Real-time human control of robots for robot skill synthesis (and a bit about imitation)

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IMITATION IN ARTIFICIAL SYSTEMS

- **(1) Robotic systems that are able to imitate via vision**

  - Difficult

  - Mainly problem of pattern recognition

- **(2) Artificial systems as a model of human imitation learning**

  - Difficult when biological realism is required

  - Often related to infant motor development

  - Main tools: Learning with connectionist models

- **(3) Robotic Behavior via human guided robot imitation**

  - Easier (to some extent)

  - Teleoperation, motion capture. etc.

  - Human visuo-motor learning

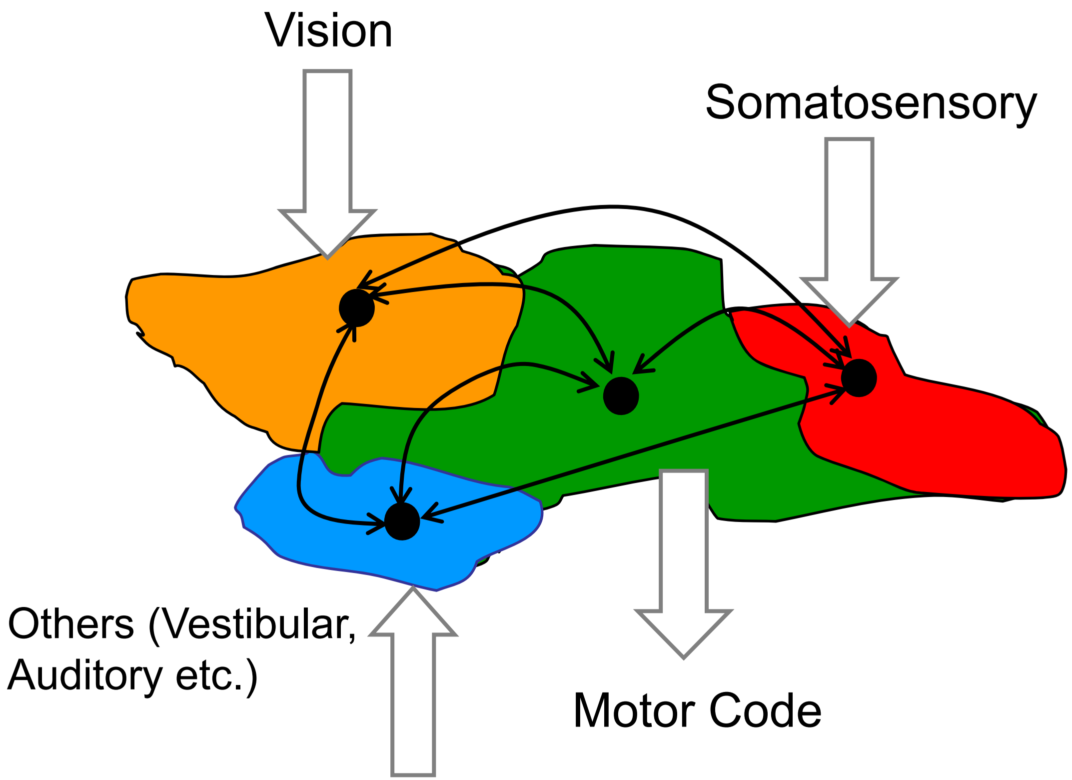
INFANT LEARNING: BECOMING AN IMITATOR

- Self observation (assumption: infants can observe their actions)
  - Agent produces action (A)
  - Agent sees consequence of the action (V)
  - Agent associates A and V

- Social (reinforcement) learning (assumption: caregivers cheer infant imitation)
  - Agent observes action (V)
  - Agent generates an action (A)
  - If social reward is collected,
    agent associates A and V

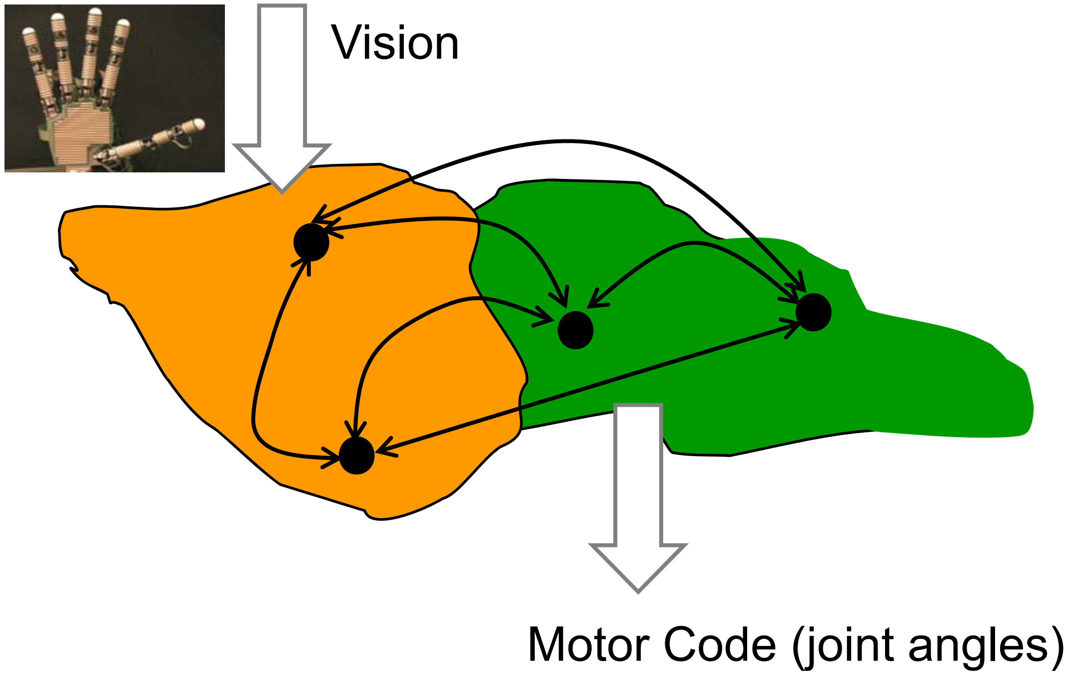
- Social (supervised) learning (assumption: caregivers are natural imitators)
  - Agent shows action (A)
  - Agent sees teacher's imitation (V)
  - Agent associates A and V

IMITATION BY SELF-OBSERVATION = HEBBIAN ASSOCIATION?



Hebb (1949): When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.

TEST ASSOCIATIVE LEARNING HYPOTHESIS WITH GIFU HAND



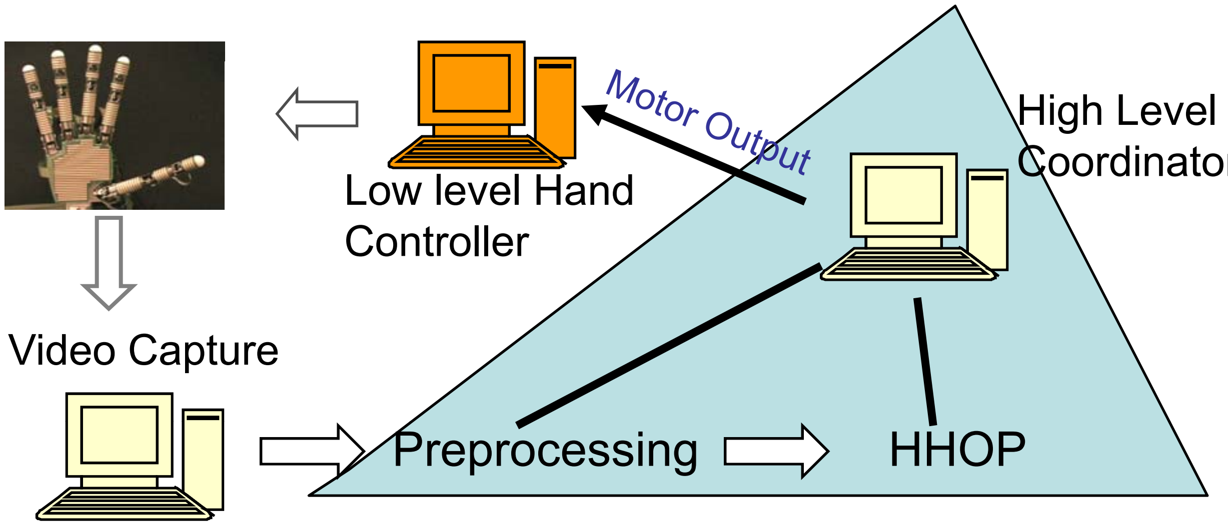
Need an appropriate neural architecture to implement the associative memory.
Simplest alternative → HOPFIELD network

GIFU HAND-HHOP-VISION INTEGRATION

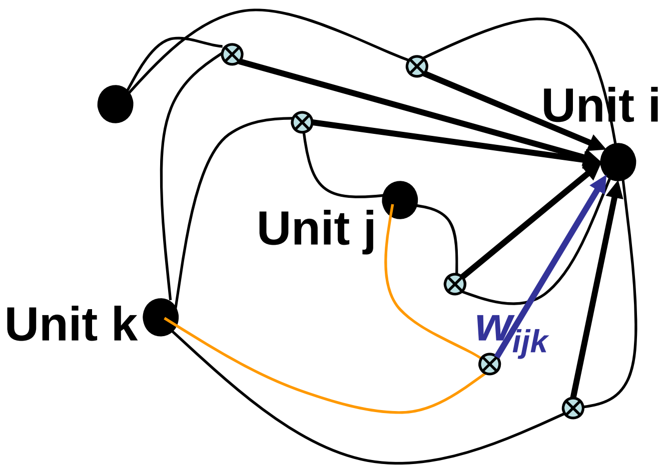
* Input video: 320x240 30fps color

* Preprocessing:
Gaussian smoothing → cropping → thresholding → Isolated point elimination

* Input to HHOP: Pixels from the preprocessed video + joint configuration of the Hand (binary)



AN ASSOCAITIVE MEMORY UTILIZING HIGHER ORDER UNITS (HHOP)

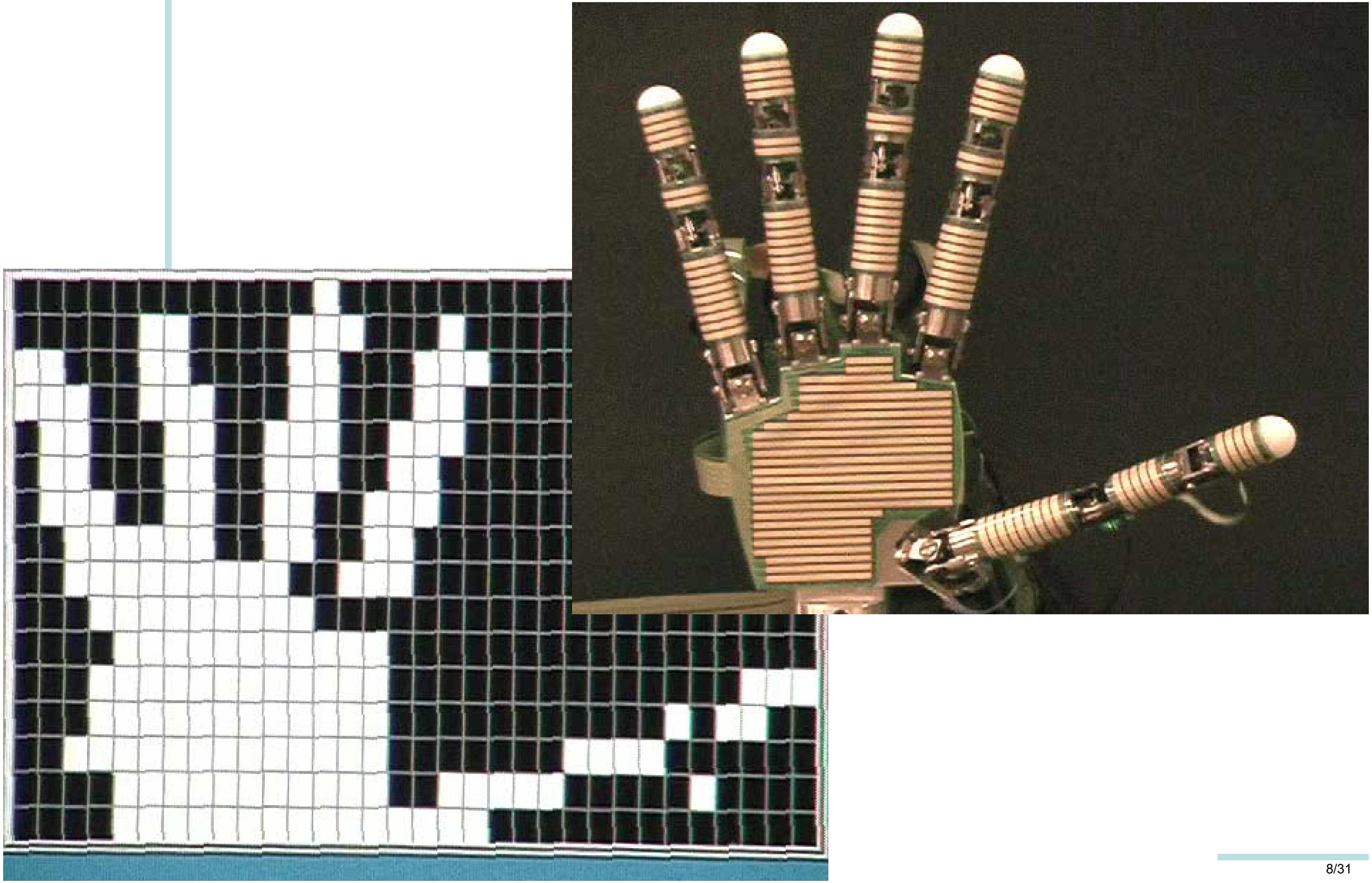


Si: output of unit i (-1 or +1)
***w**$_{ijk}$*: connection strength between units i and synapse (product) formed by units j and k
ξ_j^μ: the j^{th} bit of pattern μ
N : number of units

The update rule: $$S_i = sgn(\underbrace{\sum_{jk} w_{ijk} S_j S_k}_{\text{Net input } h_i})$$

The weights (batch): $$w_{ijk} = \frac{1}{N} \underbrace{\sum_{\mu}^{p} \overbrace{\xi_i^\mu \xi_j^\mu \xi_k^\mu}^{\text{~synaptic multiplication}}}_{\text{Hebbian update on the products}}$$

POSTURES USED FOR LEARNING



SIMPLE HAND POSTURE IMITATION

Learning: Human Hand + Gifu Motor Output (social supervised)

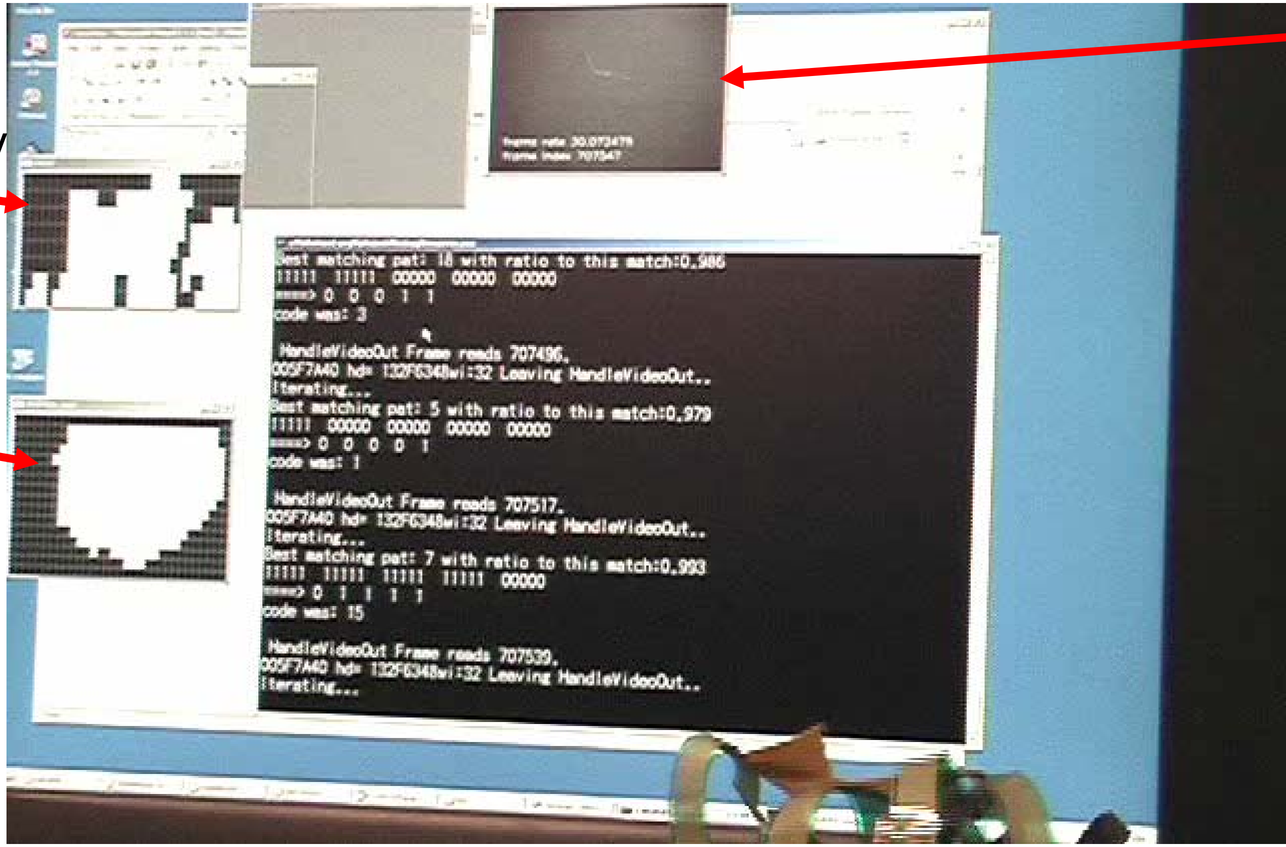
GifuHand shows action (A)
Teacher (Human) imitates
GifuHand sees teacher's imitation (V) and associates A and V

SIMPLE HAND POSTURE IMITATION

HHOP memory retreival

HHOP Input resolution

Video Input

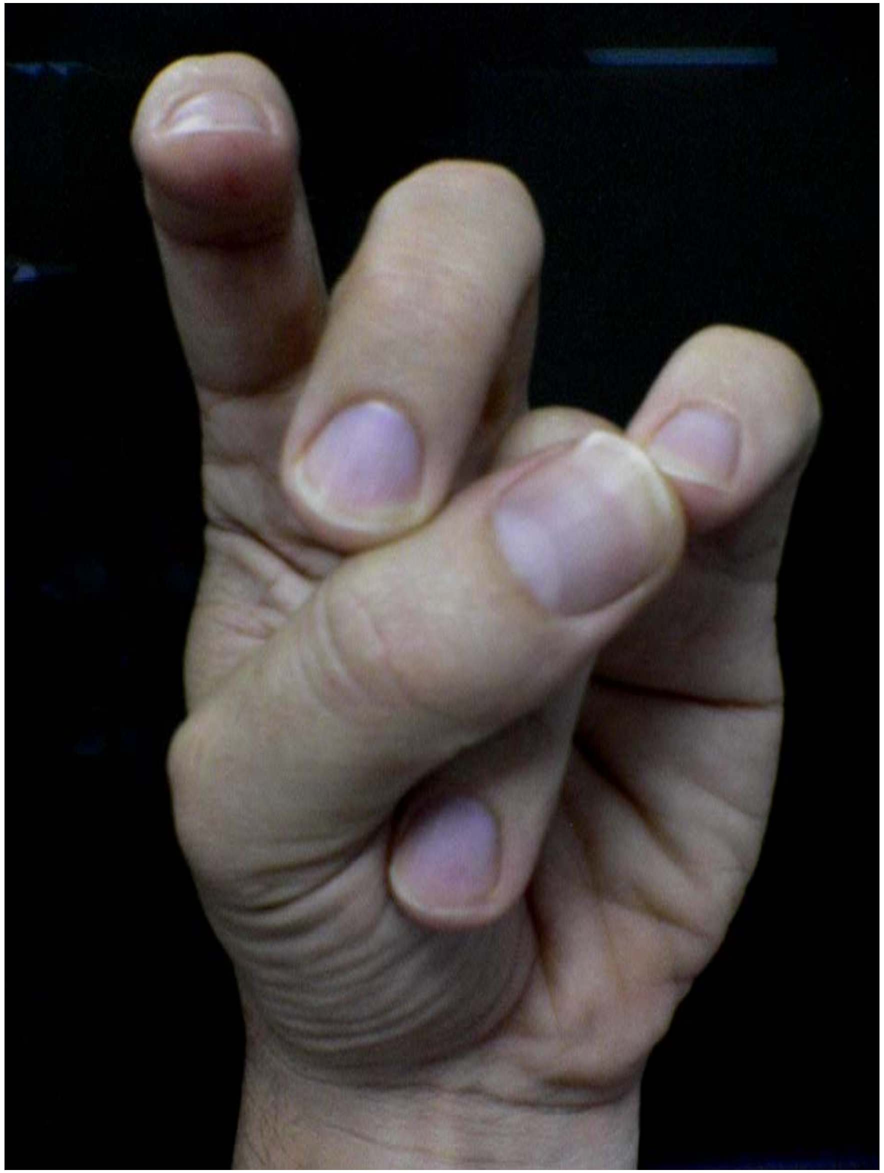


Learning: Gifu Hand + Gifu Motor Output (Self Observation)

GifuHand produces action (A)
GifuHand sees the consequence of action (V)
GifuHand associates A and V

HOW GOOD IS HUMAN IMITATION?

Can we really effortlessly imitate an uncommon hand posture?



Some notes

Self observation may allow fast but simple imitation

The quality and the complexity of the imitation capacity depends on the visual preprocessing

Applicability is limited: face and whole body imitation is not possible

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Social Learning appears to be the key for delicate imitation capability, which may require slow visual analysis

Real-time human control of robots for robot skill synthesis

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Motivation

Robot programming requires experts, and lot of expert work-hours

Can we expect non-experts teach robots

– teaching by demonstration
– robotic imitation
– robot coaching

These approaches commonly aim at making this task a natural and easy task for the human teacher

Our proposal

What we propose is 'not to be that nice to the human teacher'

- Tight connection between the robot and human
- May require extensive training on the human side

→ Build an robot interface as in teleoperation

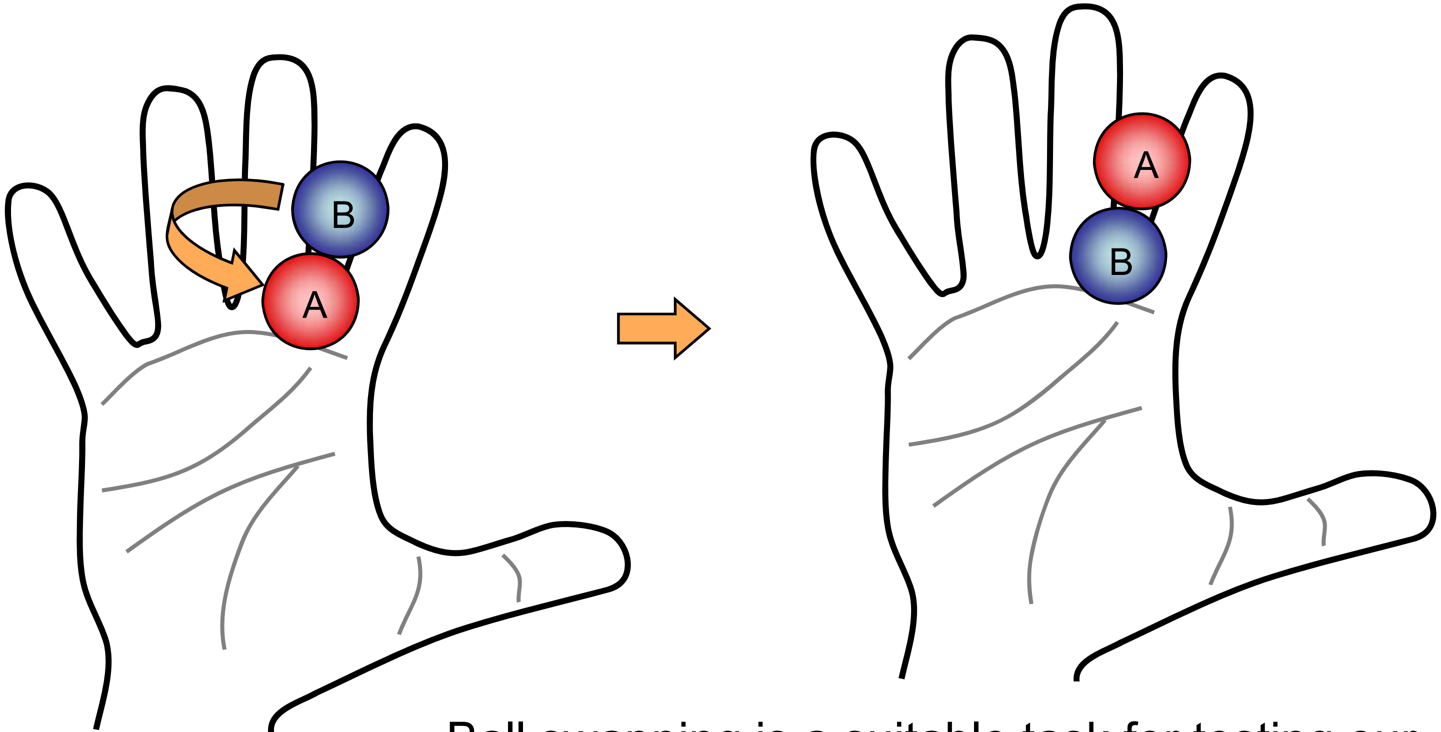
→ Train a human to perform the target task with the robot

→ Use the robot trajectory generated by the human to synthesize an autonomous controller

Why should our proposal work?

– The brain's ability to learn novel control tasks
– The robot can simply be considered as another tool (e.g. snowboarding, driving, using chopsticks)
– The flexibility of the body schema; extensive training on the human side should modify the body schema so that the robot can be controlled naturally (c.f. when you hold chopsticks, they become part of your body so that it can be controlled effortlessly)
– c.f. Experiments with monkeys shows that representation of hands are expanded instantaneously as soon as a tool is grabbed that can be utilized to manipulate the space (Iriki et al. 1996; Obayashi et al. 2001)

Ball swapping task



Ball swapping is a suitable task for testing our proposal since:

- It is complex: it is not possible to determine how difficult the task will be with the Gifu Hand
-Not straightforward to manually program the task (learning is possible but requires dimensionality reduction etc.)

Human Control of the Robot

Human hand movement

Data Capture ↓

VizualEyez data

Build hand Referenceframe ↓

Finger tip positions

Calibration ↓

Finger tip positions For Gifu Hand

Inverse Kinematics ↓

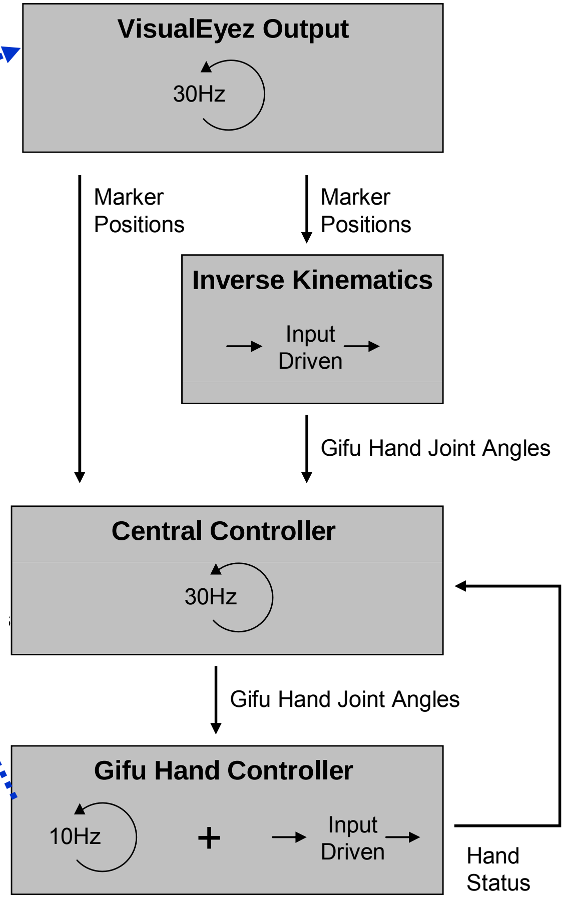
Raw joint angles

Filtering ↓

Desired joint angles

PD Control ↓

Gifu Hand actuation



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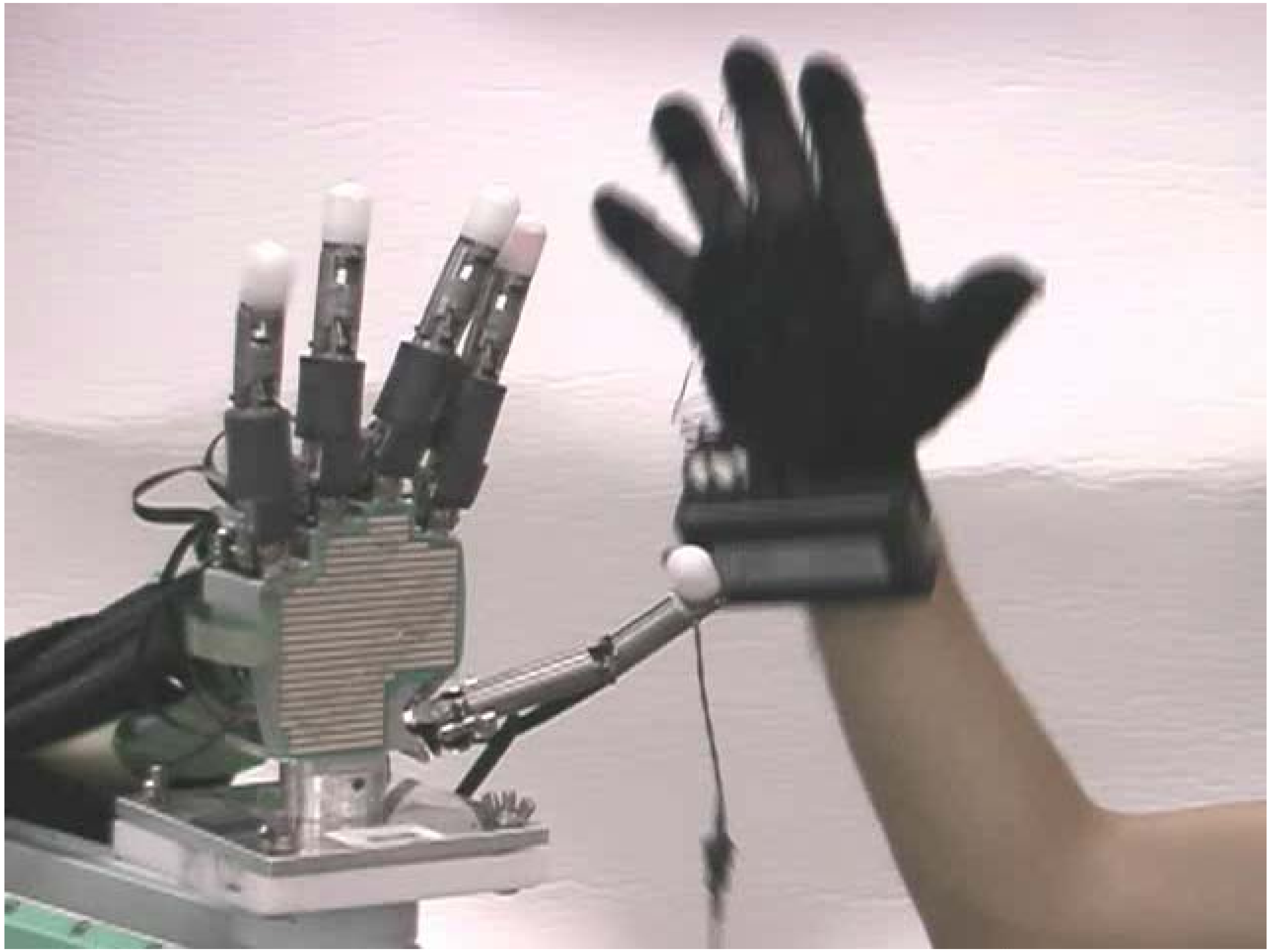
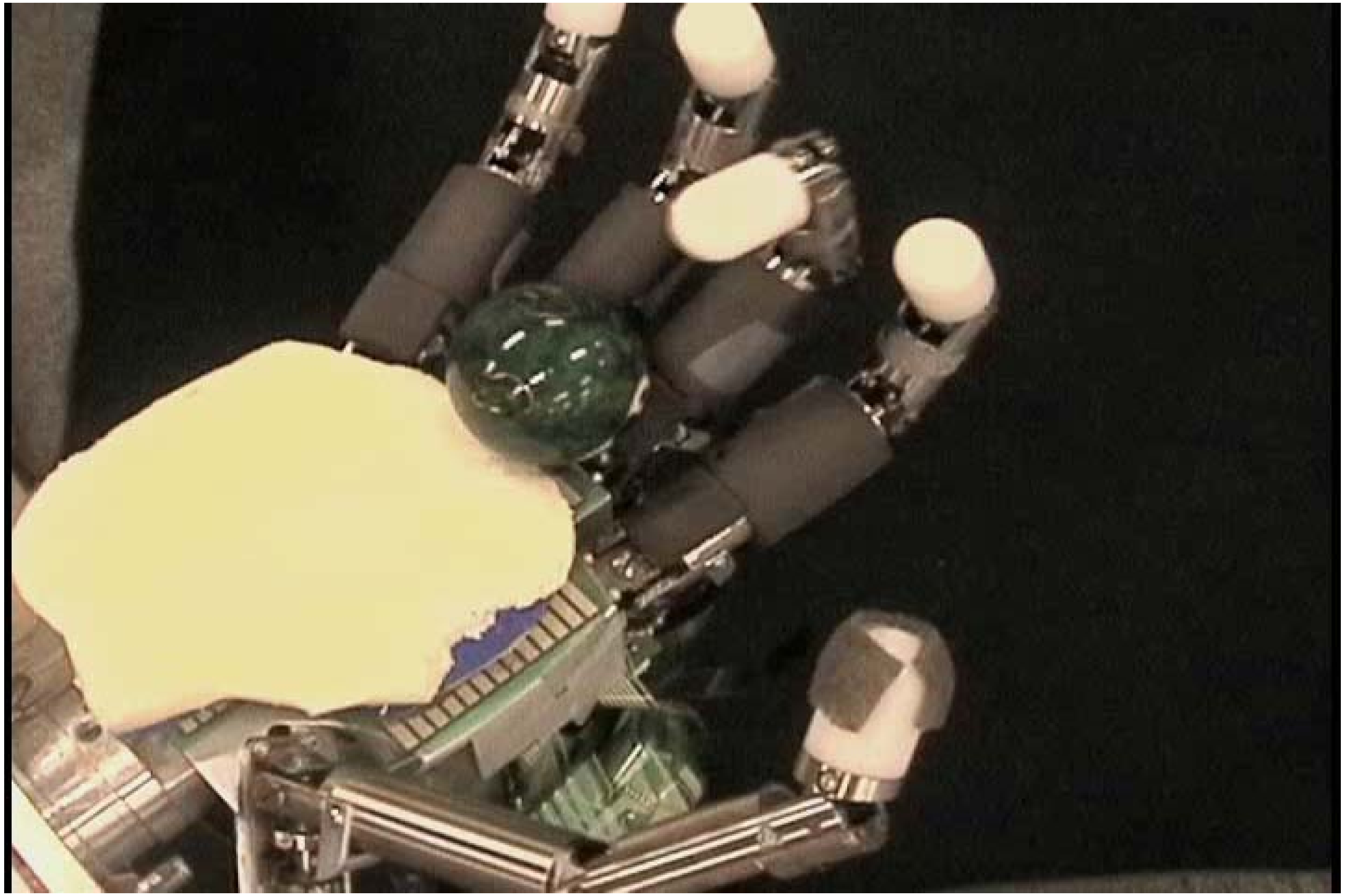


Playing with single ball: building motor primitives ?



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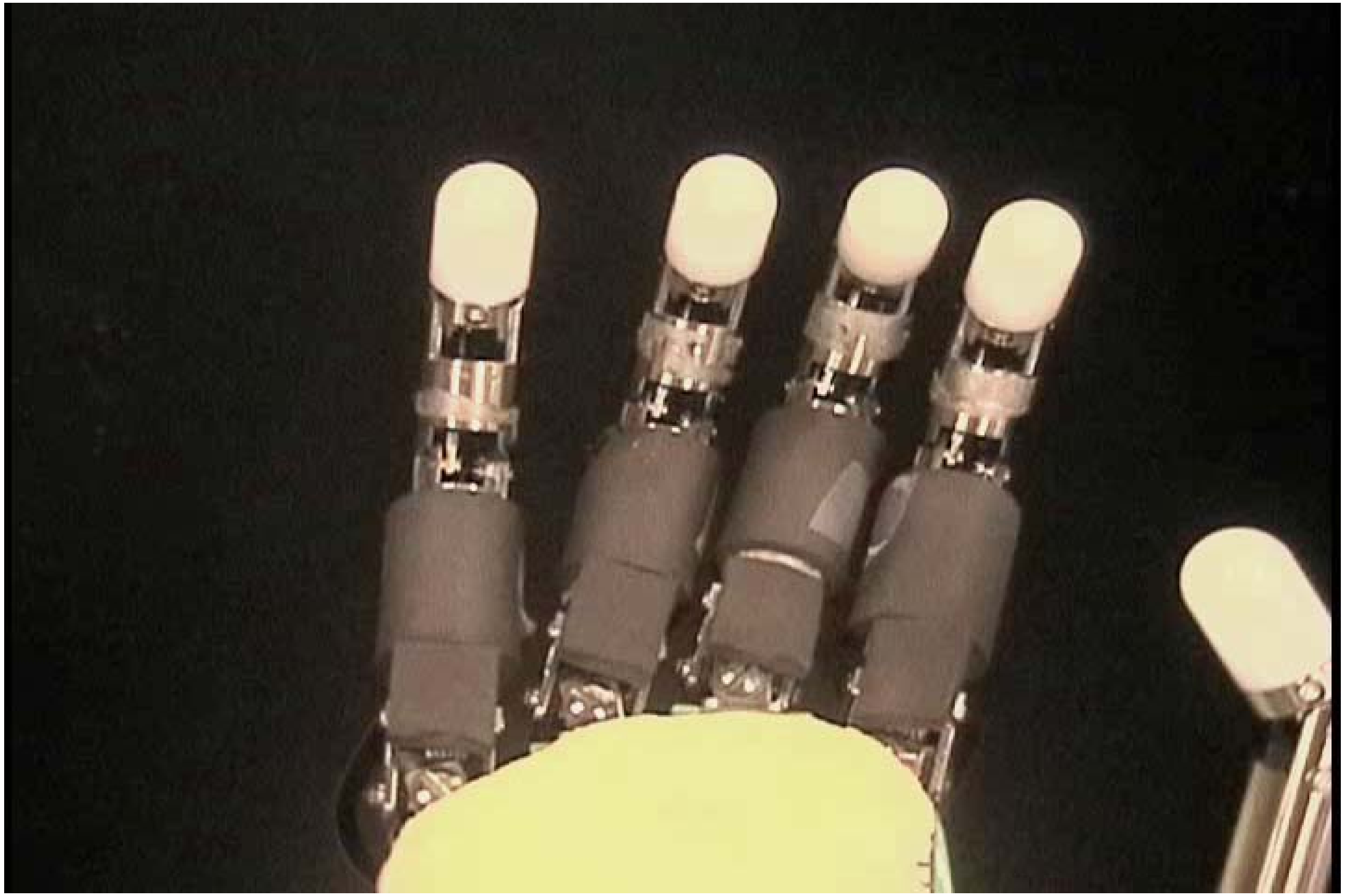
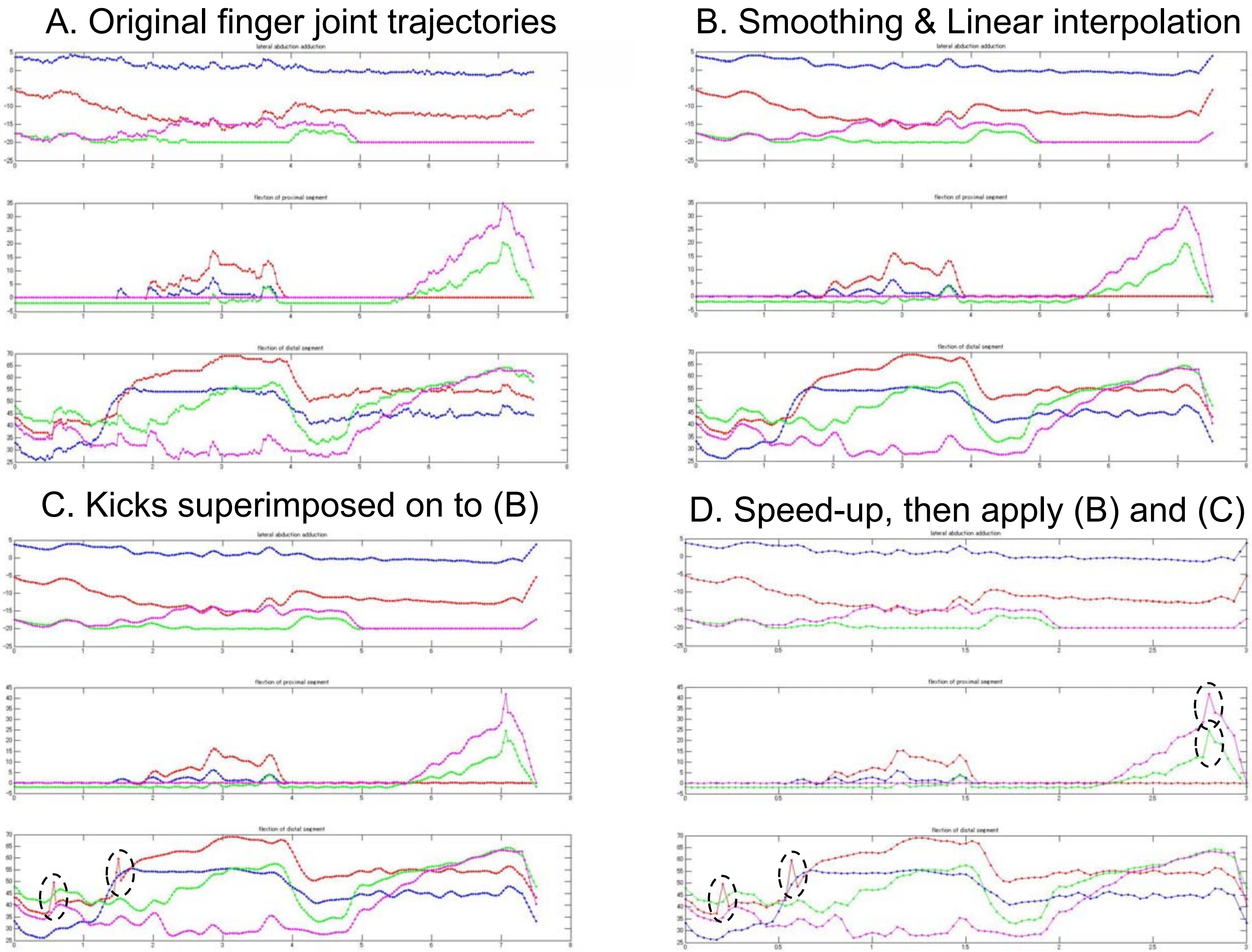
Finally success…

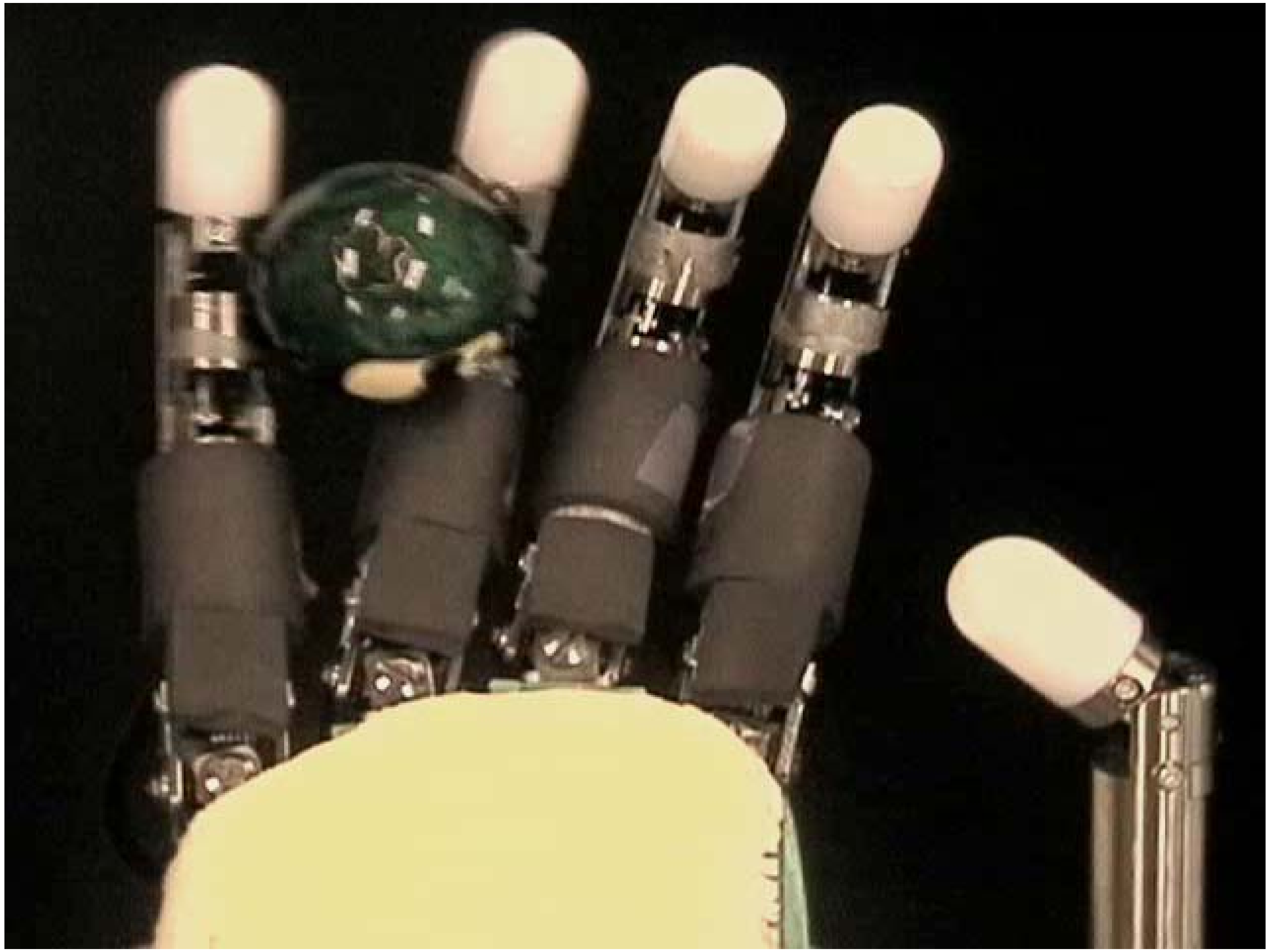


Improving Performance

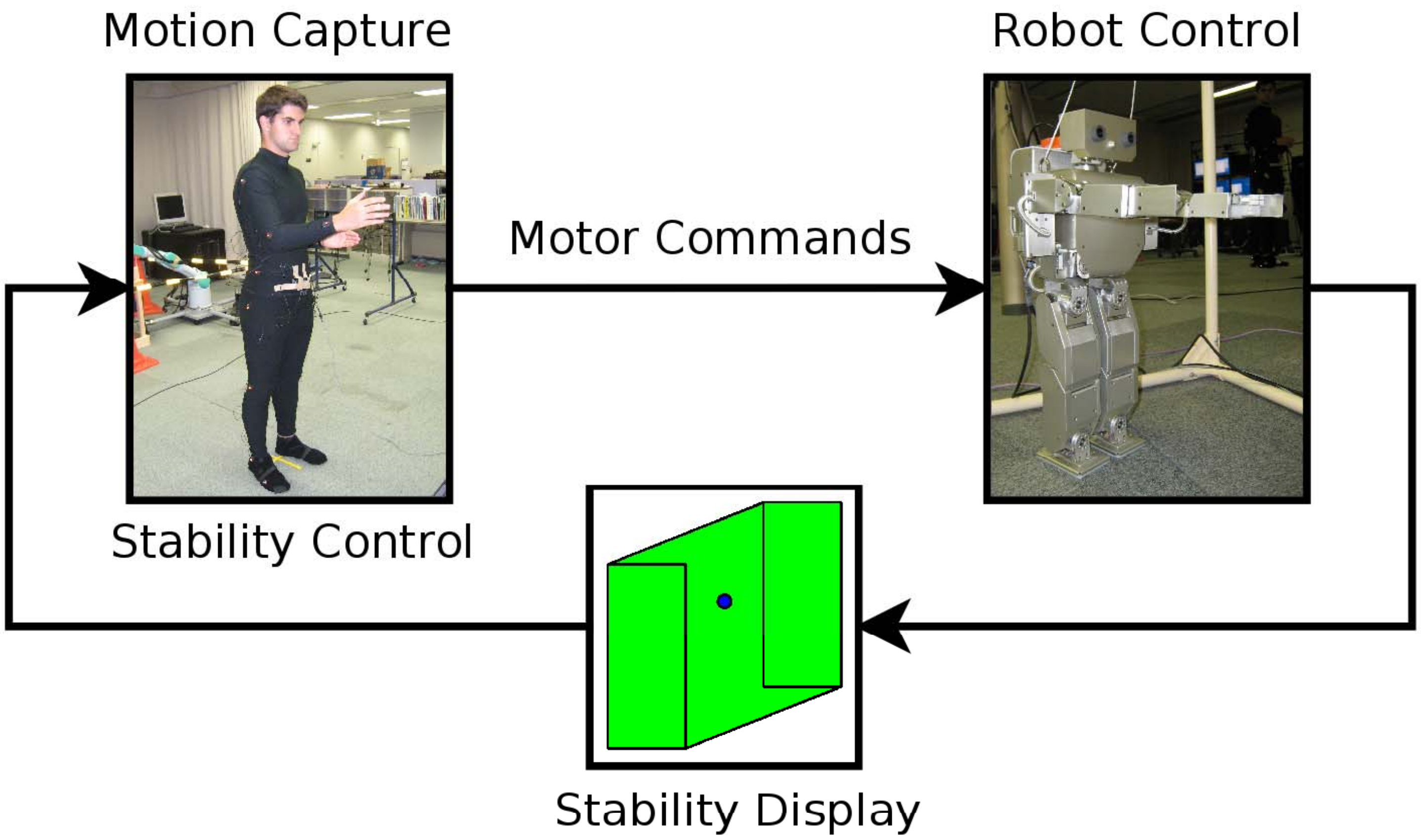


Index finger
Middle finger
Ring finger
Little finger

Swapping speed up x 2.2



Stable Reaching with a Small Humanoid Robot



Human Control of Robot

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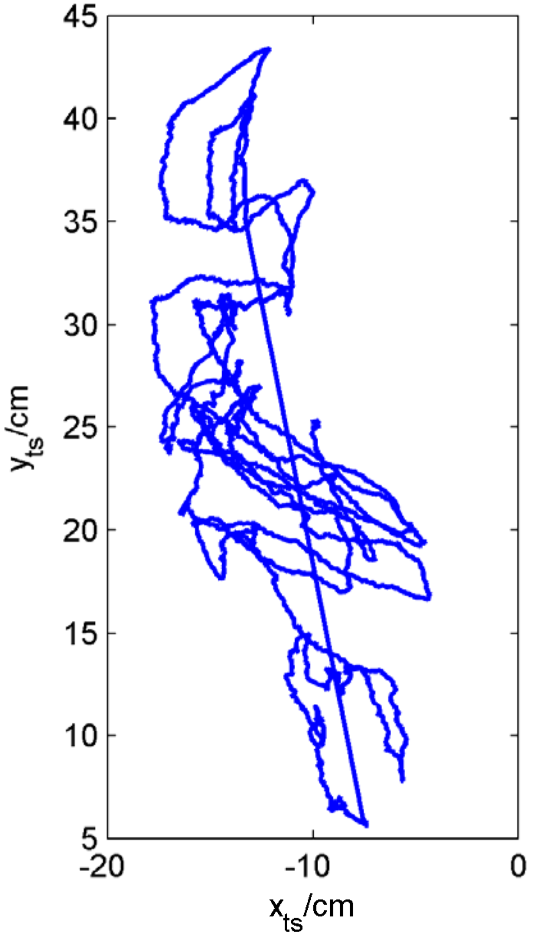
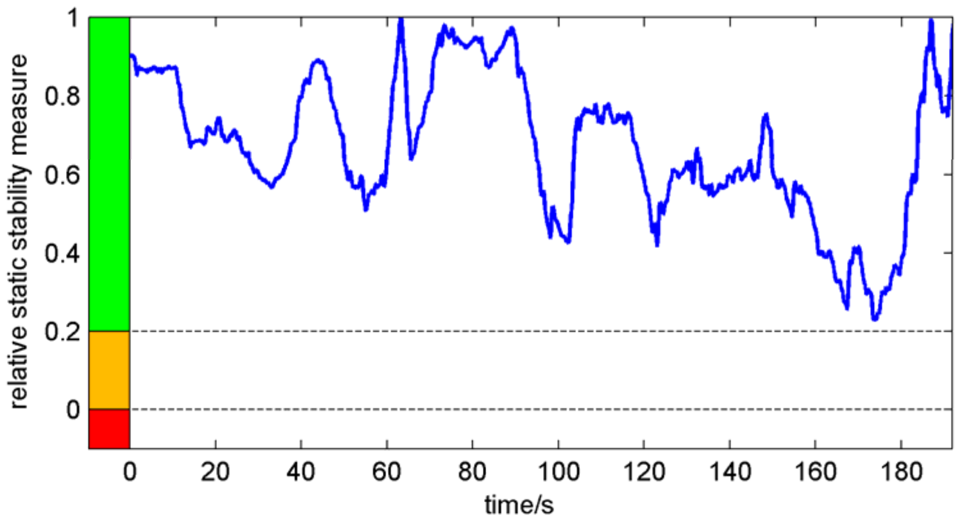
Humanoids 2008
Imitation and Coaching in
Humanoid Robots

Motion & Stability Obtained by Human





Statically Stable Trajectory Generation

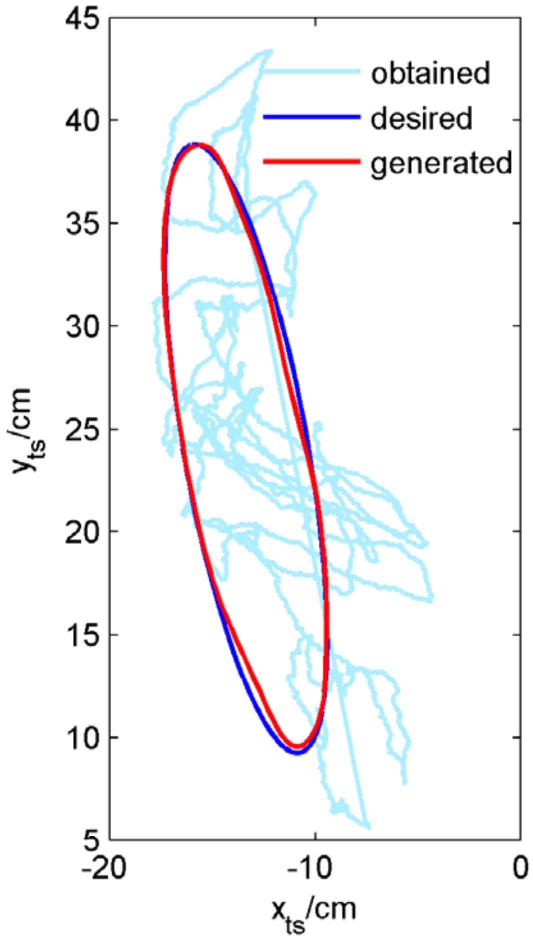
$$\mathbf{XW} = \mathbf{Q} \qquad \mathbf{W} = \mathbf{X}^{\dagger}\mathbf{Q}$$

$$\varphi_i(\mathbf{x}) = e^{(\mathbf{x}-\boldsymbol{\mu}_\mathbf{i})/\sigma^2}$$

$$\mathbf{Z} = \begin{bmatrix} \varphi_1(\mathbf{x_1}) & \varphi_2(\mathbf{x_1}) & \cdots & \varphi_N(\mathbf{x_1}) \\ \varphi_1(\mathbf{x_1}) & \varphi_2(\mathbf{x}_2) & \cdots & \varphi_N(\mathbf{x_1}) \\ \vdots & & \ddots & \vdots \\ \varphi_1(\mathbf{x}_m) & \varphi_2(\mathbf{x}_m) & \cdots & \varphi_N(\mathbf{x}_m) \end{bmatrix}$$

$$\mathbf{W} = \mathbf{Z}^{\dagger}\mathbf{Q}$$

$$\mathbf{q} = \left(\varphi_1(\mathbf{x}) \quad \varphi_2(\mathbf{x}) \quad \cdots \quad \varphi_N(\mathbf{x})\right)\mathbf{W}$$



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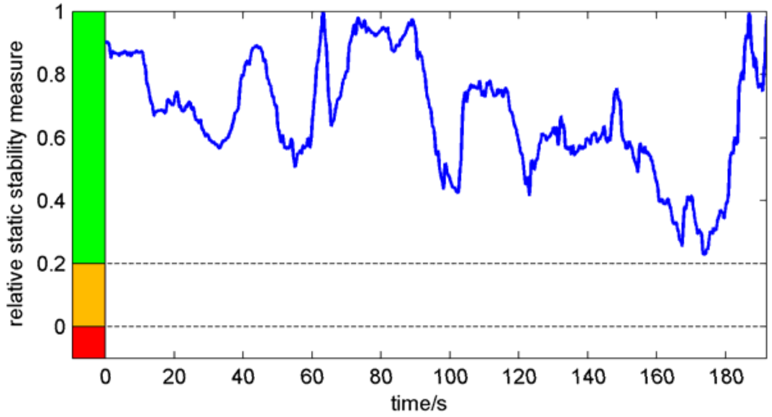
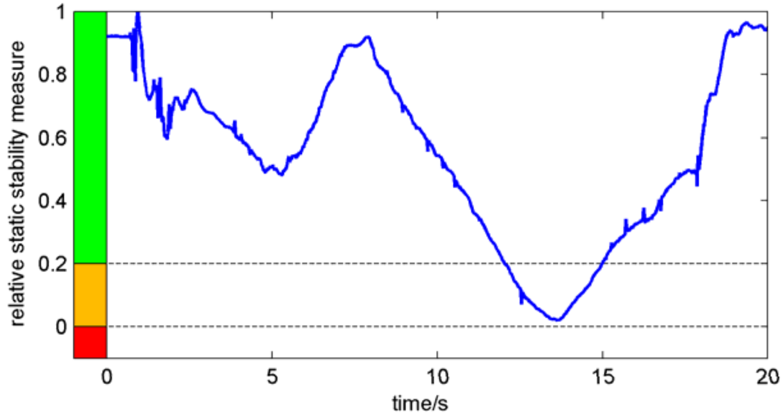
Autonomous Trajectory Tracking

Stability During Robot Execution

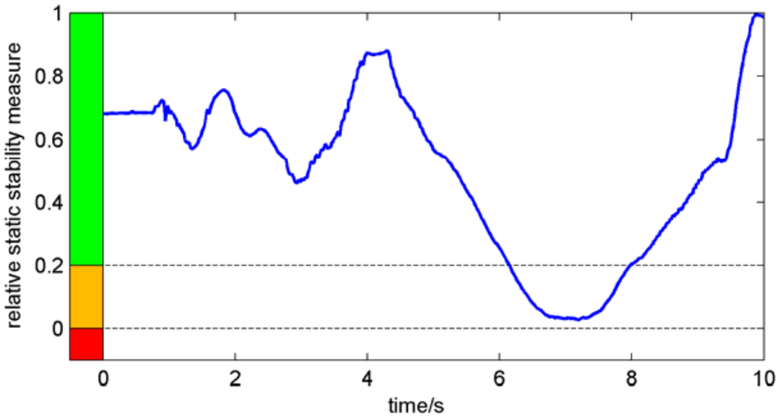
Human controlled (slow)



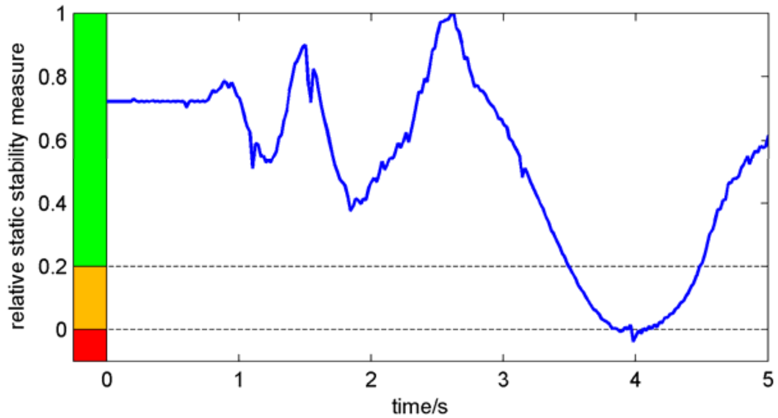
Human controlled (20sec.)



Human controlled (10sec.)



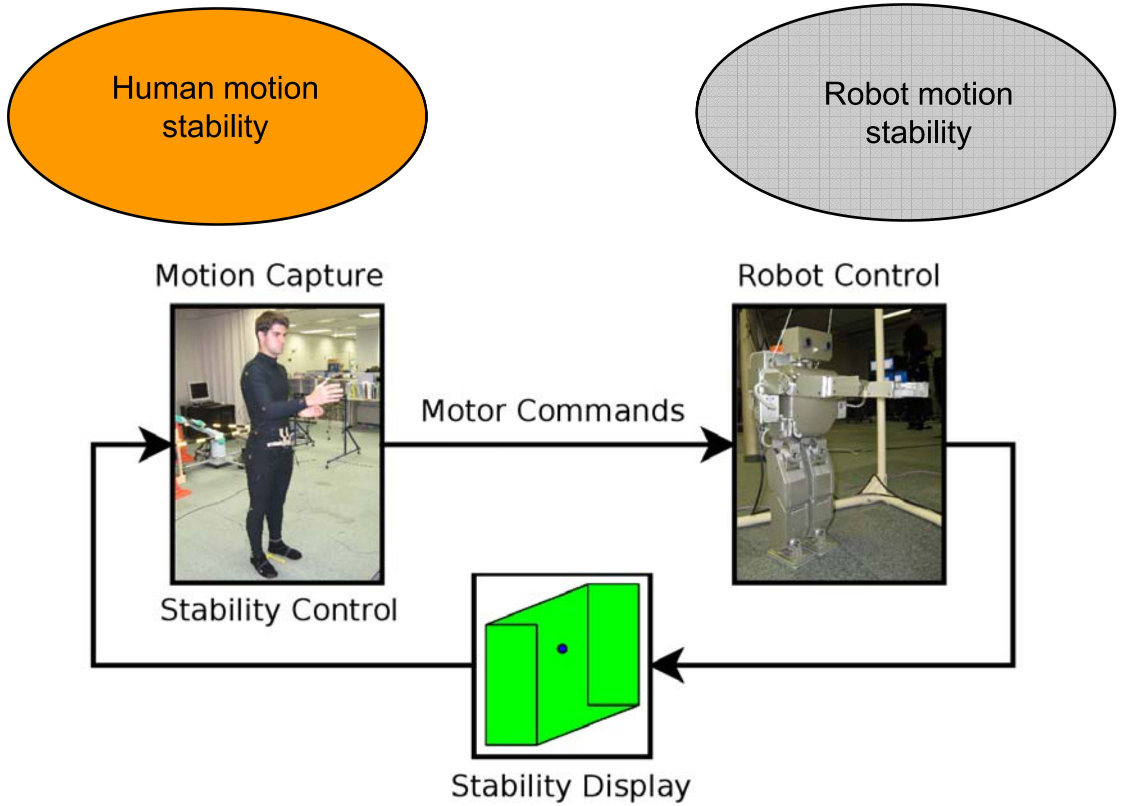
Human controlled (5sec.)



Rethinking the stable reaching task: Two Tasks for the Human

The task is to make the robot reach without falling over

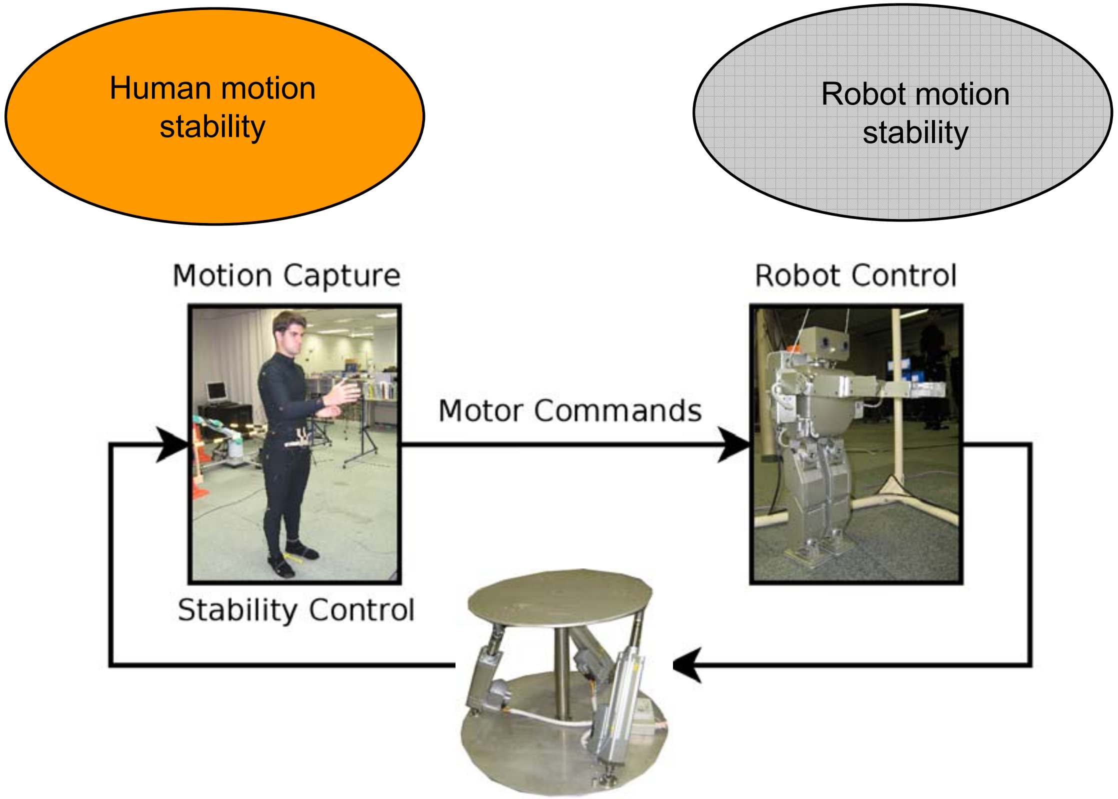
But the subject must keep self balance too !



Current Work: Improving the paradigm

Increasing the motion range of the human

Richer feedback to the human



Improving the Paradigm: 3DOF Articulated Platform (slow)

Improving the Paradigm: 3DOF Articulated Platform (fast)

fast_sine_mpeg4.avi

Improving the Paradigm: 3DOF Articulated Platform

jan-ride-mpeg4.avi

CONCLUSION

Results: Synthesizing robot behavior by human training is a viable approach

Implication: A new employment area may emerge in the coming decades: robot trainers

Future Work: incorporating robot adaptation during human learning

Future Work: Dynamic task on a humanoid robot