Robot skill synthesis through human sensorimotor learning

Jan Babič
Jožef Stefan Institute, Slovenia

Grasping vs. full body motion

Outline

Human sensorimotor learning → Robot skill synthesis

- Ball swapping
- Grasping
- Reactive postural control
- Concluding remarks

Robots in everyday life…

- Robots in daily life require new methods for synthesis of skillful behaviour
- Classical approach requires experts, and lot of expert work hours.

  How could non-experts teach robots is an active research topic in robotics:

    Teaching by demonstration

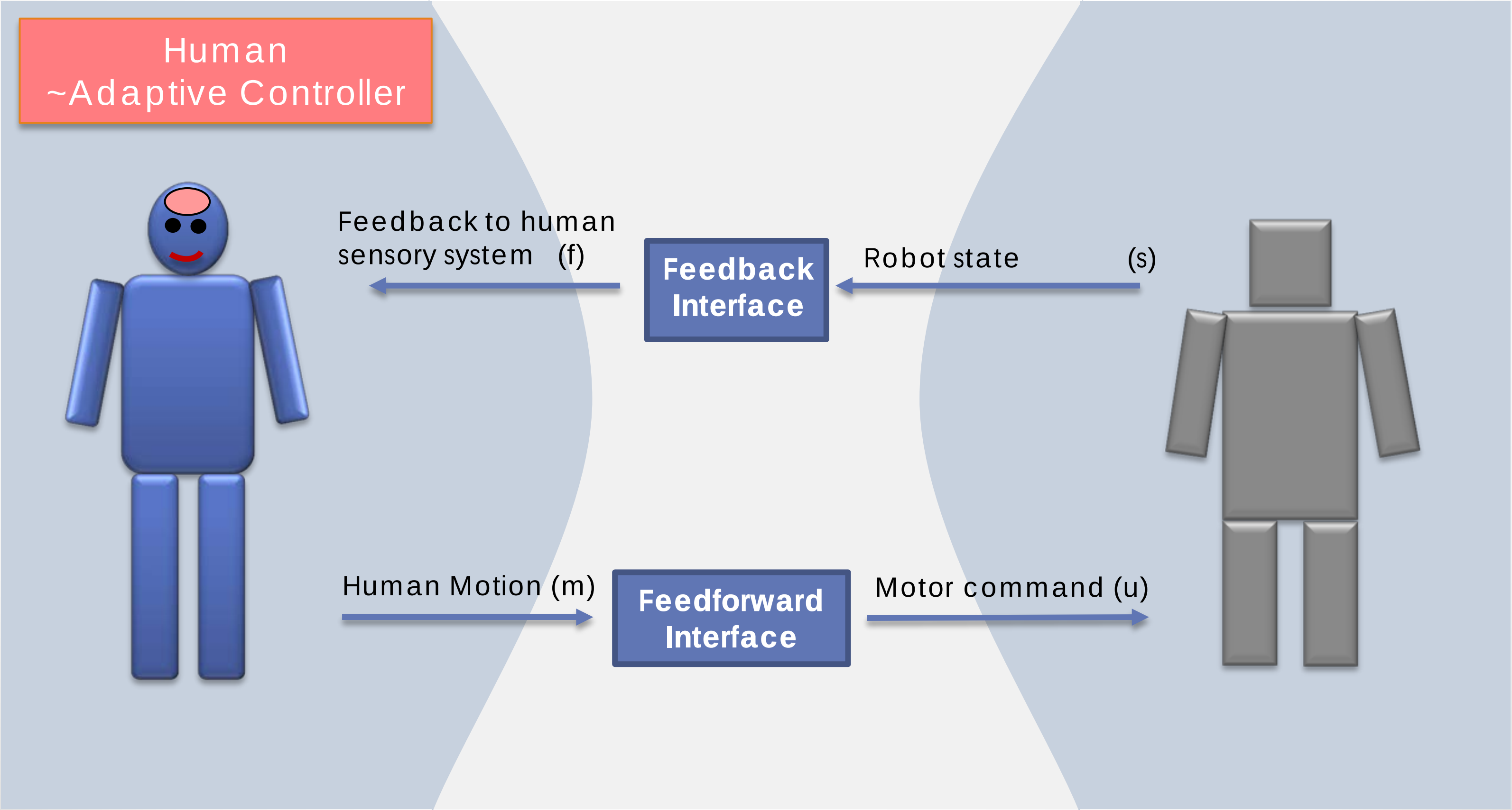
    Robotic imitation

    …

- To make the task as natural and easy for the human teacher
- The human provides an initial demonstration but is NOT part of the motor control loop

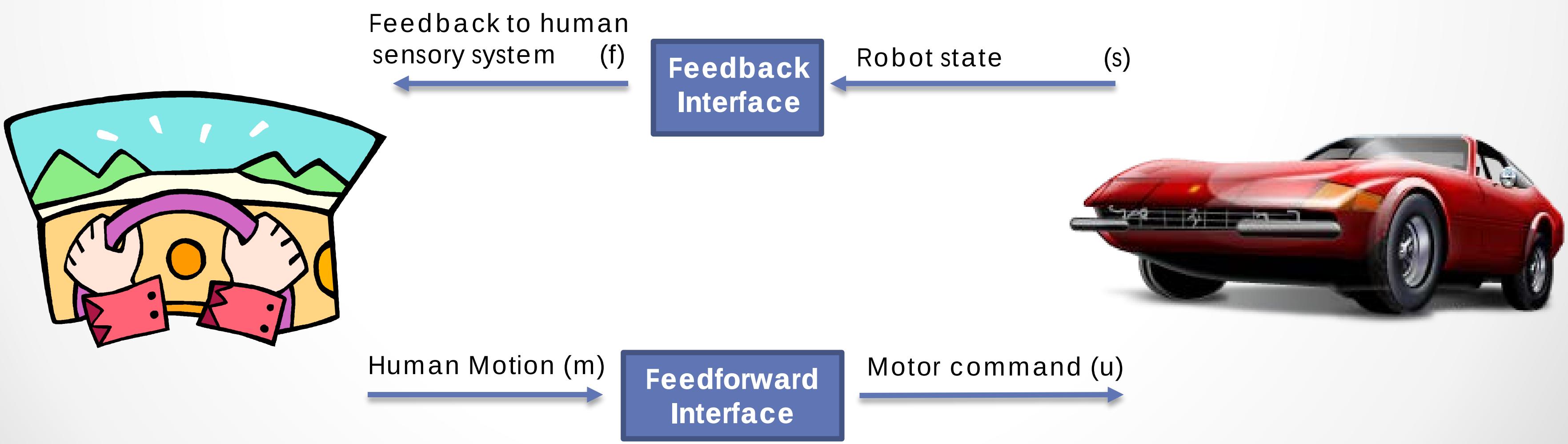
The paradigm

- 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



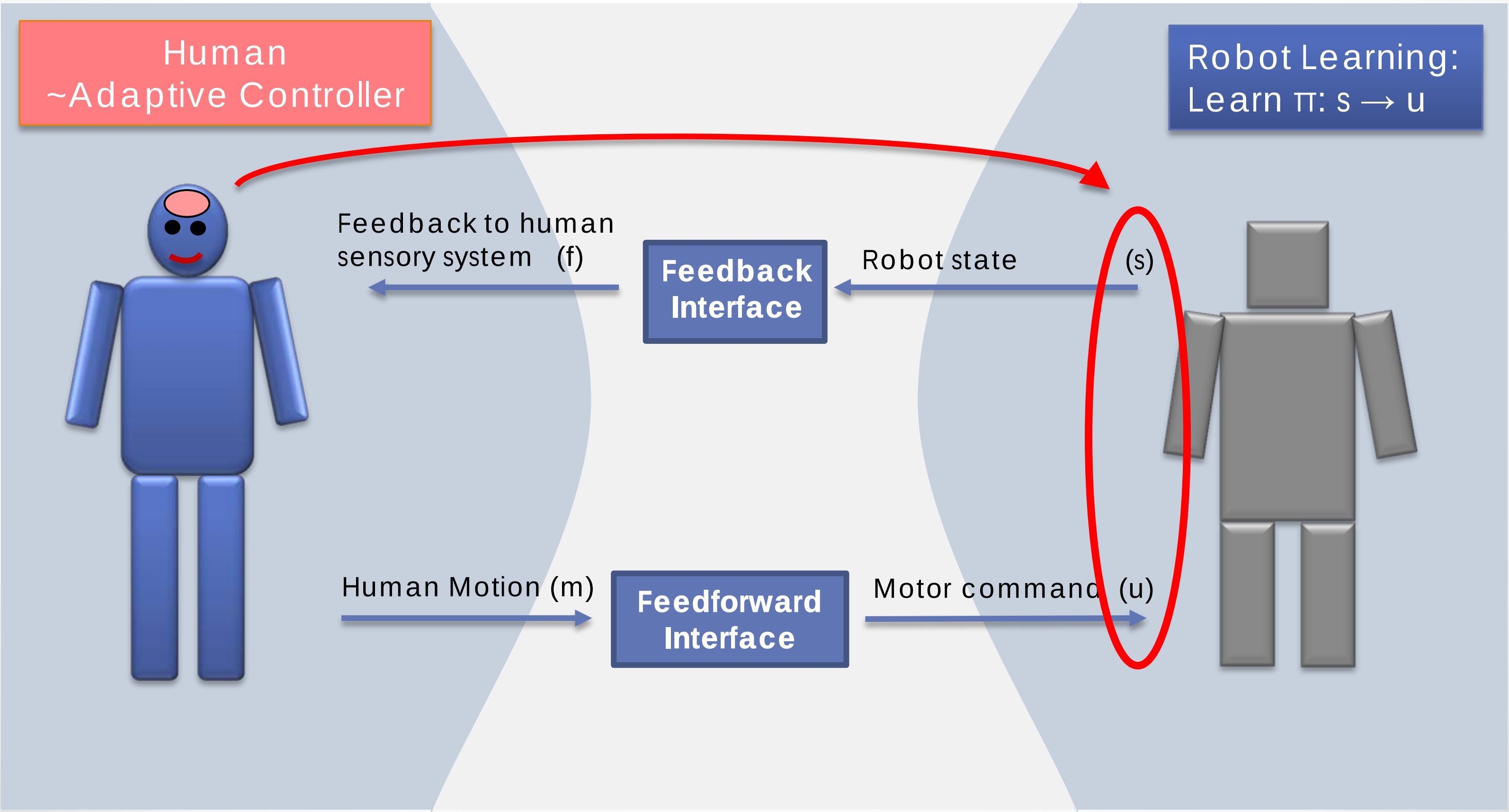
Sensorimotor learning

- Sensorimotor learning is fundamental for adaptive and intelligent behavior
- Driving a car
- Using a pair of chopsticks
- Using a computer mouse
- ...



Skill synthesis for autonomy

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



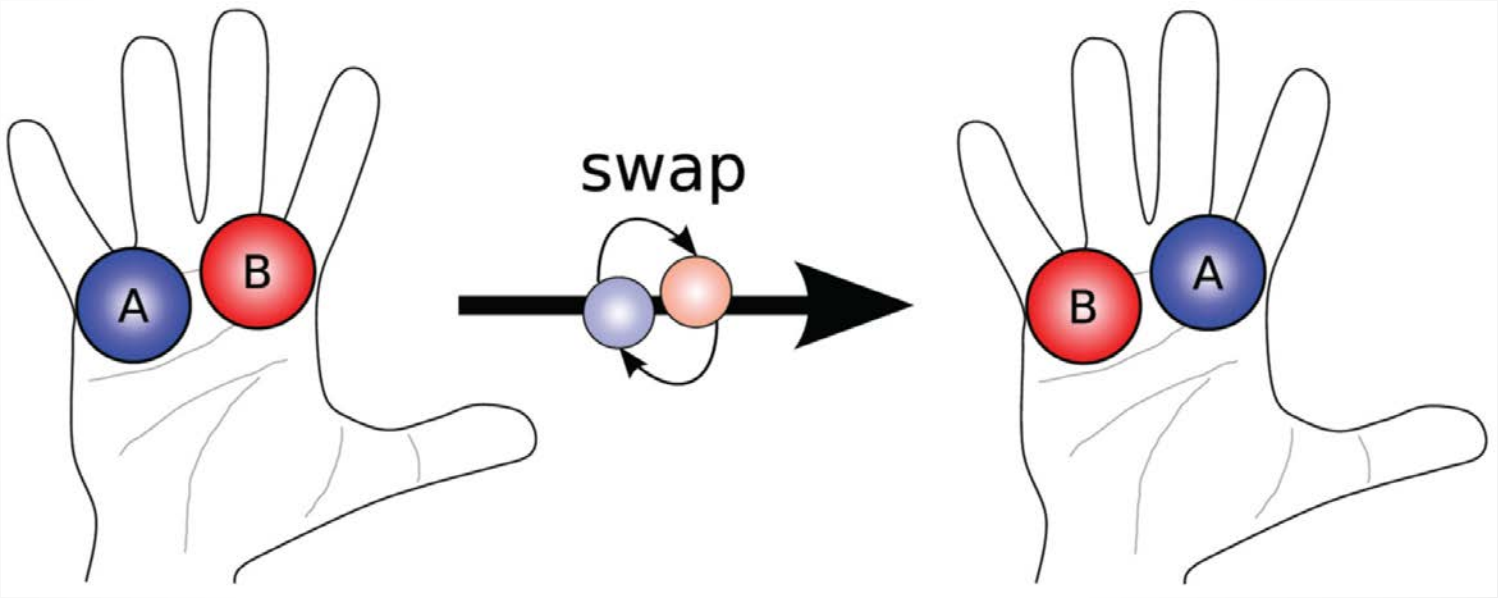
Why should this paradigm work?

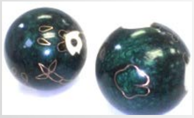
- The ability of the brain to learn novel control tasks by forming internal models. The robot can be considered as a tool (e.g. as driving a car, playing an instrument, using chopsticks)

- The flexibility of the body schema; extensive human training modifies the body schema so that the robot can be naturally controlled

Ball swapping

work of Erhan Oztop

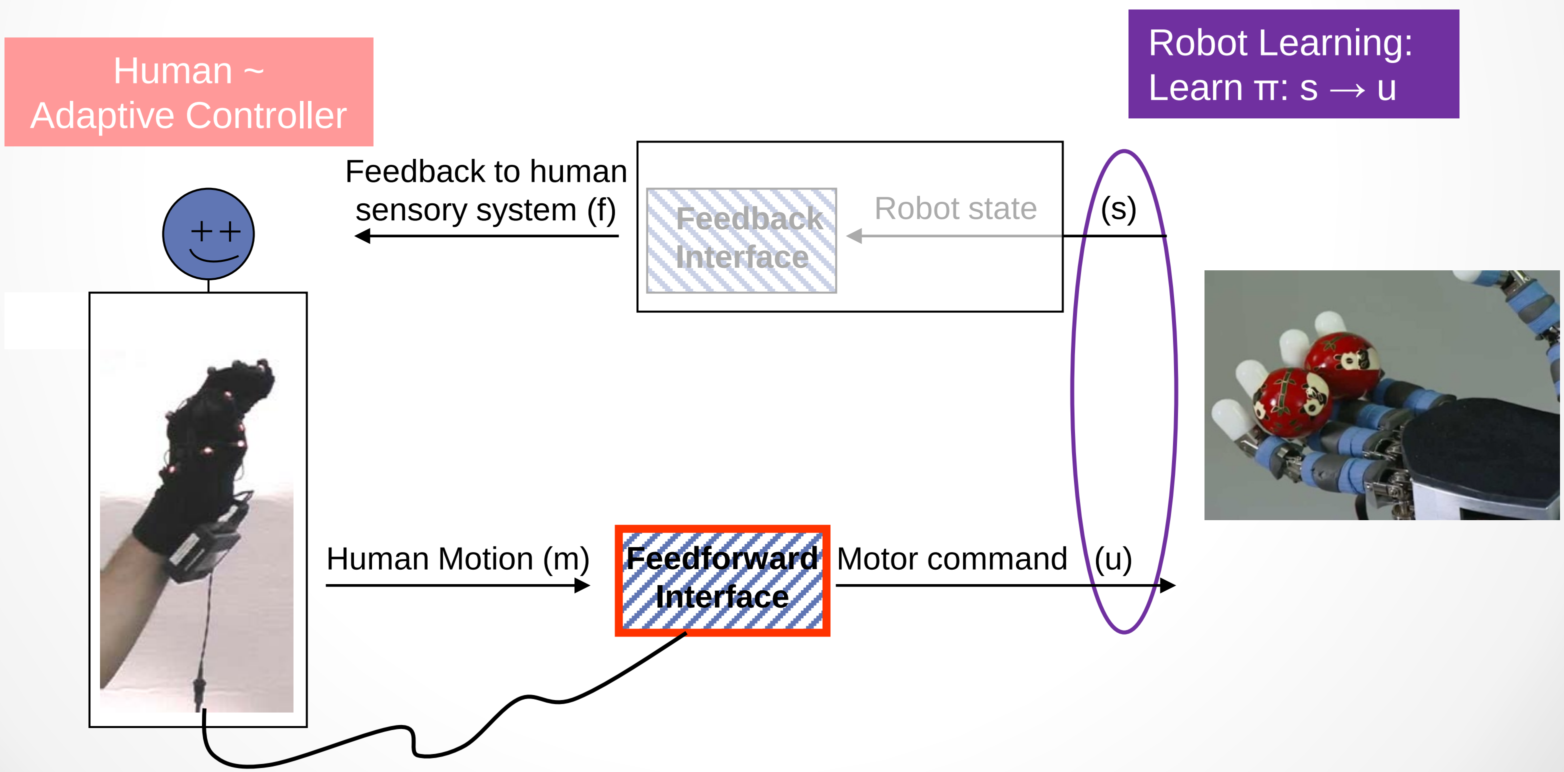




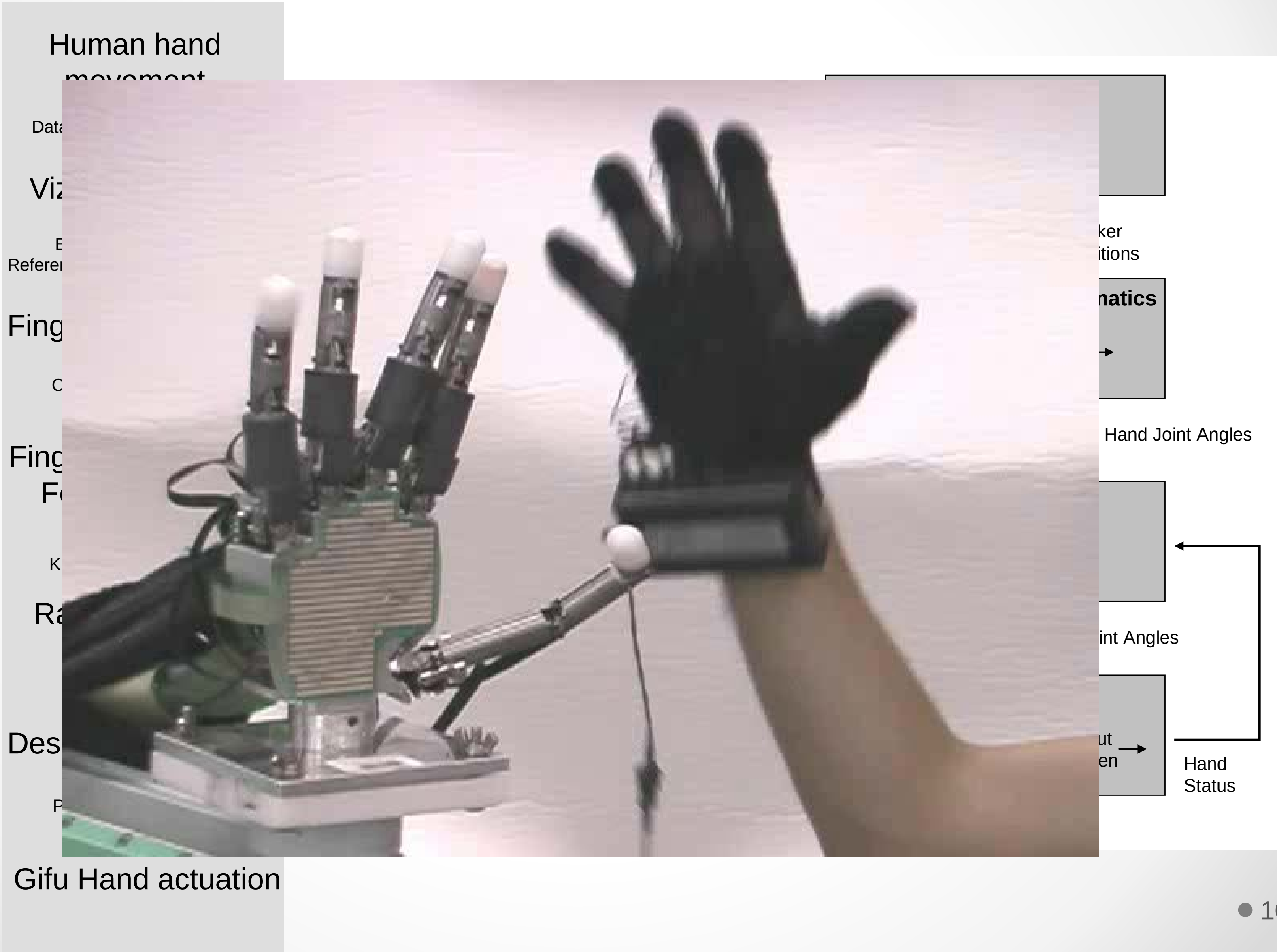
Ball swapping is a suitable task for testing the proposal since it is complex and not straightforward to manually program on a robotic hand

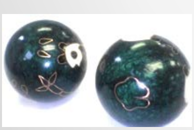
Ball swapping interface

Feedback to human: DIRECT VISION

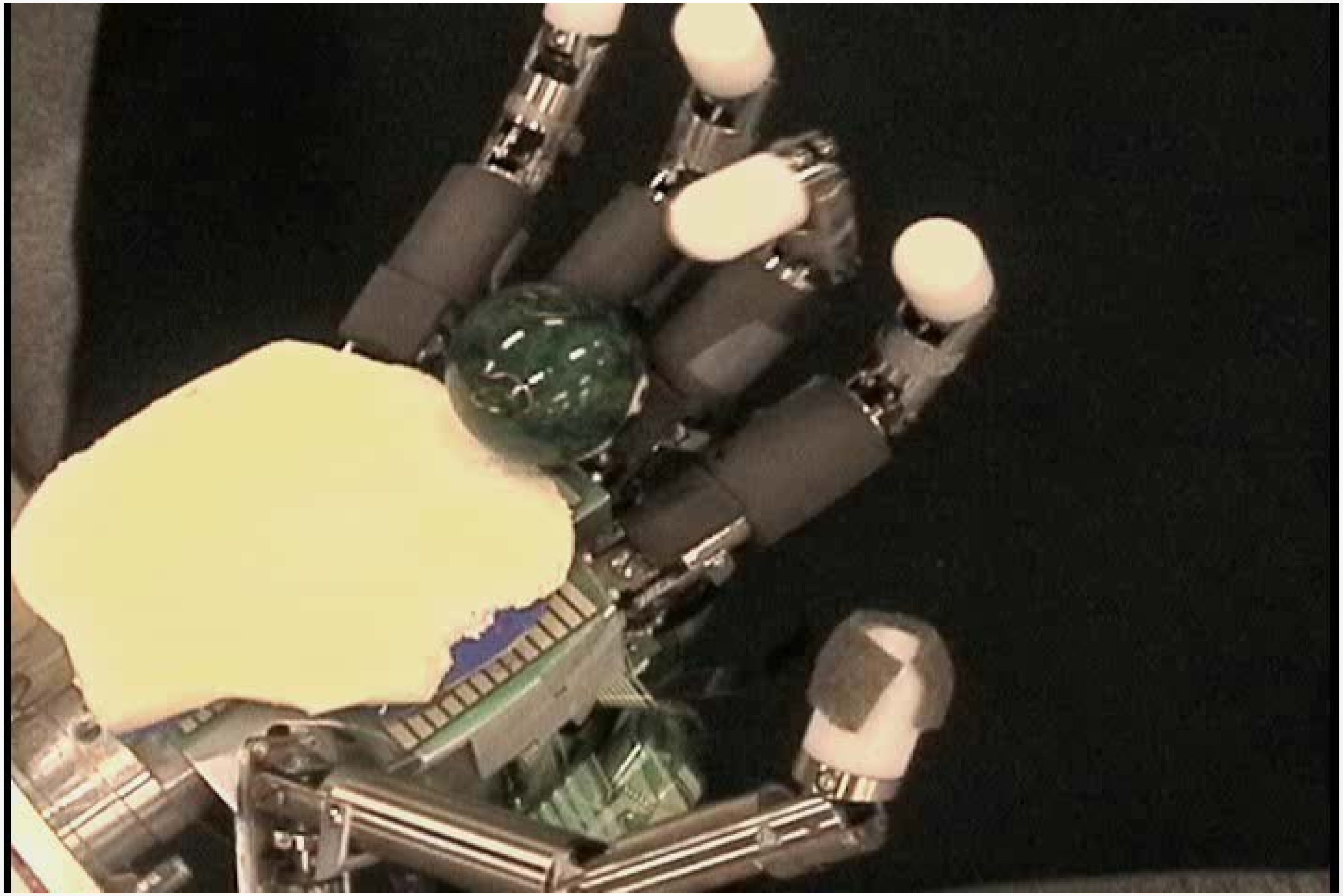


Human control of the robot

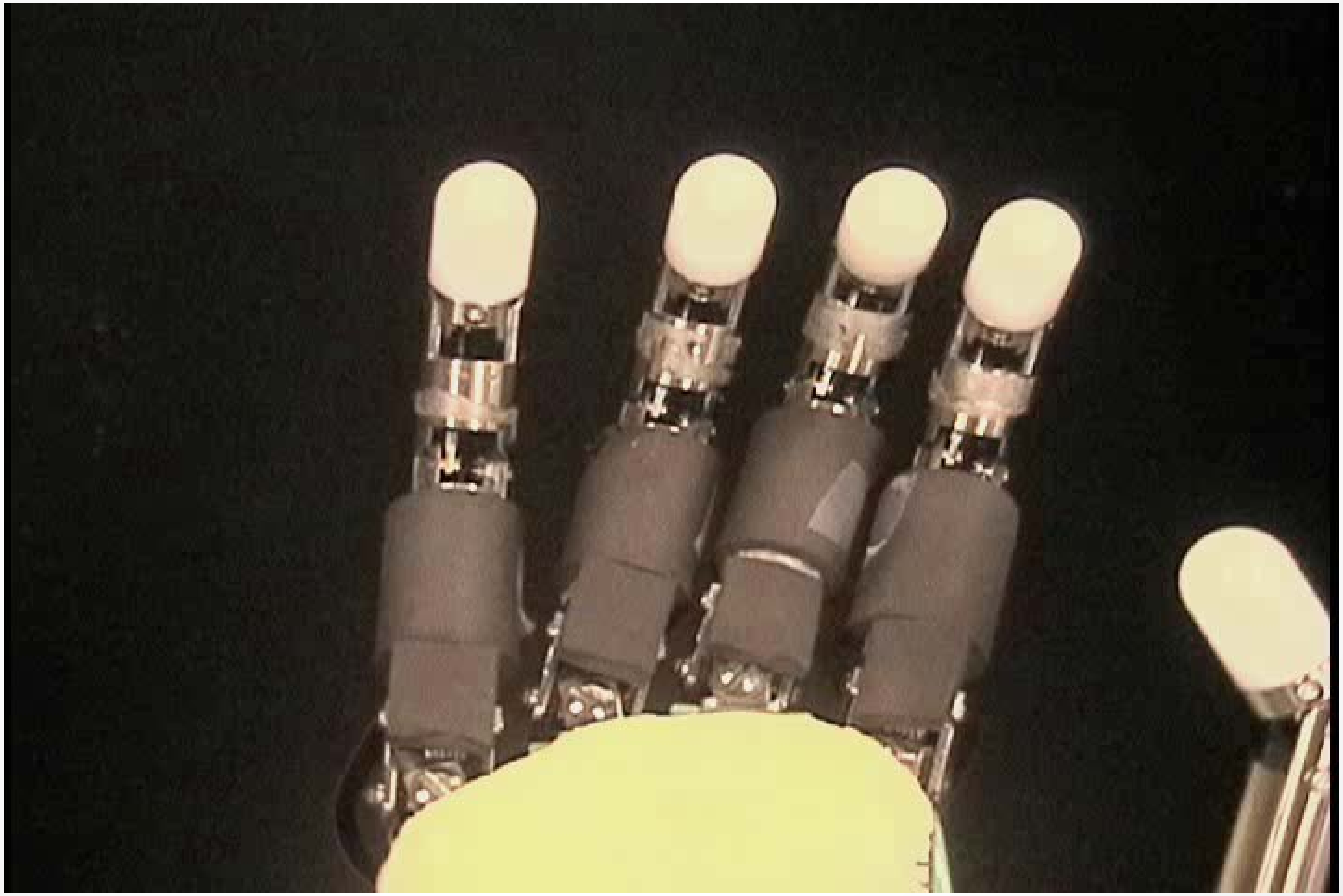




Human learning…

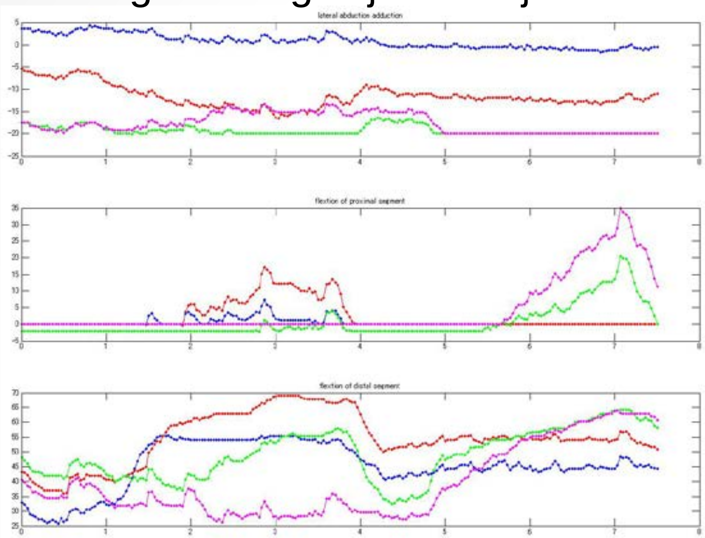


Finally human learns to swap balls

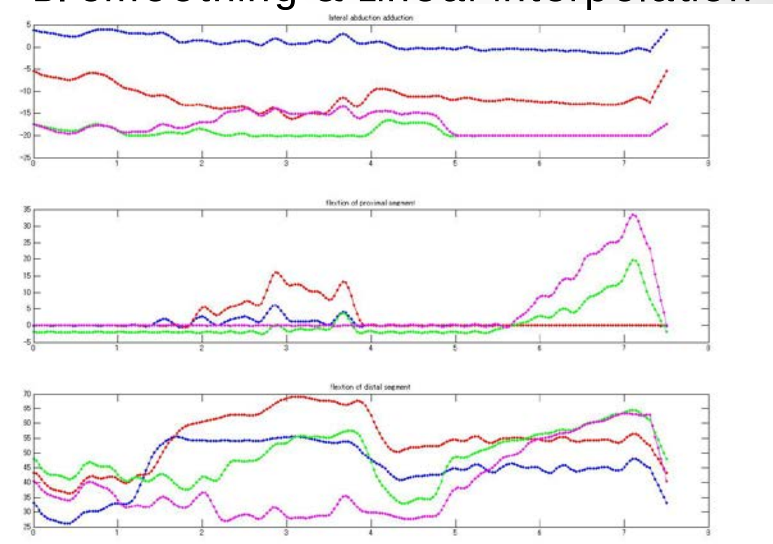


Offline analysis & improving performance

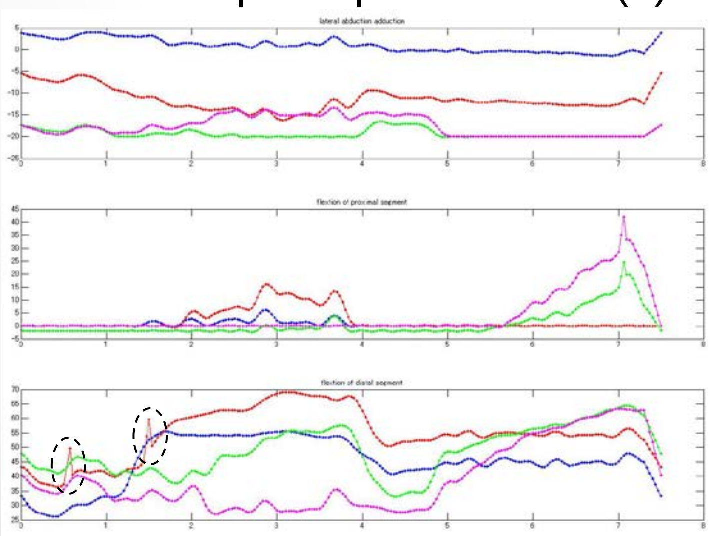
A. Original finger joint trajectories



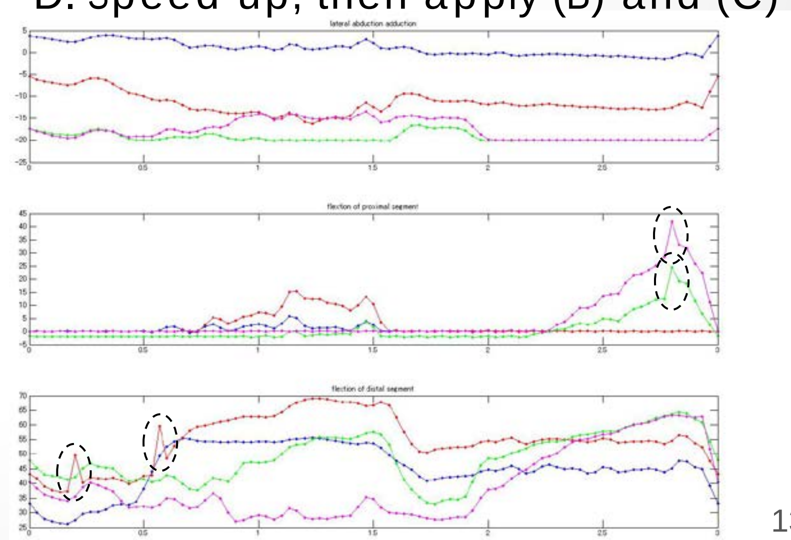
B. Smoothing & Linear interpolation



C. Kicks superimposed on to (B)

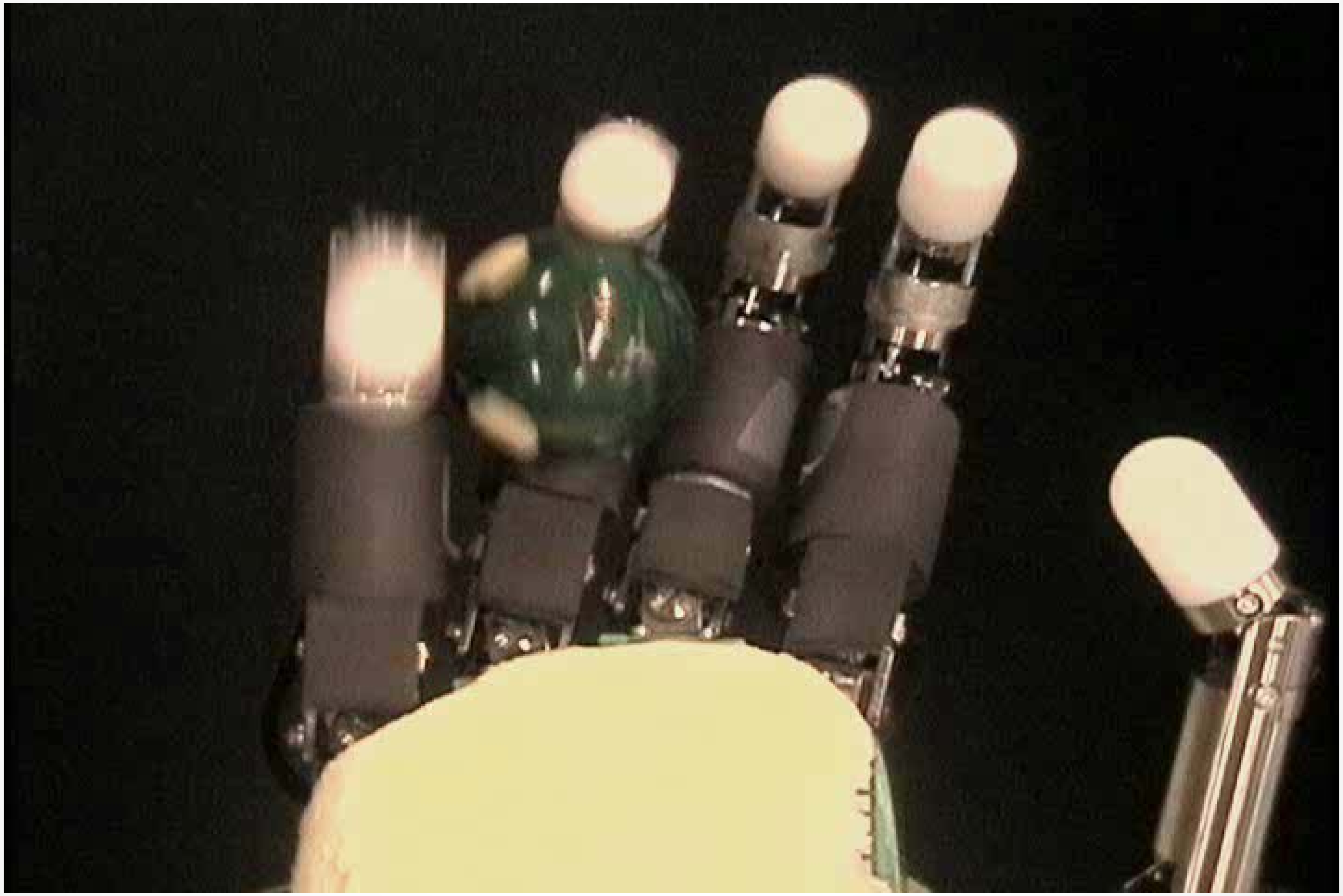


D. Speed-up, then apply (B) and (C)



- Index finger
- Middle finger
- Ring finger
- Little finger

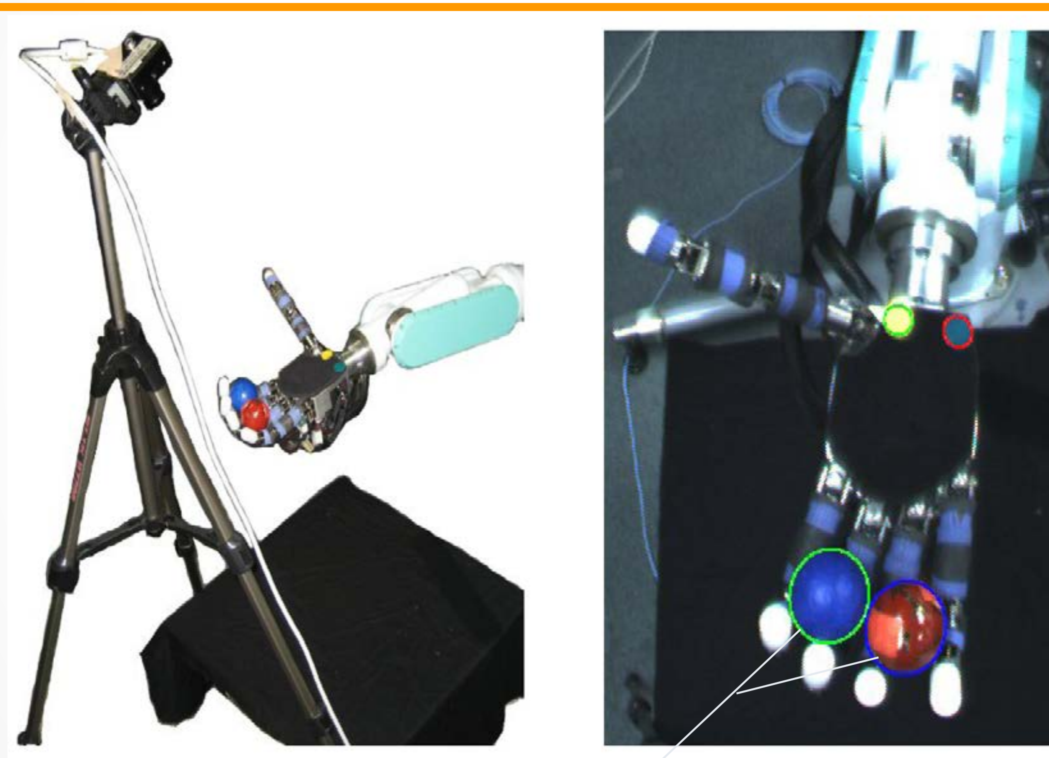
Ball swapping at x2 speed up



Open loop control
u=π(time)

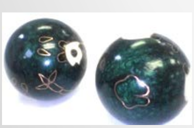
Ball swapping with visual feedback

In collaboration with Jan Steffen from Bielefeld University



Color tracking

Color tracker developed in house by Ales Ude

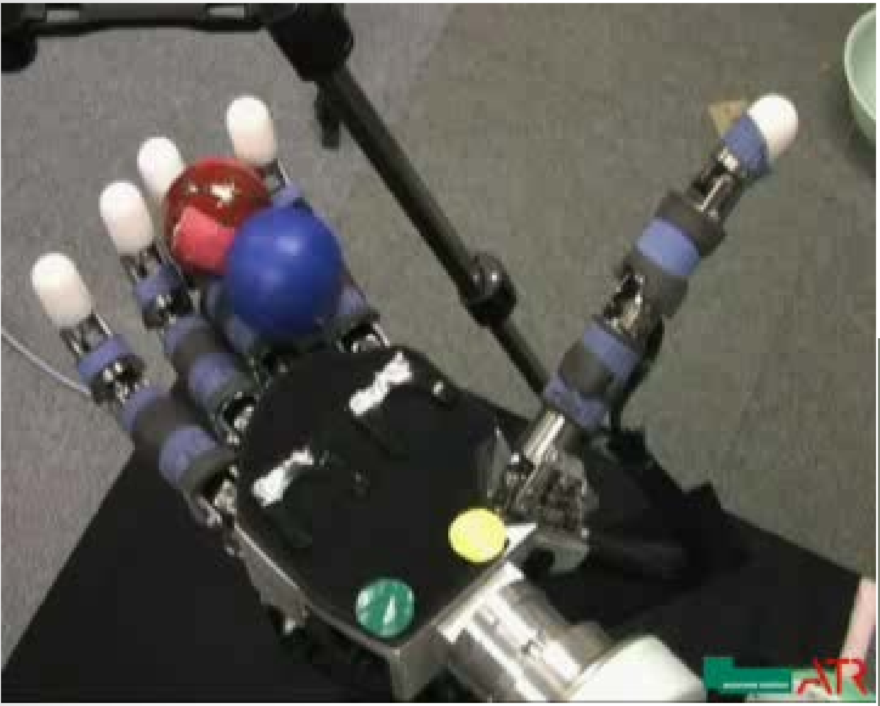


policy **u = f(s,v)**

u: desired joint angles
s: finger joint angles
v: position of the balls

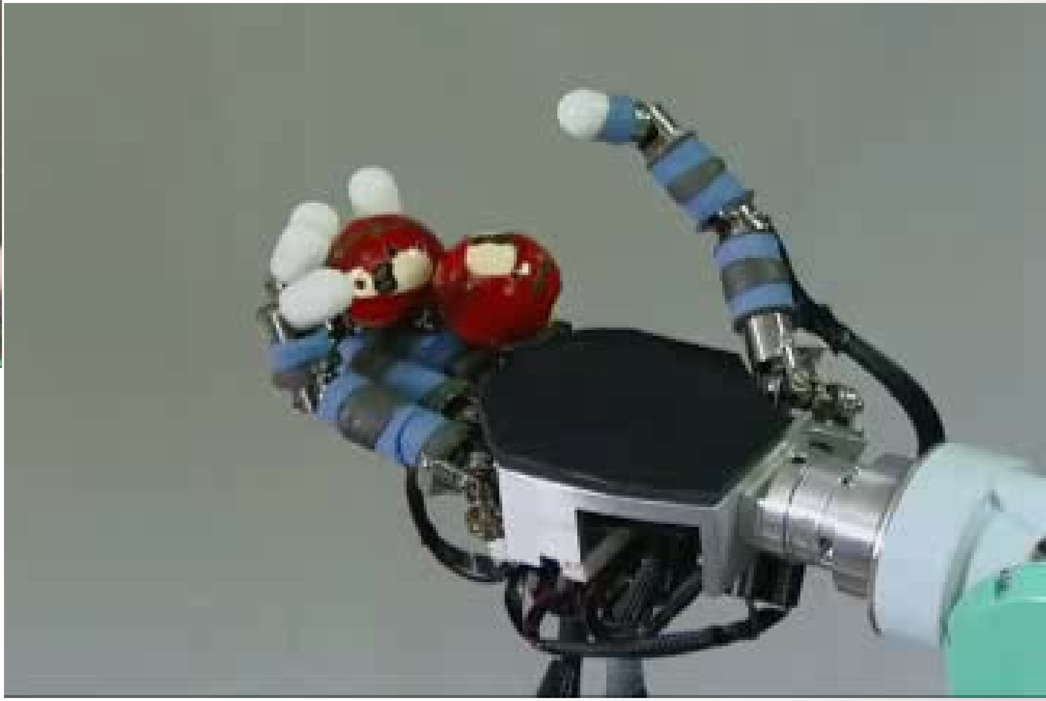
Learning Technique:
Unsupervised Kernel Regression (UKR)

Ball swapping: feedback vs. open loop



Closed loop (feedback) control
u=π(angles, ball positions)

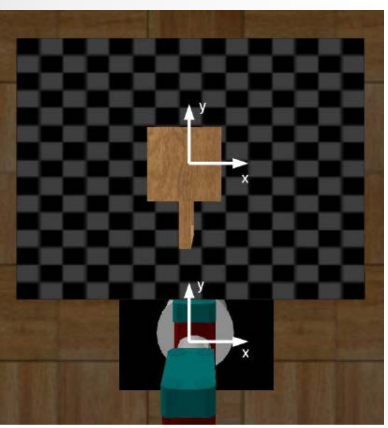
Open loop control
u=π(time)

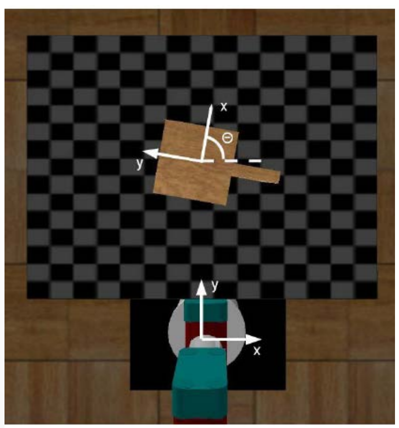


Extending the paradigm to visual grasping

in collaboration with Brian Moore

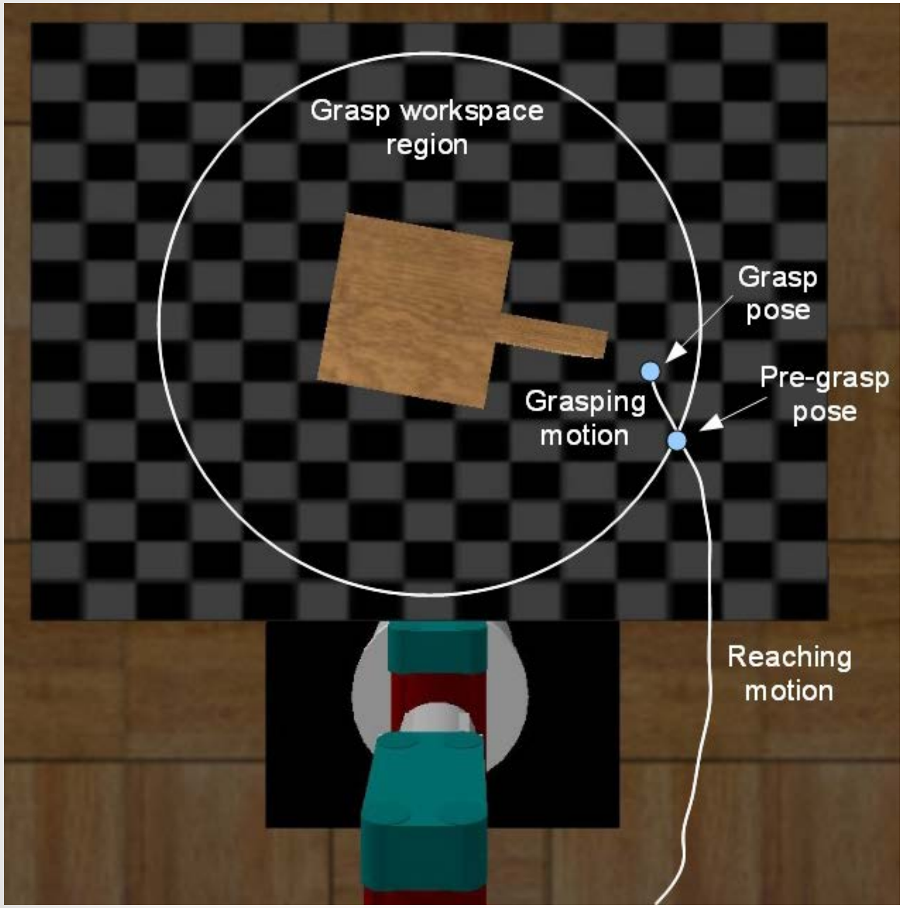
Visual grasping

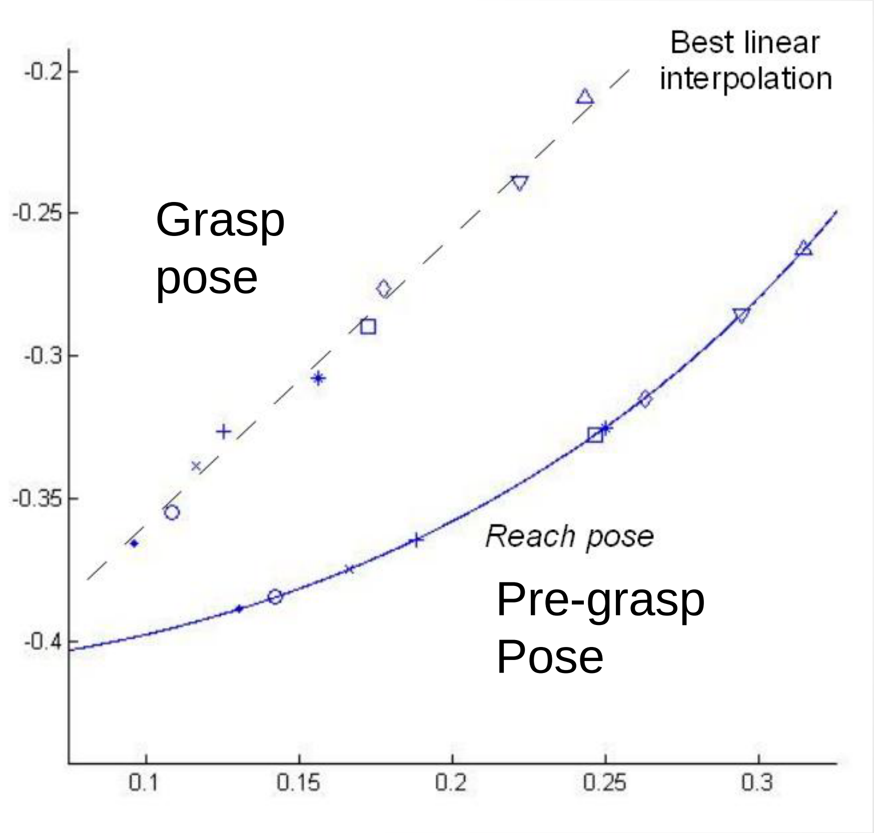




in collaboration with Emre Ugur

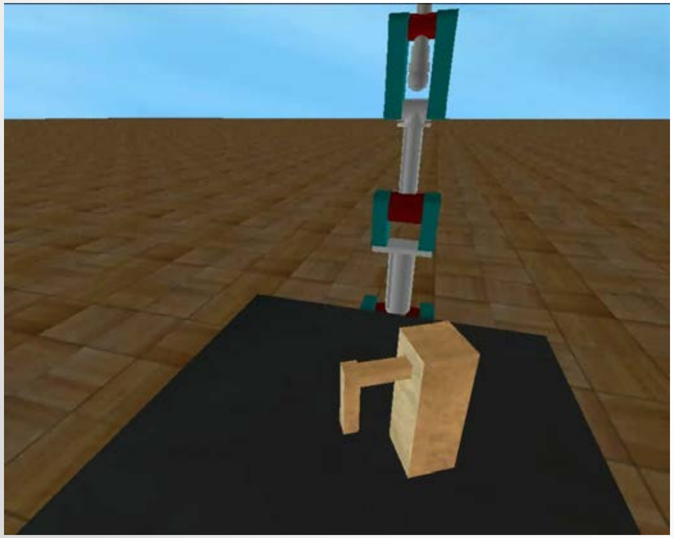
Analysis and preliminary findings





Moore B, Oztop E (2012) Robotic grasping and manipulation through human visuomotor learning. Robotics and Autonomous Systems 60: 441-451

Limited success in simulation to robot transfer

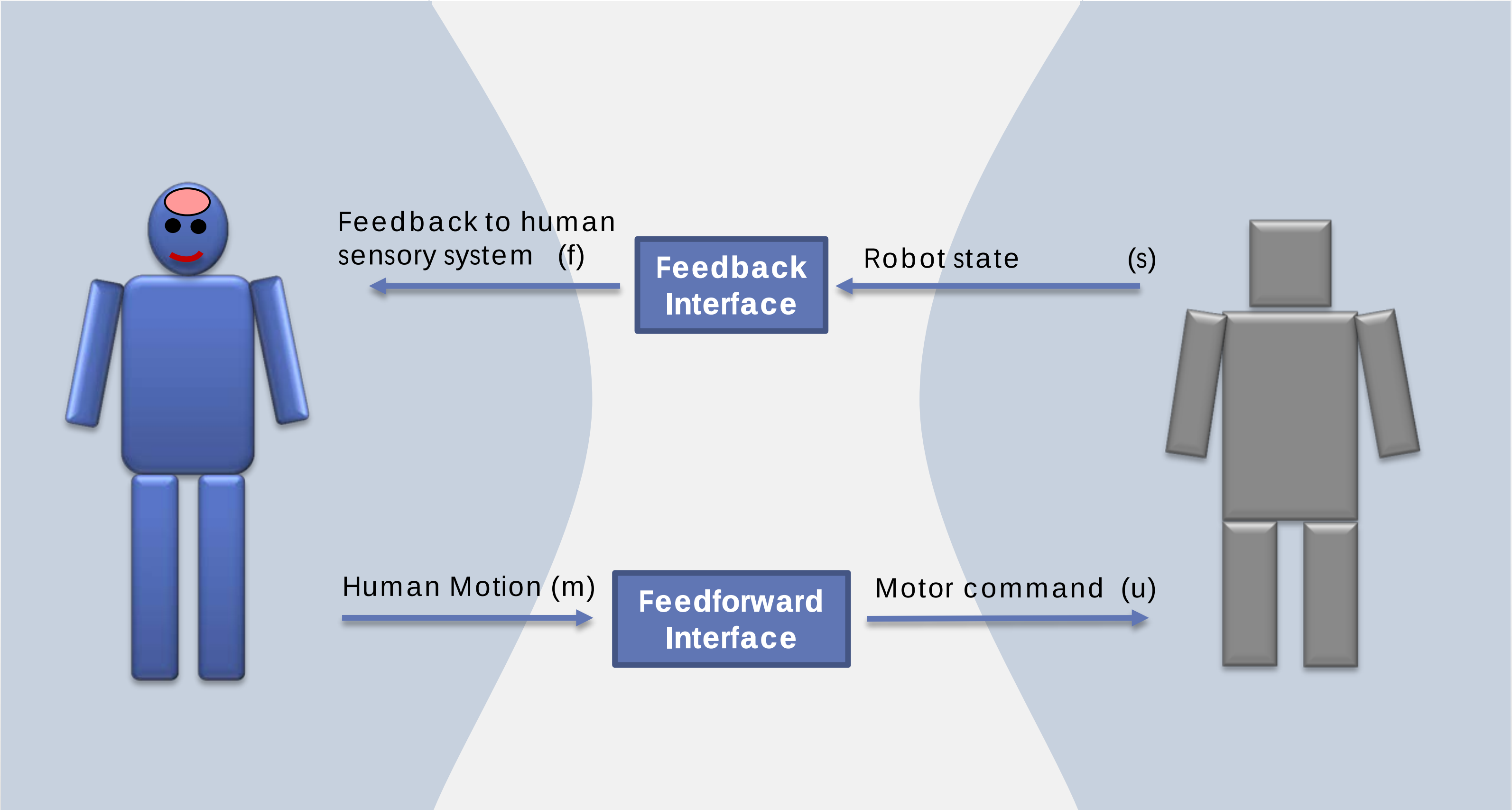


The skill obtained in the simulator was satisfactory. Transfer to the real robot had limited success

General observation: For efficient grasp skill generation there should be low level tactile controller at the fingers (work in planning ☺

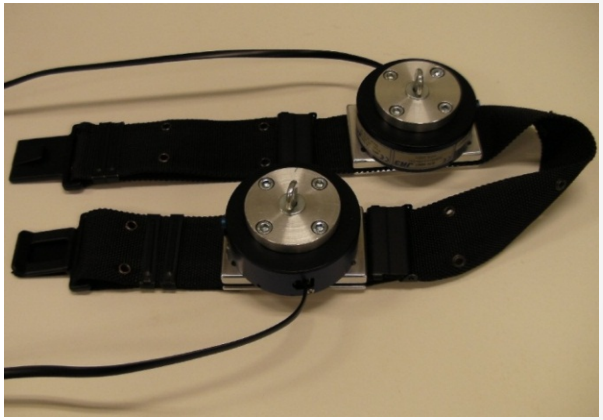
Reactive postural control

- teach the humanoid robot to counteract external postural perturbations
- choices of feedback interface:
  - abstract visual feedback
  - motion of the support polygon
  - force impulses at human's COM

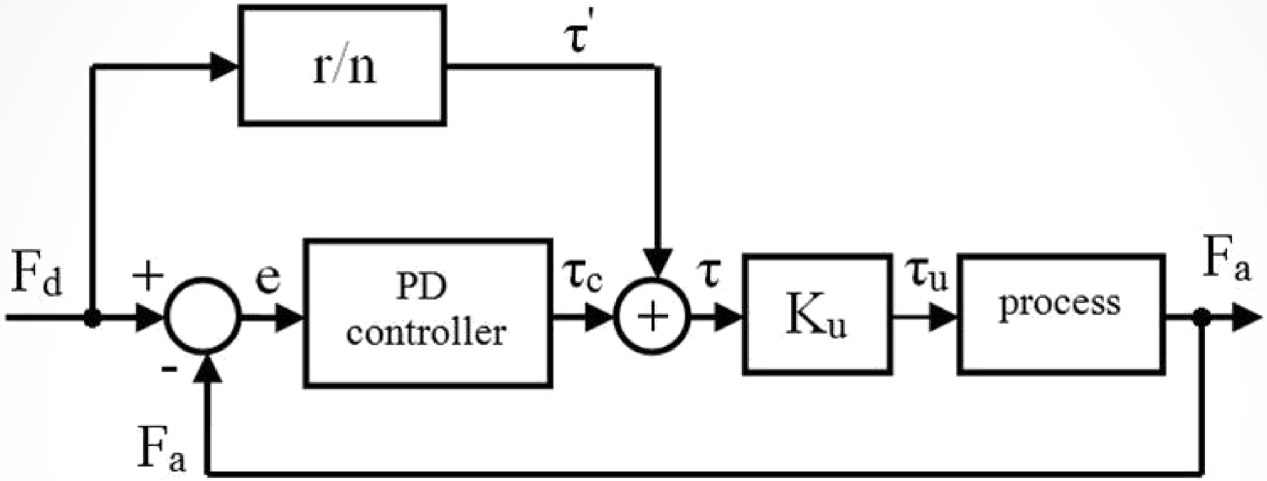


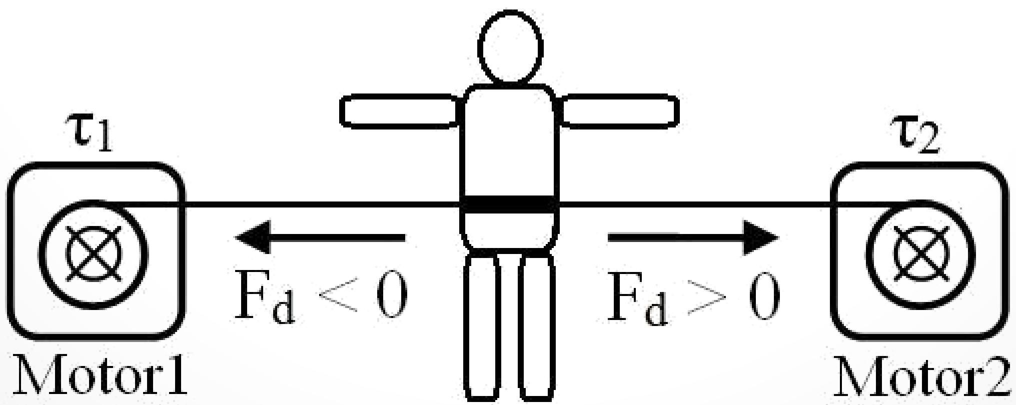
„COM force“ iterface

- The key factor for muscle activation during postural control is COM information [Lockhart et al, 2007]
- An interface between robot COM and human COM



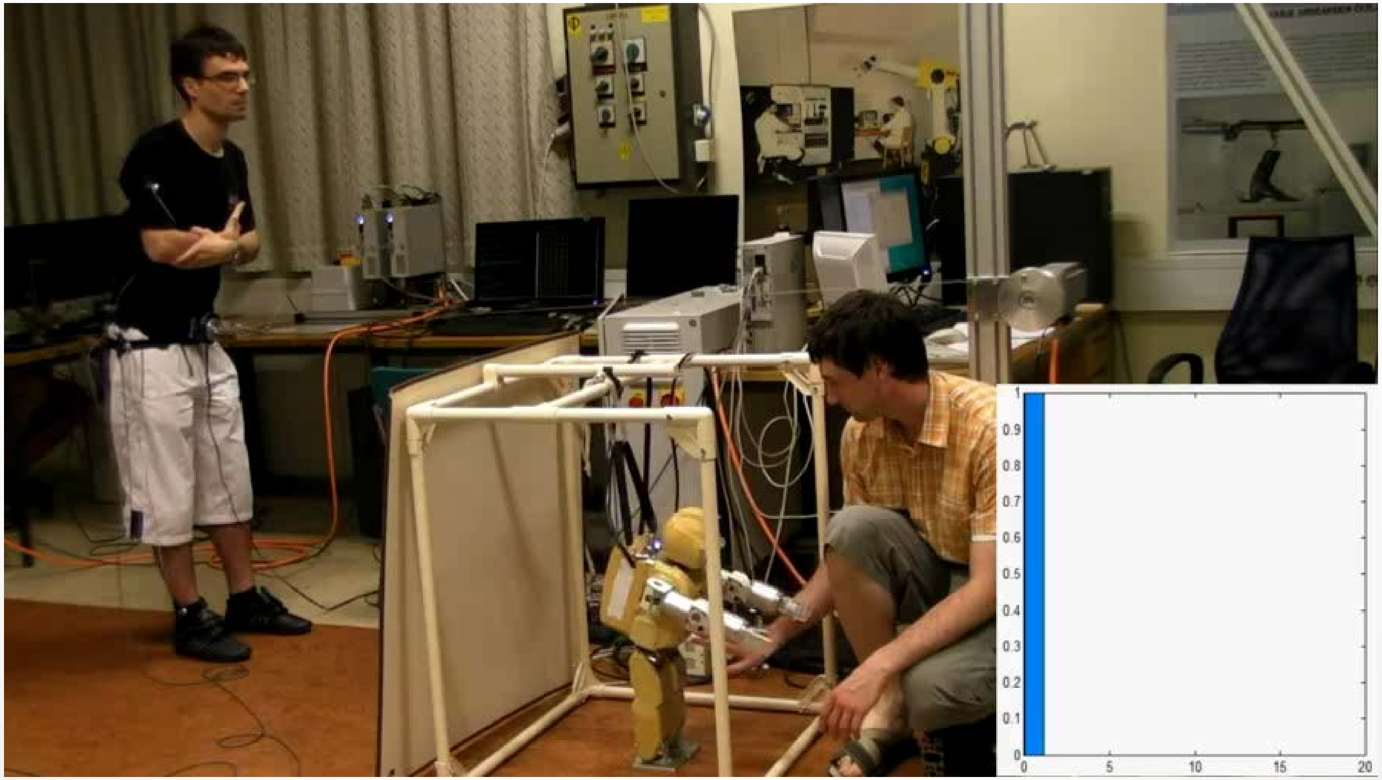
„COM force“ iterface





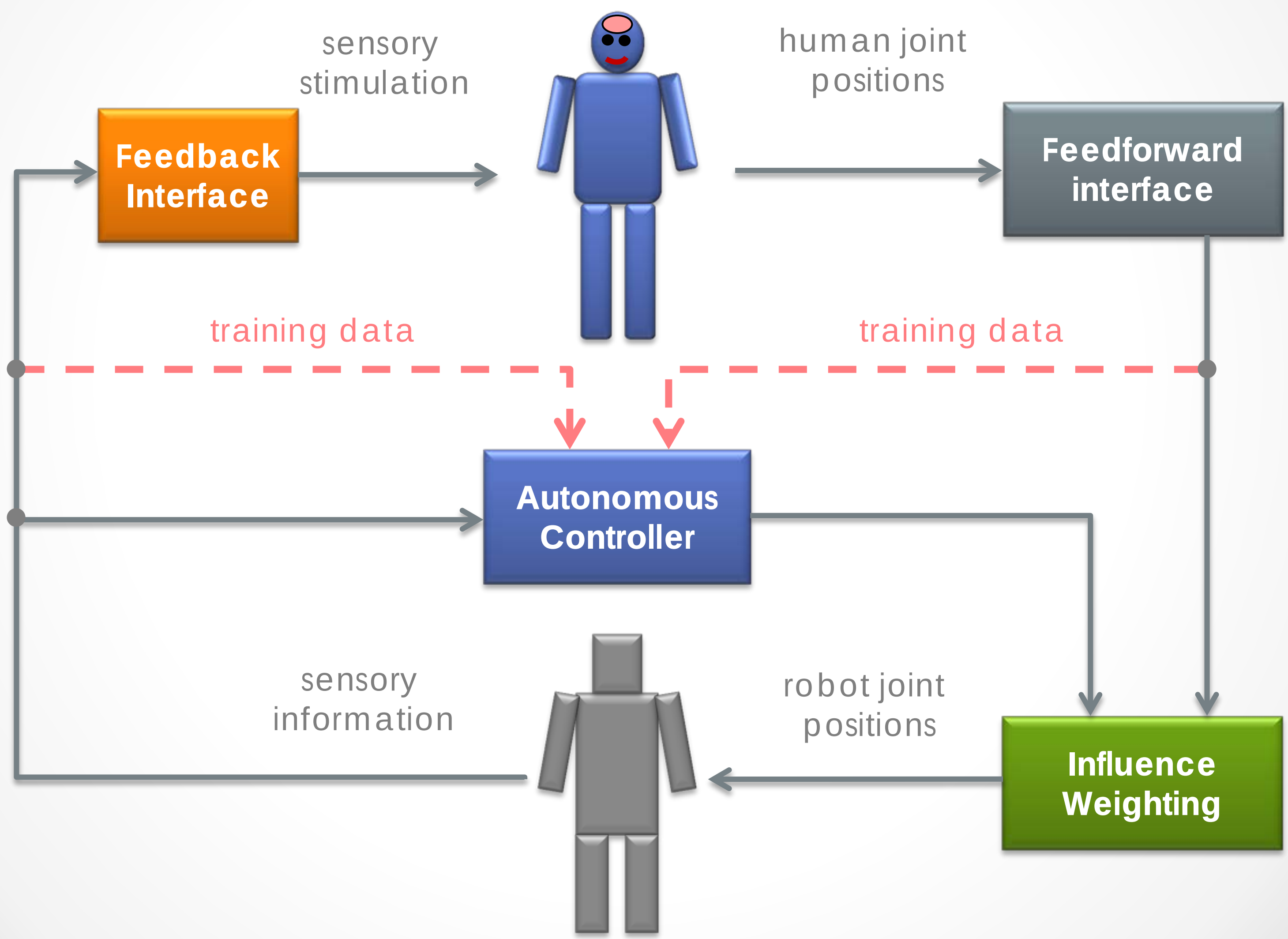
Reactive postural control

- Goals:
  - teach the robot to counteract external postural perturbations
  - on-line learning
  - gradually transfer control responsibility from human to autonomous robot controller



- submitted for ICRA 2013

Principles



sensory
stimulation
human joint
positions
Feedback
Interface
Feedforward
interface
training data
training data
Autonomous
Controller
sensory
information
robot joint
positions
Influence
Weighting

Machine learning

- To teach the robot the demonstrated task we used Locally Weighted Projection Regression [Vijayakumar et al. 2005]
- LWPR offers incremental learning and is among the fastest regression techniques [Nguyen et al. 2011]
- As oppossed to global regression (GPR) which uses entire training set, LWPR partitions the training set into more sections
- Each section is described by a local model:

$$\bar{y}_k = \bar{x}_k^T \theta_k$$

- Influence of each model is determined by the weights characterized by Gaussian kernel:

$$w_k = \exp(-\frac{1}{2}(x-c_k)^T D_k (x-c_k))$$

- The output prediction for an input *x* is a sum of contributions from all models weighted by w_k:

$$\hat{y} = \frac{\sum_{k=1}^{N} w_k \bar{y}_k(x)}{\sum_{k=1}^{N} w_k}$$

Responsibility transfer

- The influence weighting algorithm calculates the mean square error (MSE) between the human reaction and predicted reaction over a period *T* during the demonstration.
- The maximum MSE is set as a reference for the weighting criterion:

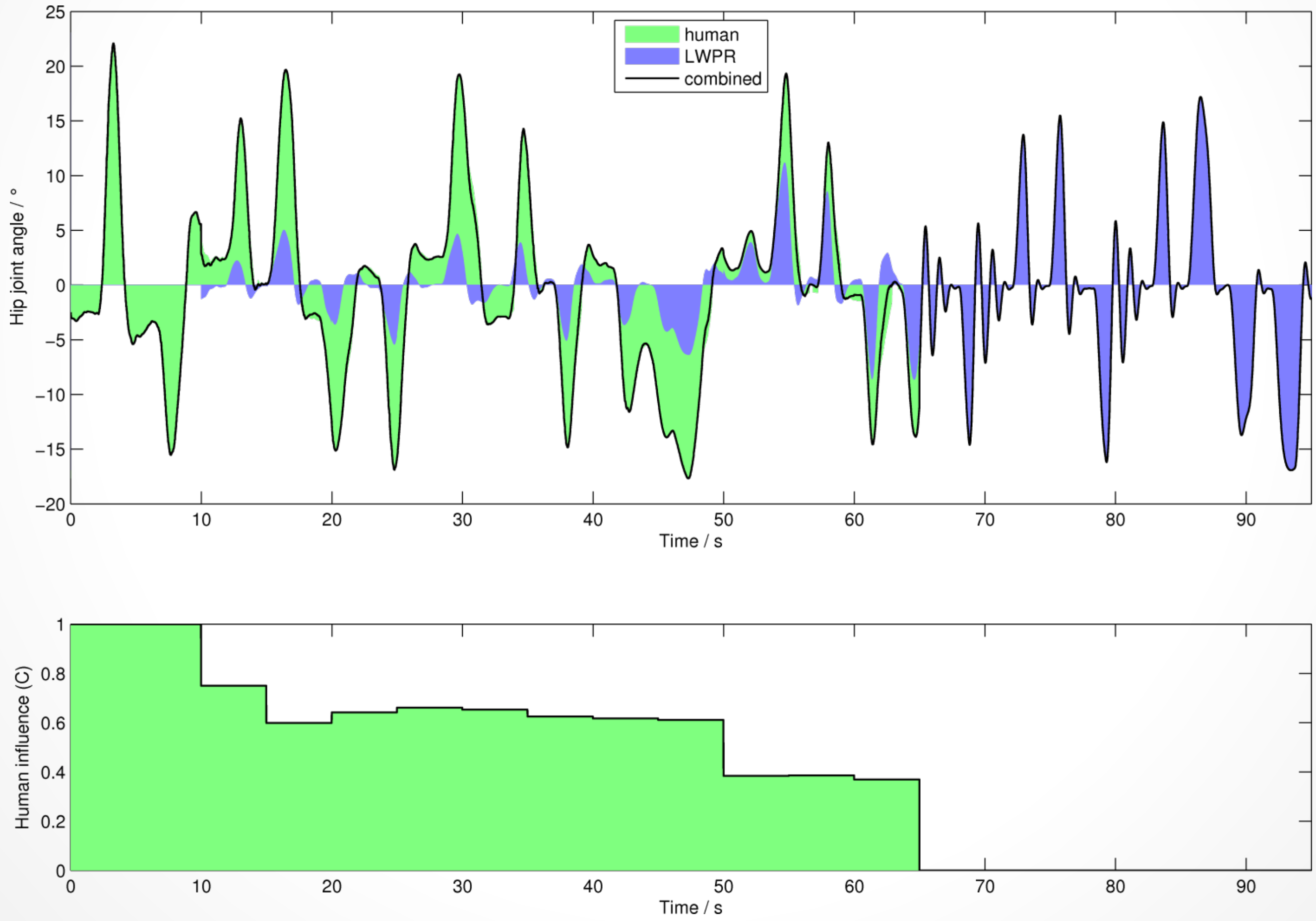
$$C = \frac{MSE_{total}}{MSE_{\max}}$$

- The criterion is used to weight the human influence and the influence of the autonomous controller.
- The output that is controlling the robot is calculated by:

$$y = Cy_{human} + (1 - C)y_{predicted}$$

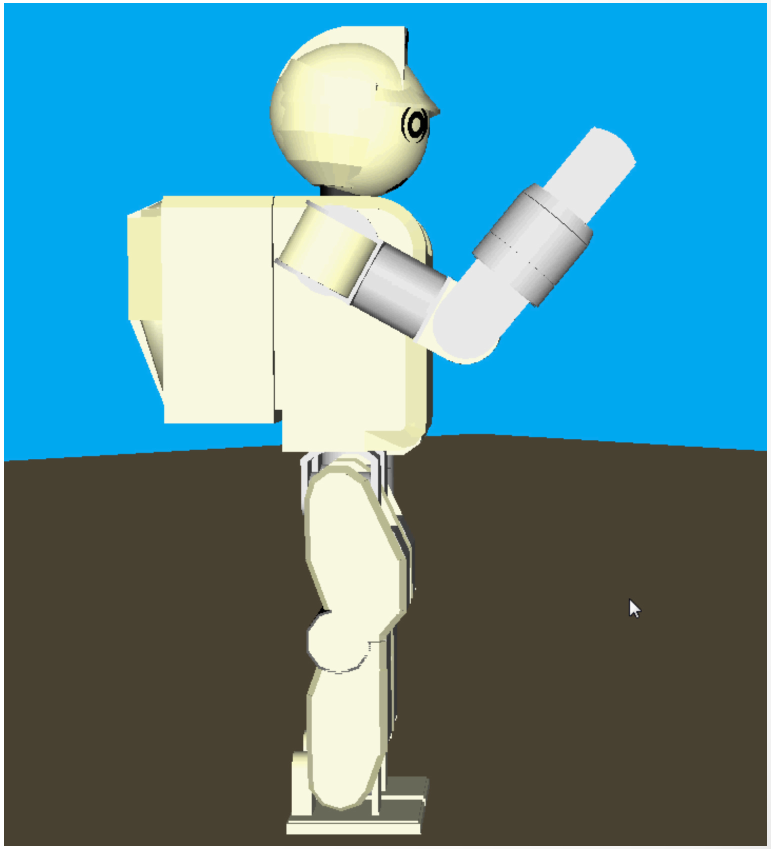
- If the MSE fails to improve over *N* periods the algorithm disconnects the human from the control loop.
- At that point the robot is considered trained.

Responsibility transfer



Stability algorithm + manipulation task

- Combine learned skill with an additional arbitrary task
- Stability algorithm can influence the manipulation task but only if necessary.
- Manipulation task must not influence the postural stability of the robot.
- Null space exploration



- in collaboration with Leon Žlajpah

Concluding remarks...

Our work so far indicates that

- Obtaining robot skill via human sensorimotor learning is a viable approach
- Since the paradigm reverse engineers the control policy obtained by the brain, the behaviors obtained should be natural and human-like
- Help built smart prosthetics that can be controlled intuitively via high level signals or brain machine interface (BMI)
- Shed light on mechanisms of internal models, agency and body image
  - Help ameliorate impairments related to these brain mechanisms
  - Offer new design principles for robot self exploration and learning

THANK YOU FOR YOUR ATTENTION!

Collaborators:

Erhan Oztop, Ozyegin University, Turkey
Luka Peternel, Jožef Stefan Institute, Slovenia
Joshua Hale, Cyberdyne, Japan
Mitsuo Kawato, ATR, Japan