Intelligent Robot Control

Lecture 6: Impedance control

Tadej Petrič

tadej.petric@ijs.si

Institut
"Jožef Stefan"
Ljubljana, Slovenija

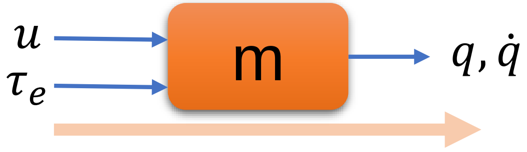
Impedance control

- Robots also interact with the environment without the need to **control** interaction forces. But the controller must be at least aware that contact may happen and be ready to react.

Video source: Youtube

Impedance control

- Assume the robot is a point mass sliding on the table without friction, which is controlled with a PD position controller. What is the effect of an **external force**?

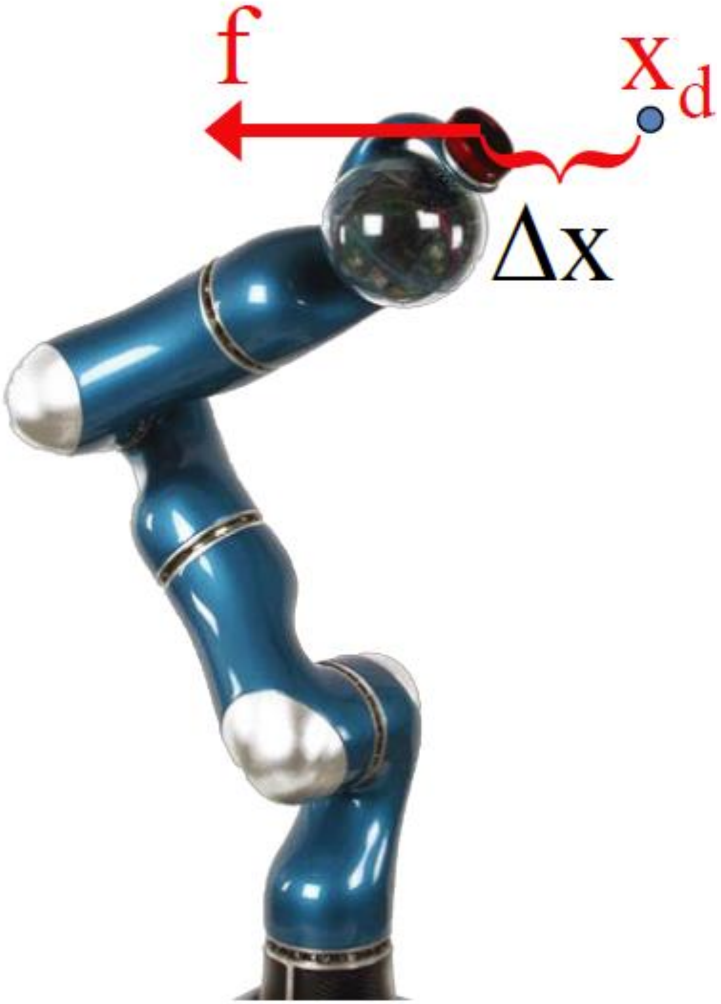


$m\ddot{q}$ = u

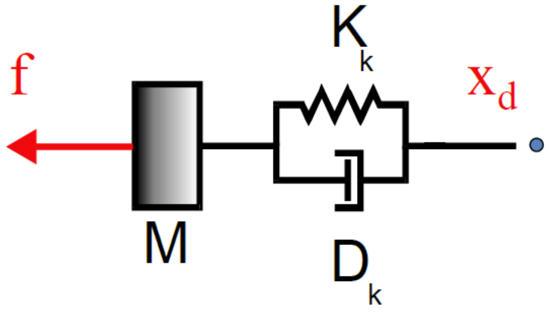
$$u = K(q_d - q) + D(\dot{q}_d - \dot{q}) + \tau_e$$

- Assuming there is no reference, we obtain:
  - $m\ddot{q} + D\dot{q} + Kq = \tau_e$
- which is the dynamic equation of a mass-spring-damper system.
- *NOTE*: we can adjust the spring and the damping parameter, but not the mass.
- With the dynamic model of the robot given as $\boldsymbol{f_d(q, \dot{q}, \ddot{q})}$, a possible control approach is: $u = K(q_d - q) + D(\dot{q}_d - \dot{q}) + \tau_e + f_d(q, \dot{q}, \ddot{q})$

Cartesian impedance control

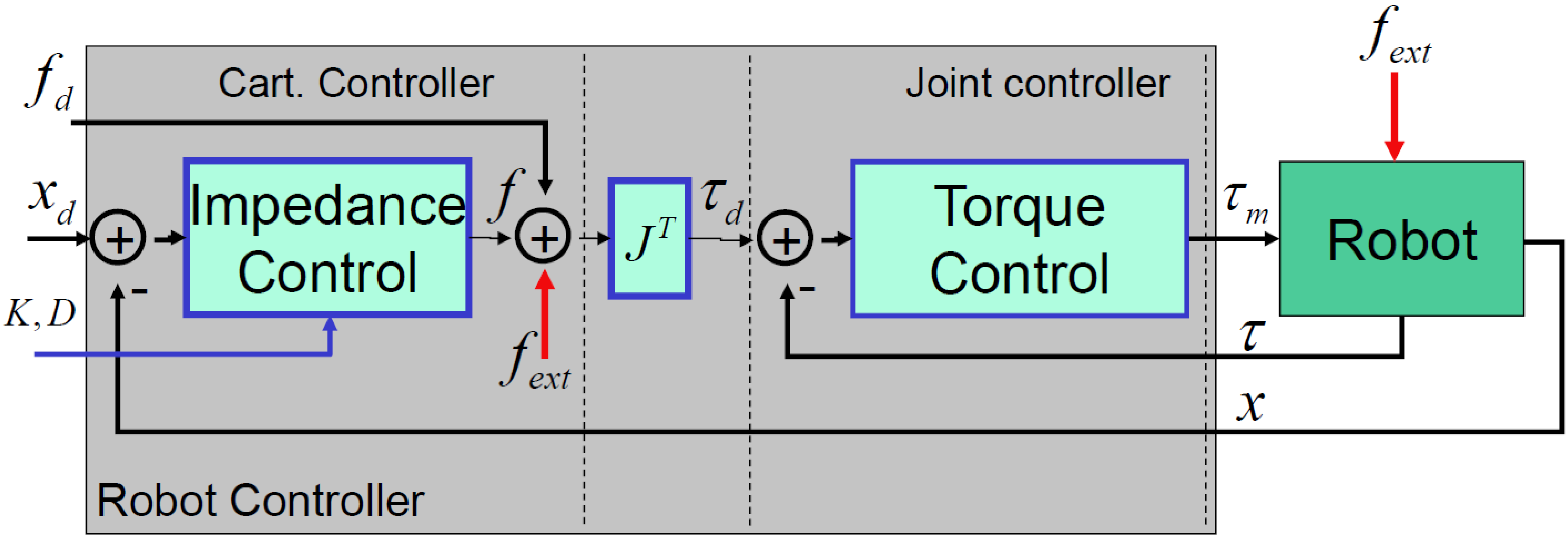


$\equiv$



$$f = M\Delta\ddot{x} + D_k\Delta\dot{x} + K_k\Delta x$$

Principle of Impedance control



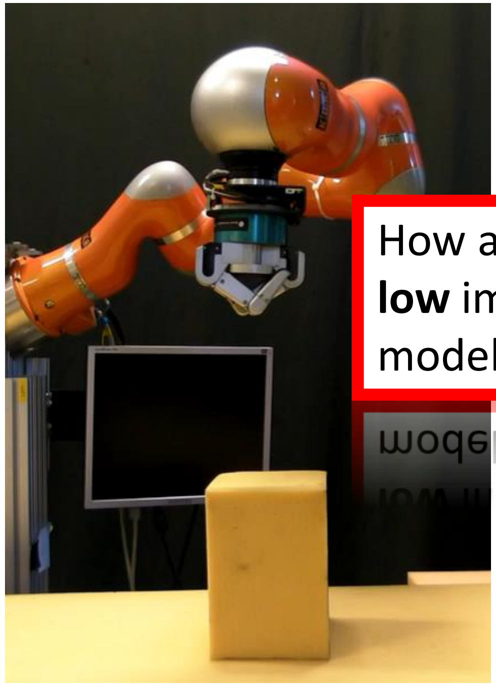
- Inner loop: compliant
- Outer loop: increases stiffness

Cartesian Impedance Control

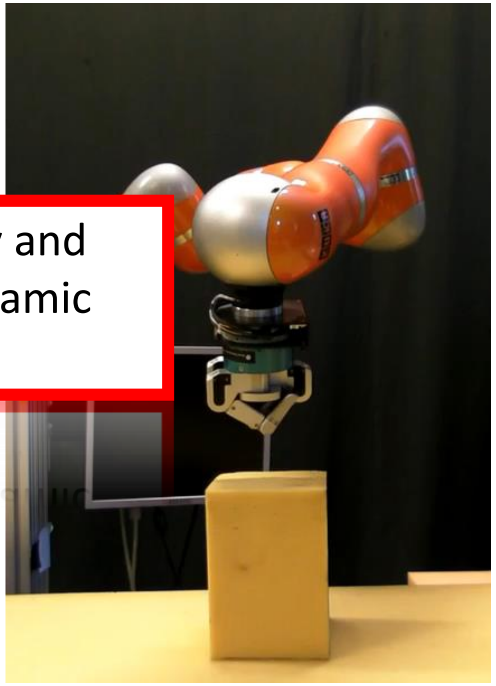
- For a non-redundant, non singular robot with torque interface a simple PD controller in Cartesian coordinates can do the job.
- Cartesian PD-Controller with gravity compensation
  - $F = K_P(x_d - x) - K_d\dot{x}$
- Transformation of the desired Cartesian Forces to desired joint torques
  - $\tau = J^T(q)F + g(q) + \tau_N$
- Null-space torque component for a redundant robot
  - $\tau_N = \left(I - J^T J^{T\#}\right)\tau_0$
  - τ_0 is an arbitrary joint space torque
  - Pseudoinverse has the property $J^{\#T} J^T = I$

Cartesian Impedance Control Example

- In contact: environment imposes position, controller wants to impose position…



How about **high** tracking accuracy and **low** impact forces? „Accurate dynamic model is required!“



High gains

- **High** tracking accuracy
- **High** impact forces

Low gains

- **Low** tracking accuracy
- **Low** impact forces

Impedance control

- In general we would like to have:
  - Good tracking performance, when there is no external force;
  - High reactivity (compliance), when external forces are applied.

- These two requirements are conflicting, in fact:
  - If we increase the gains, we obtain good tracking performance, but the system is robust with respect to external disturbances;
  - If we decrease the gain, the system accommodates for external forces, but the positioning performance are lower.

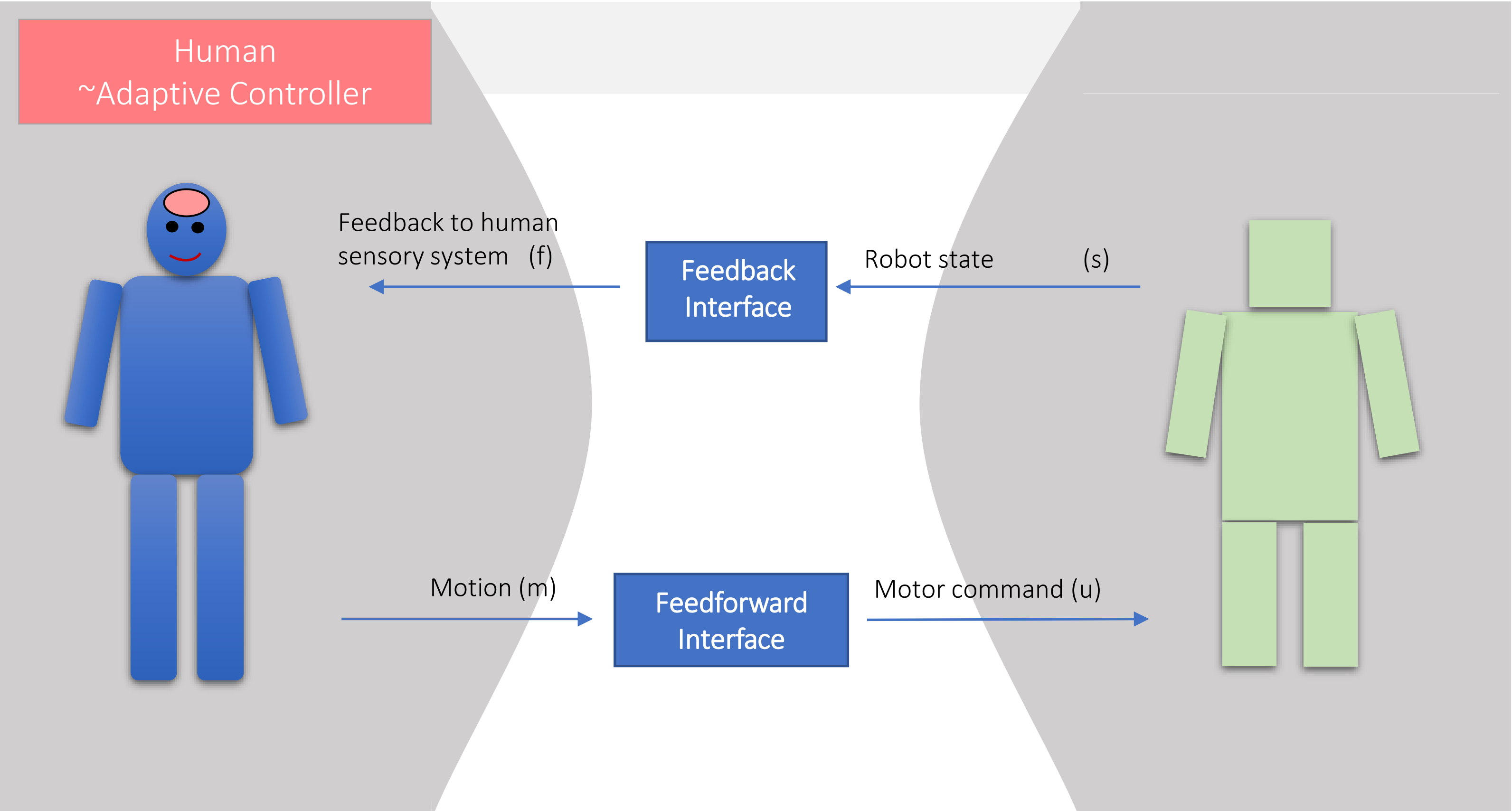
- What shall we do to obtain both?
  - Accurate dynamic model, for exampel use Compliant Movement Primitives;
  - or we can use **high gains** and modify the reference position! (Admittance control)

How to set impedance?

Human-robot collaboration for skill synthesis

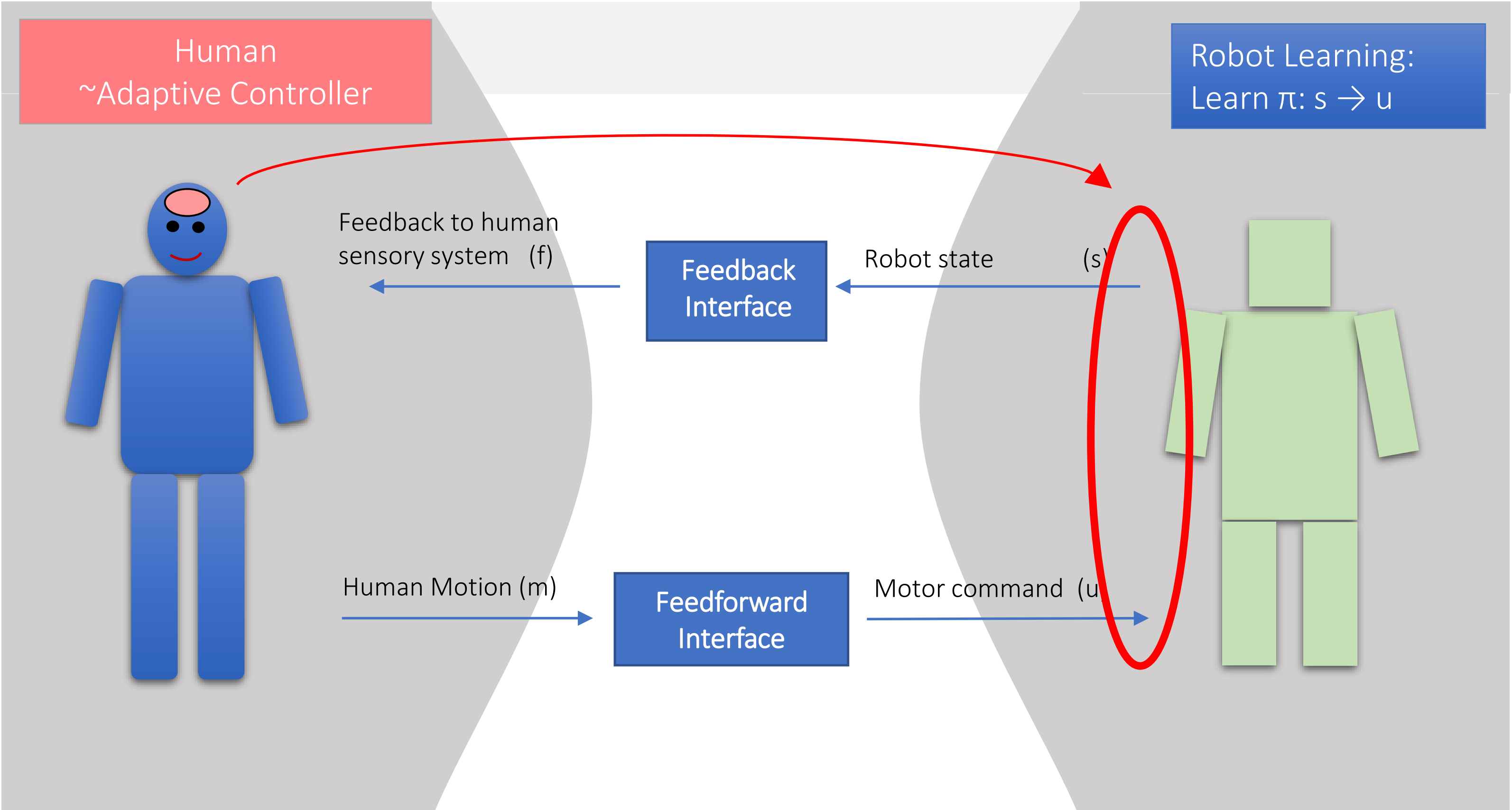
The paradigm

- Use human sensorimotor learning ability to obtain robot behaviors
  - Include the human in the control loop
  - May ask human to do extensive training
  - Utilize the human brain as the adaptive controller



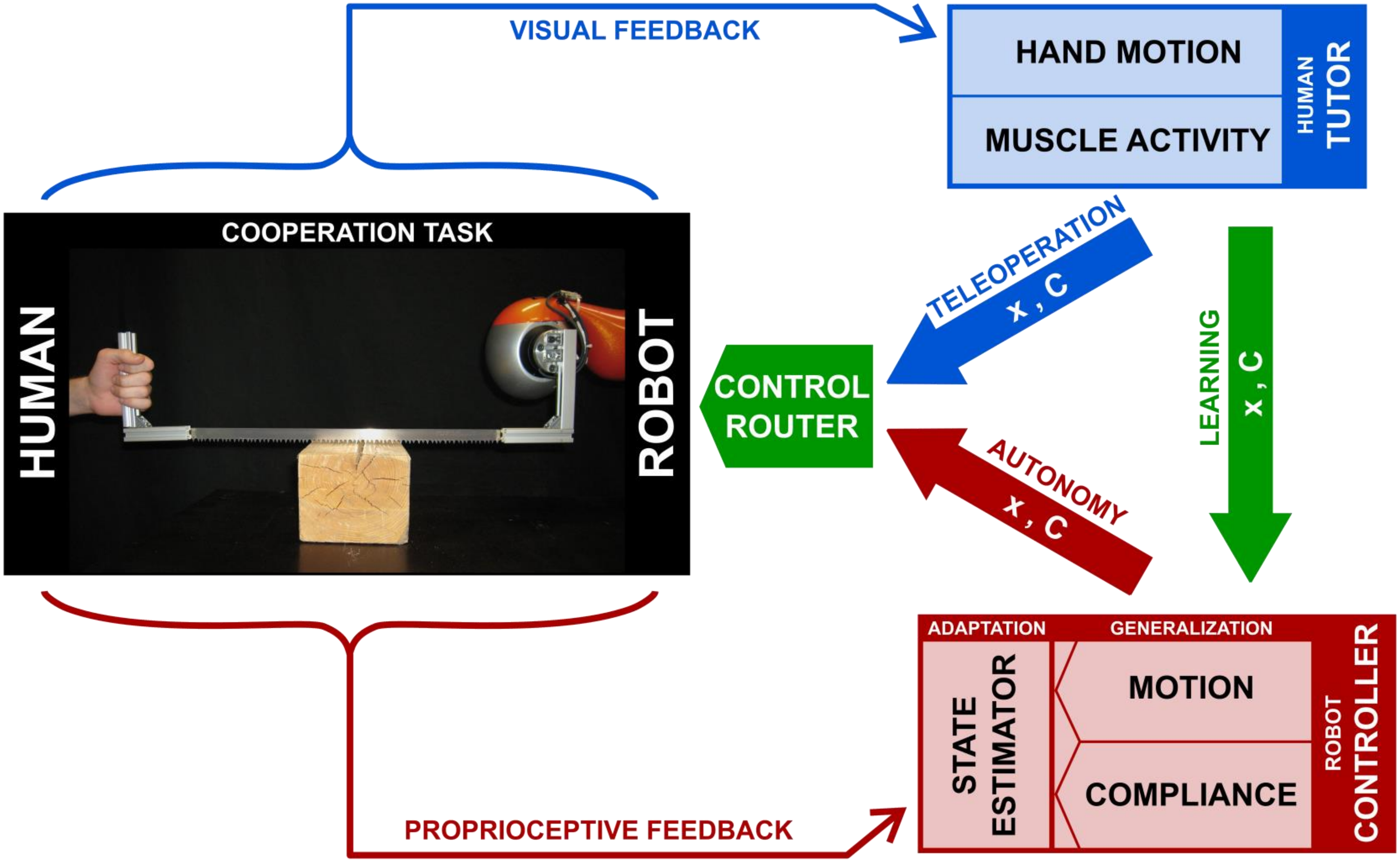
Skill synthesis for autonomy

For autonomous operation, the key issue is transferring the **control policy** learnt by human to the robot



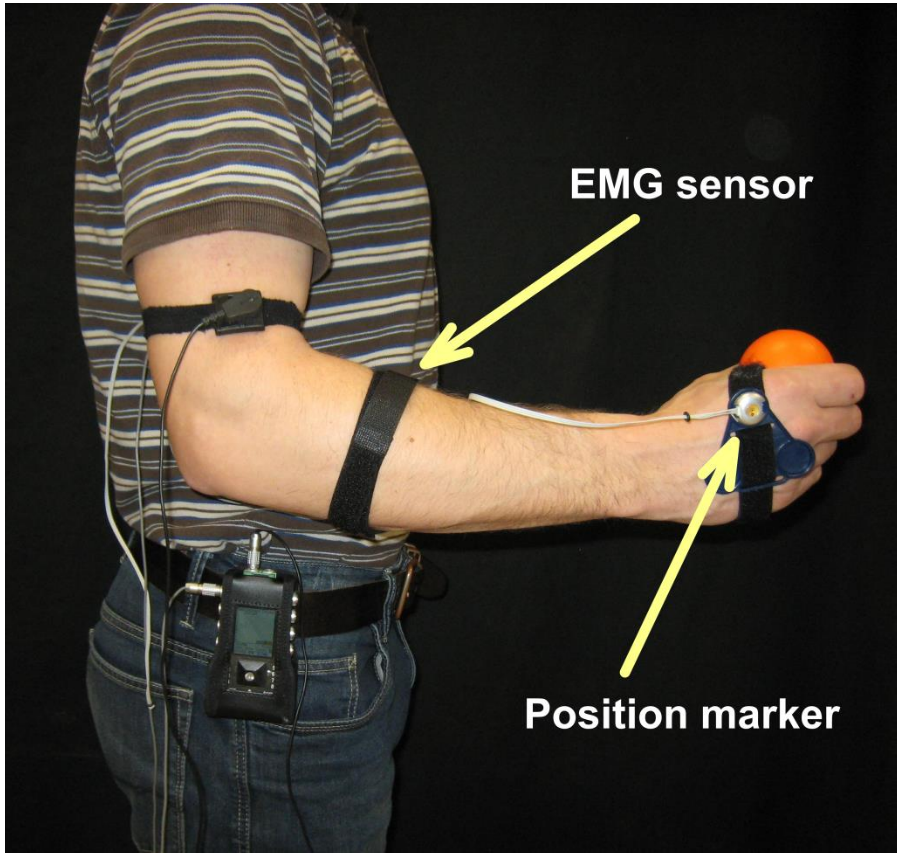
Why should this paradigm work?

- The ability of the brain to learn novel control tasks by forming internal models. The robot can be considered as a tool (e.g. as driving a car, playing an instrument, using chopsticks)
- The flexibility of the body schema; extensive human training modifies the body schema so that the robot can be naturally controlled


VISUAL FEEDBACK
HAND MOTION
MUSCLE ACTIVITY
HUMAN
TUTOR
COOPERATION TASK
HUMAN
ROBOT
TELEOPERATION
x , C
CONTROL
ROUTER
LEARNING
x , C
AUTONOMY
x , C
ADAPTATION
GENERALIZATION
STATE
ESTIMATOR
MOTION
COMPLIANCE
ROBOT
CONTROLLER
PROPRIOCEPTIVE FEEDBACK

Teleoperation using EMG and MOCAP interface

- Real time transfer of:
  - tutor‘s hand position to robot‘s end-effector position
  - tutor‘s muscle activity to robot‘s end-effector compliance



TEACHING ROBOTS TO COOPERATE WITH HUMANS IN DYNAMIC MANIPULATION TASKS BASED ON MULTI-MODAL HUMAN-IN-THE-LOOP APPROACH

Luka Peternel*, Tadej Petrič*, Erhan Oztop' and Jan Babič*

2013

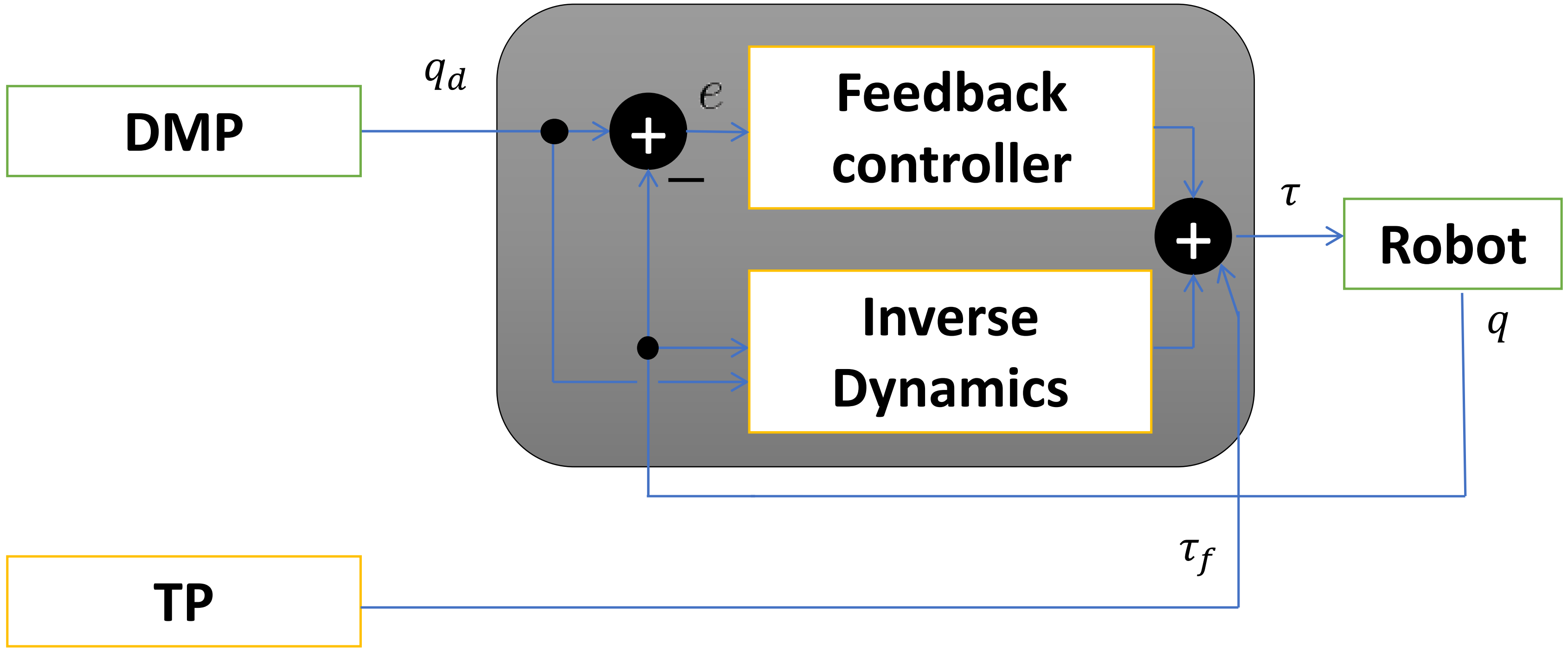
*Jožef Stefan Institute, Slovenia
'Özyeğin University, Turkey

e-mail: luka.peternel@ijs.si

How to improve tracking accuracy when low impedance controlled is used?

Compliant movement primitives - CMPs

Compliant Movement Primitives



- CMP – Compliant Movement Primitive
- We propose a controller
- Iterative learning process using low feedback gains
- Dynamic model of the task is not required

$$\boldsymbol{\tau_u} = \mathbf{K}(\boldsymbol{q_d} - \boldsymbol{q}) + \boldsymbol{D}(\dot{\boldsymbol{q}}) + \boldsymbol{f_d}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}) + \boldsymbol{\tau_f}$$

Compliant Movement Primitives

- We define complaint movements as a combination of desired position trajectories and corresponding torque signals :

$$\boldsymbol{h}(t) = \left[\boldsymbol{q}_d(t), \boldsymbol{\tau}_f(t)\right]$$

- Human demonstration is used to gain a set of example motion trajectories

$$\boldsymbol{Q}_x = \left\{\{\boldsymbol{q}_{x1}(t), \boldsymbol{c}_{q1}\}, \{\boldsymbol{q}_{x2}(t), \boldsymbol{c}_{q2}\}, \ldots, \{\boldsymbol{q}_{xN}(t), \boldsymbol{c}_{qN}\}\right\},$$

where $\boldsymbol{c}$ denotes task descriptors, i.e., query points.

- Motion trajectories are encoded as DMPs

Compliant Movement Primitives

- With the dynamic model given as $\boldsymbol{f}_{\boldsymbol{d}}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}})$, we propose a controller:

$$\boldsymbol{\tau}_{\mathbf{u}} = \mathbf{K}(\boldsymbol{q}_{\boldsymbol{d}} - \boldsymbol{q}) + \boldsymbol{D}(\dot{\boldsymbol{q}}) + \boldsymbol{f}_{\boldsymbol{d}}(\boldsymbol{q}, \dot{\boldsymbol{q}}, \ddot{\boldsymbol{q}}) + \boldsymbol{\tau}_{\boldsymbol{f}}$$

- Corresponding torques are gained by using iterative recursive regression with cost

$$\boldsymbol{e}_r = \mathbf{J}^T\left(\alpha(\boldsymbol{x}_d - \boldsymbol{x}) + \beta(\dot{\boldsymbol{x}}_d - \dot{\boldsymbol{x}})\right)$$

- A set of example torques is gained

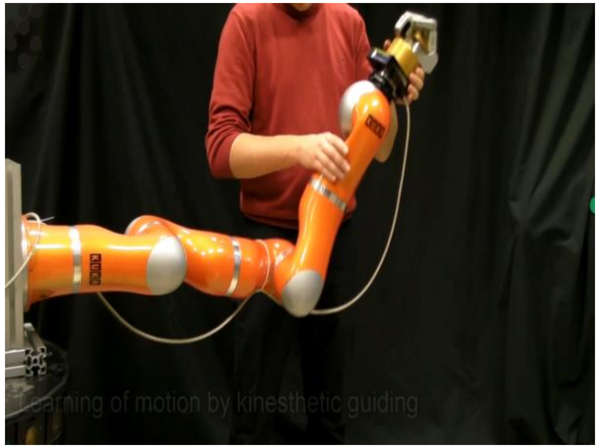
$$\boldsymbol{T}_x = \left\{\{\boldsymbol{\tau}_{x1}, \boldsymbol{c}_{\tau 1}\}, \{\boldsymbol{\tau}_{x2}, \boldsymbol{c}_{\tau 2}\}, \dots, \{\boldsymbol{\tau}_{x(NM)}, \boldsymbol{c}_{\tau(NM)}\}\right\}$$

  - Torque trajectories are encoded as a linear combination of basis functions

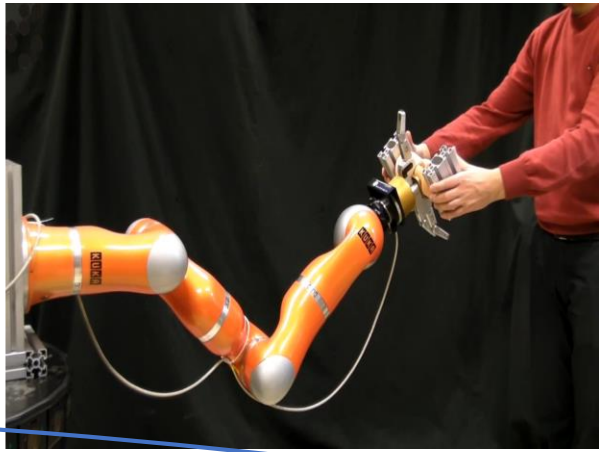
$$\tau_x(s) = \frac{\sum_{i=1}^{N} w_{\tau i}\psi(s)}{\sum_{i=1}^{N} \psi(s)}$$

CMP Task Learning

- CMP is defines a task as a pair of signals: $\boldsymbol{h(t)} = [\boldsymbol{q_d(t)}, \boldsymbol{\tau_f(t)}]$
- Three step process:
    1. Motion trajectory $\boldsymbol{q_d(t)}$ is gained by human demonstration



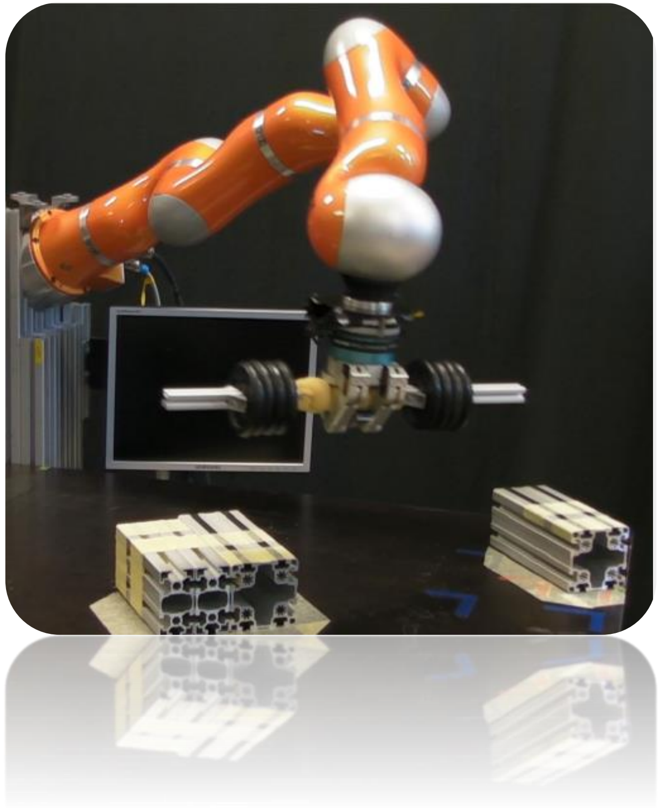
    2. Iterative leaning of torque primitives $\boldsymbol{\tau_f(t)}$. Learning is updated based on kinematic trajectory



    3. Movement and torque primitive are gained, stored and possibly executed.

Evaluation - tracking error

- Pick and place task using a Kuka LWR robot with a BarrettHand
- The task was learned for 3 object weights varying for 2 kg
- The task was executed with varying stiffness using
  - Feedback control
  - Proposed control using learned task-specific dynamics

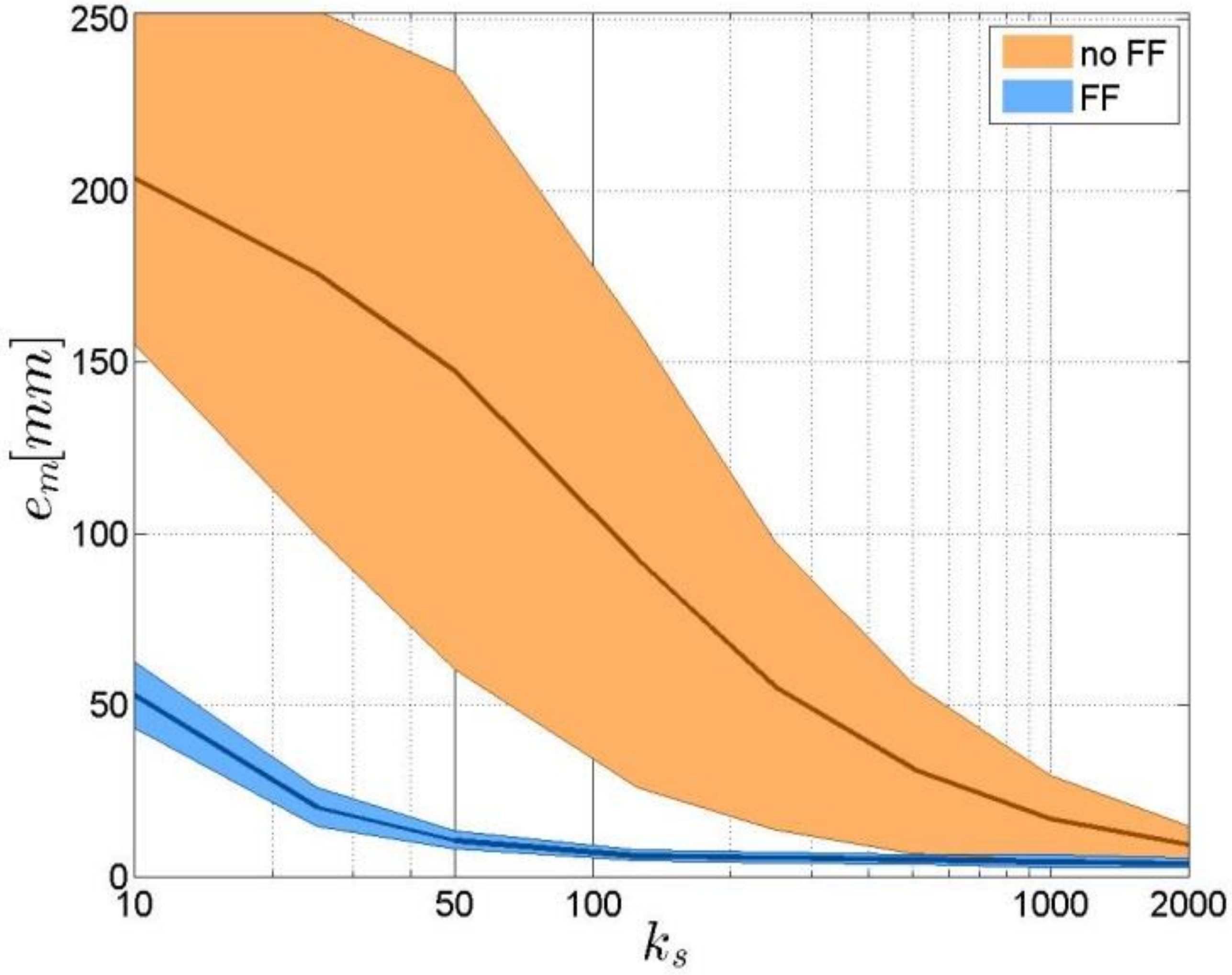


Evaluation - tracking error

- Maximum error for each task:

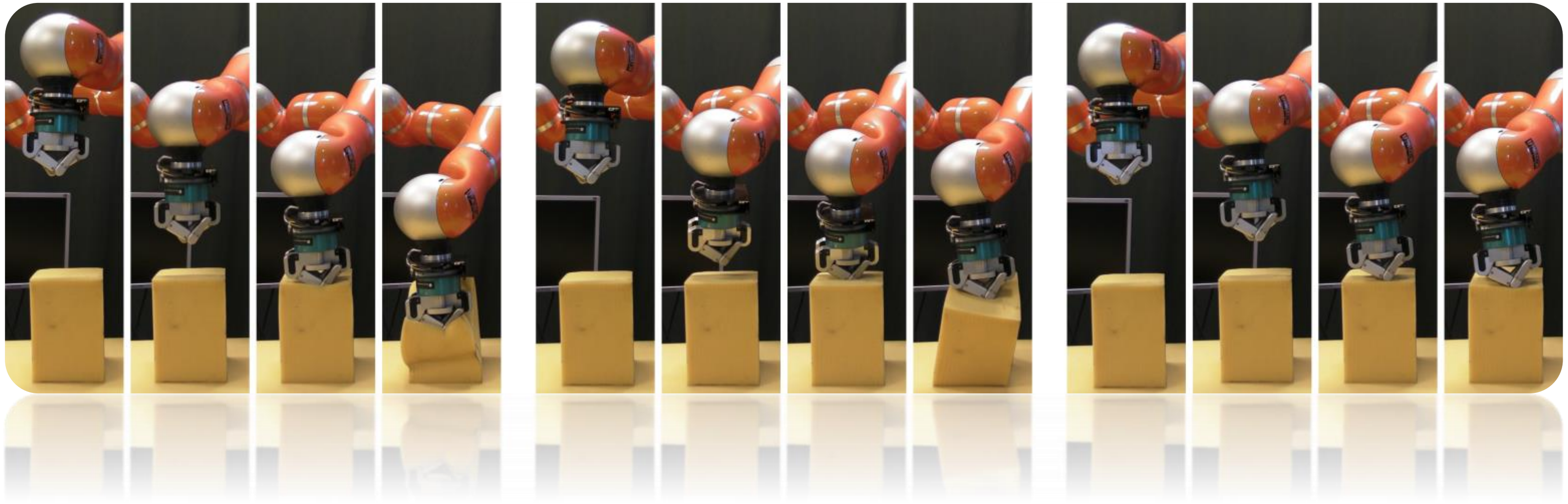
$$e_m = \max(||\boldsymbol{p}(t) - \boldsymbol{p_d}(t)||).$$

- Tracking error is marginal with stiffness >50
- This low stiffness value was selected for collision evaluation



Evaluation – unexpected collision

- A simple downward task was learned
- Unexpected collision with an object
- Three different control approaches
  - High gain feedback
  - Low gain feedback
  - Proposed approach



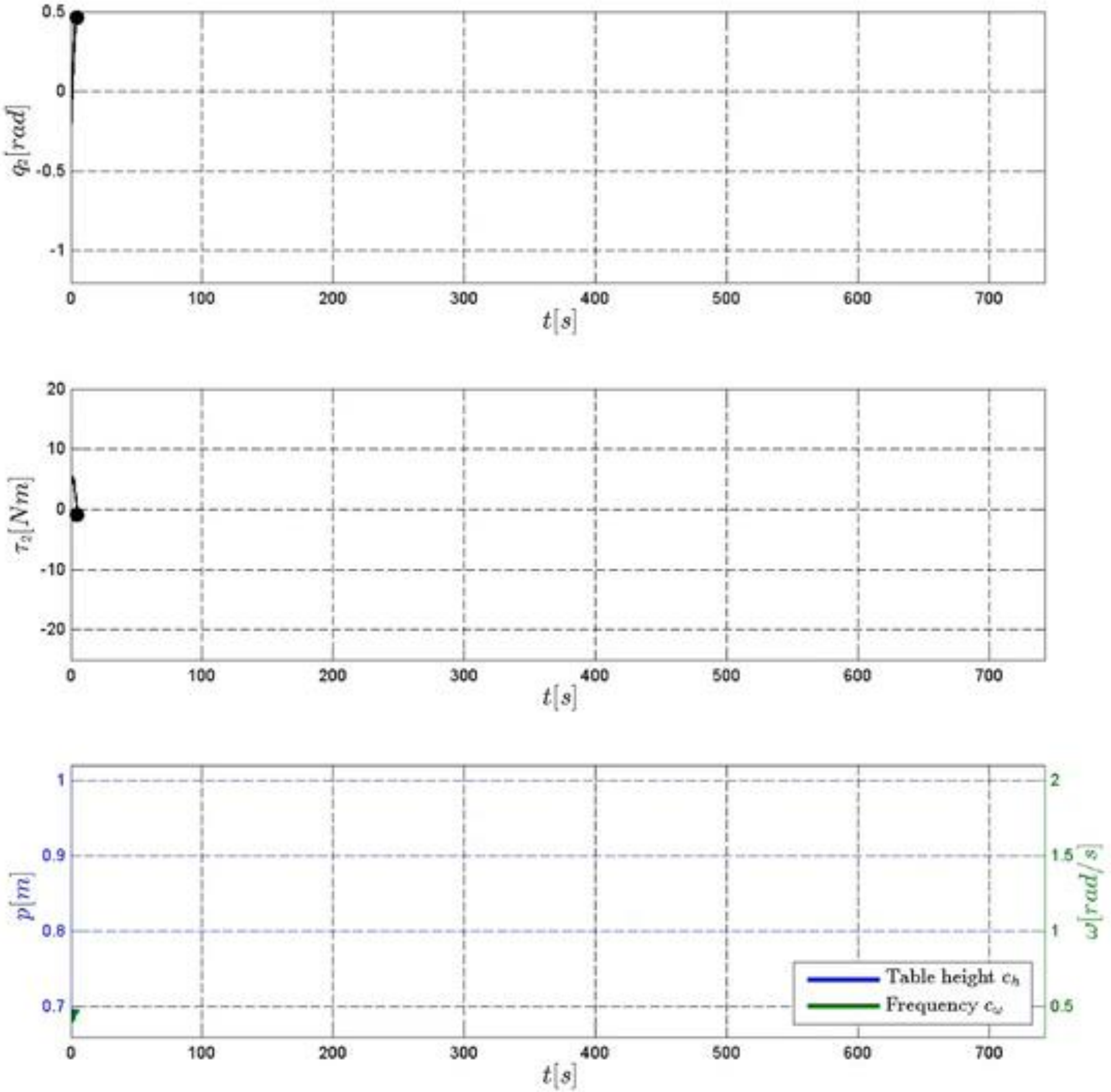
Collision evaluation

High gain feedback control

-

High tracking accuracy,

high impact forces



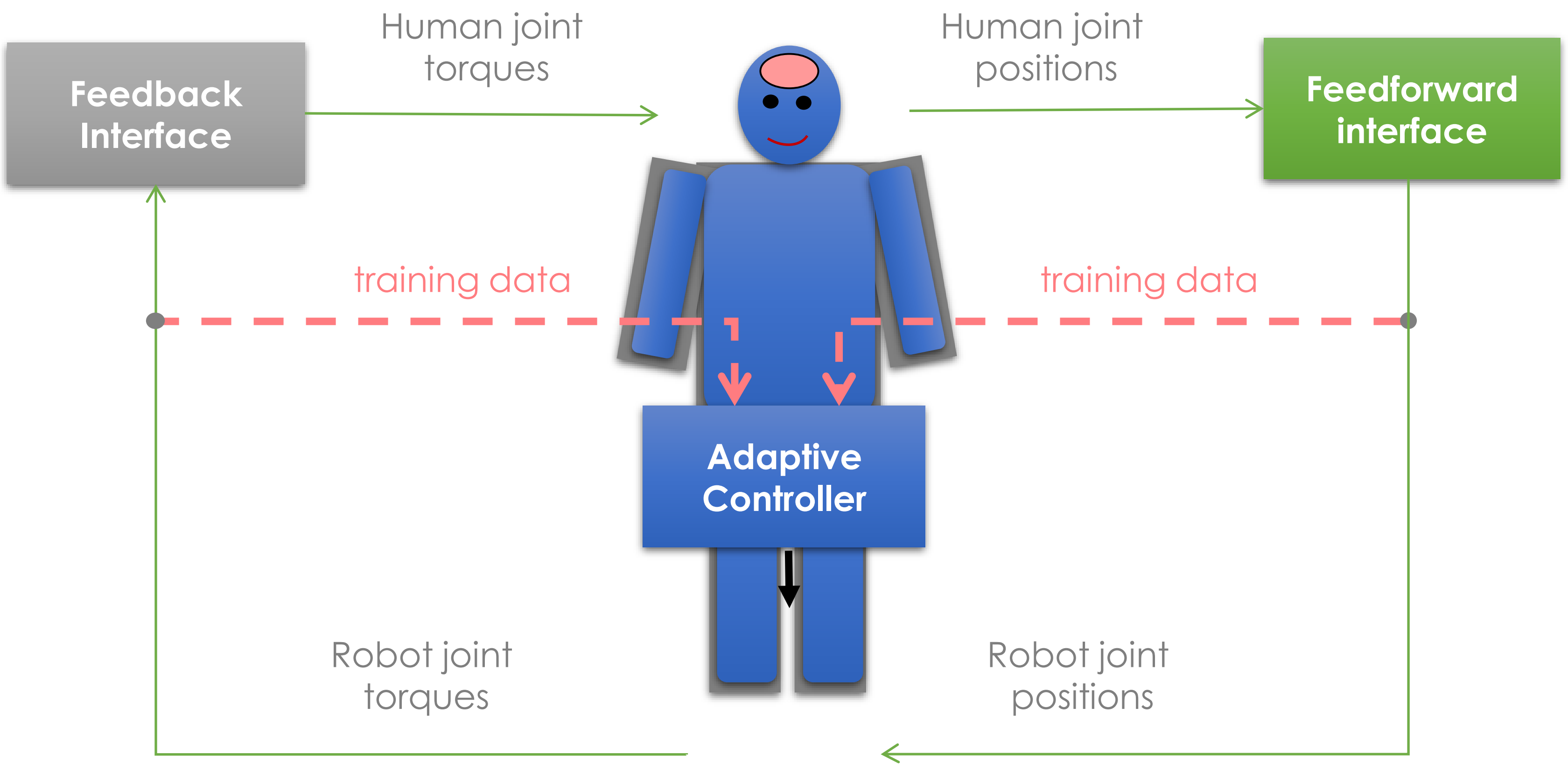
q2[rad]
0.5
0
-0.5
-1
0
100
200
300
400
500
600
700
t[s]
τ2[Nm]
20
10
0
-10
-20
t[s]
p[m]
1
0.9
0.8
0.7
ω[rad/s]
2
1.5
1
0.5
Table height ch
Frequency cω
t[s]

Exoskeleton control

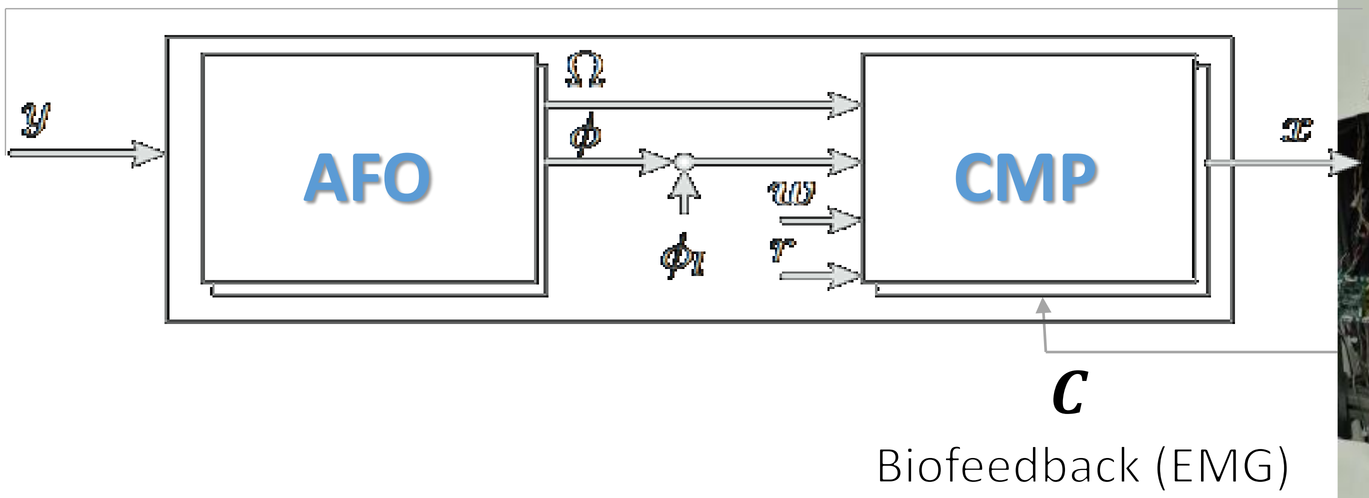
Learning from and like humans

Human and robot are physically coupled!!!

Exoskeleton-robot interaction

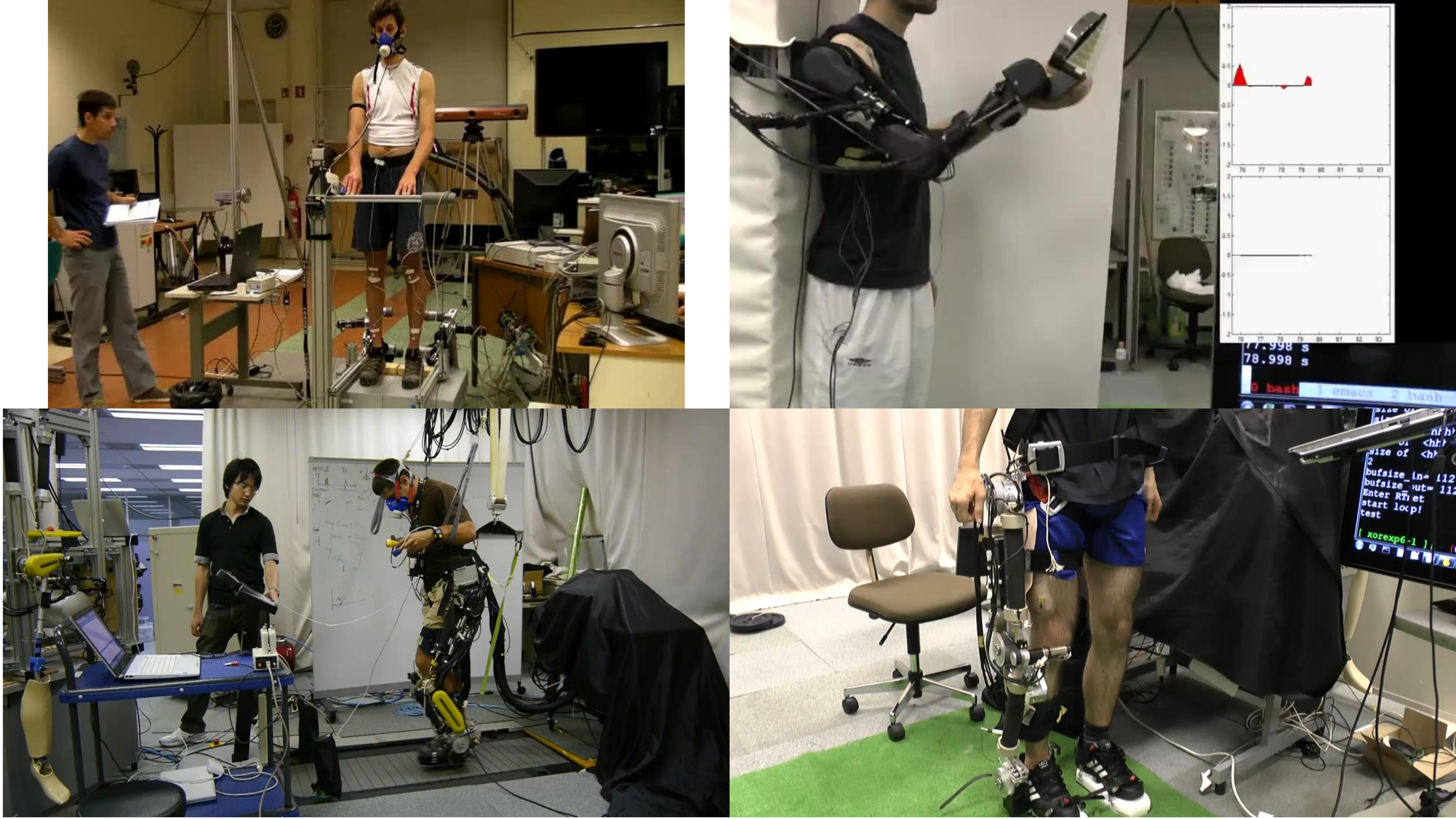


Exoskeleton control



- Trajectory was updated with the use of human biofeedback signal
- Human muscle activity from each of the antagonist muscle groups that operate a certain joint by the means of electromyography (EMG) was used

Physically coupled


77.998 s
78.998 s
bash
emacs
start loop!
test