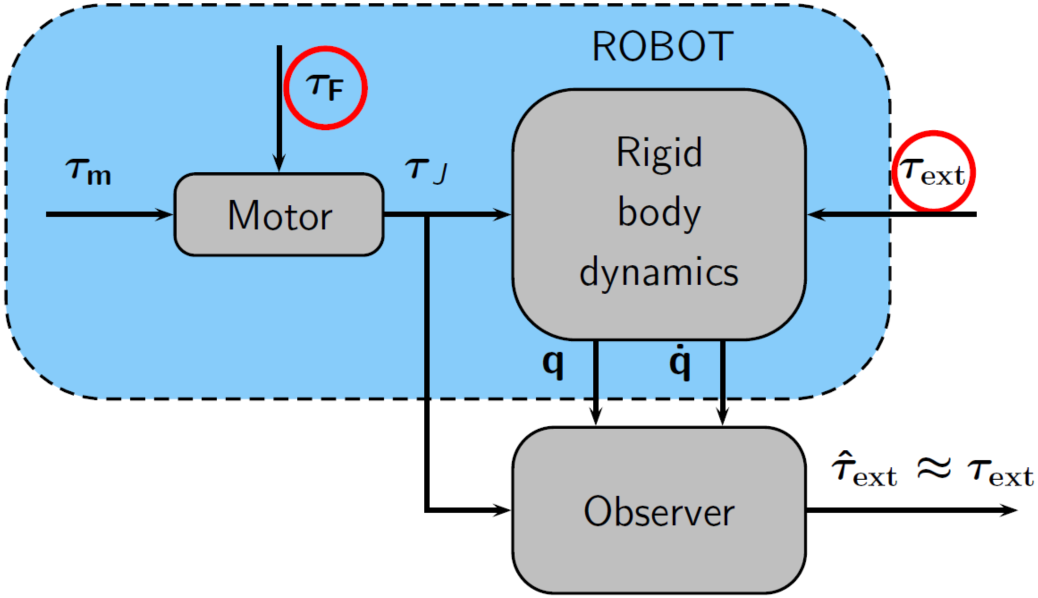


Collision Detection and Estimation

Flexible Joint Dynamics:

$$M(\mathbf{q})\ddot{\mathbf{q}} + C(\mathbf{q},\dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \boldsymbol{\tau}_J + \boldsymbol{\tau}_{\text{ext}}$$

$$B\ddot{\boldsymbol{\theta}} + \boldsymbol{\tau}_J = \boldsymbol{\tau}_m$$



Observer Design

Idea: Observe generalized momentum

$$\mathbf{p} = M(\mathbf{q})\dot{\mathbf{q}}$$

Reformulated dynamics:

$$\dot{\mathbf{p}} = \boldsymbol{\tau}_J - \boldsymbol{\beta}(\mathbf{q}, \dot{\mathbf{q}}) - \boldsymbol{\tau}_{\mathrm{ext}}$$

Residual model:

$$\hat{\mathbf{r}} = \hat{\boldsymbol{\tau}}_{\mathrm{ext}} \qquad \dot{\hat{\mathbf{r}}} = \mathbf{0}$$

Observer design:

$$\hat{\mathbf{r}} = K_O \left(\int_0^T \left[\boldsymbol{\tau}_J - \boldsymbol{\beta}(\mathbf{q}, \dot{\mathbf{q}}) - \hat{\mathbf{r}}\right] \mathrm{d}t - M(\mathbf{q})\dot{\mathbf{q}} \right)$$

Decoupled Estimation of External Torques

$$\hat{r}^i = \frac{1}{sT_O^i + 1}\tau_{\mathrm{ext}}^i = \frac{K_O^i}{s + K_O^i}\tau_{\mathrm{ext}}^i \approx \tau_{\mathrm{ext}}^i \quad \forall i \in \{1, \ldots, n\}$$