Transferring Human Skills to Humanoid Robots

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Transferring Human Skills to Humanoid Robots

Movements

• learning motion
• recognition
• reproduction

Manipulation

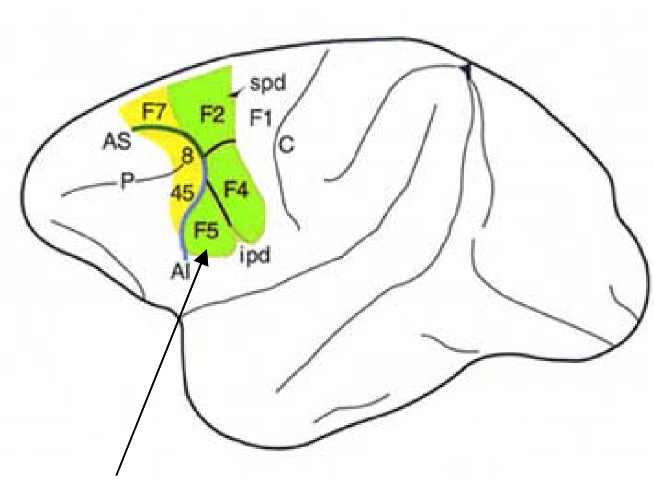
• whole body coordination
• grasping skills
• interaction force control policy

Pysical HRI

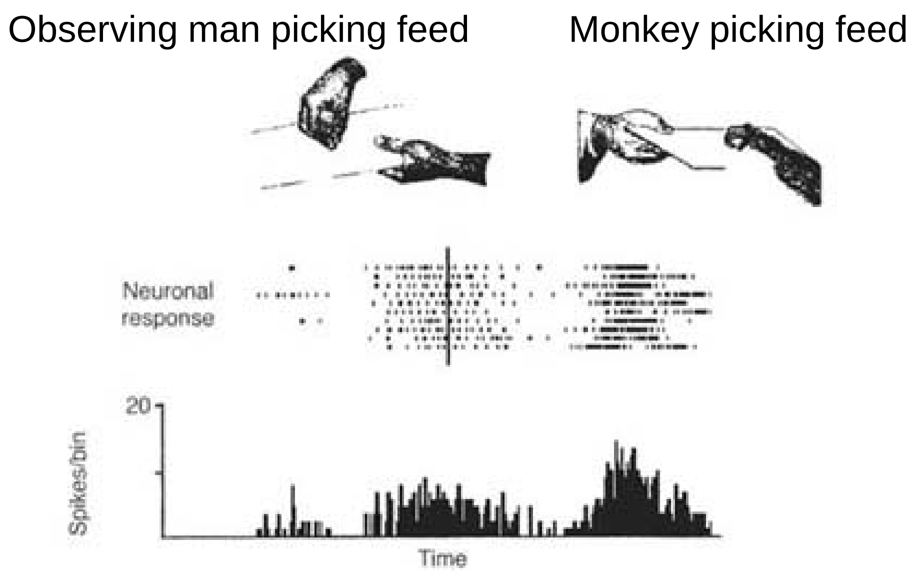
• contact estabilishment
• physical coaching
• haptic assistance in collaboration

Programming by Demonstration

Mirror Neurons



Monkey Brain: F5



Activities of Mirror Neuron（F5）

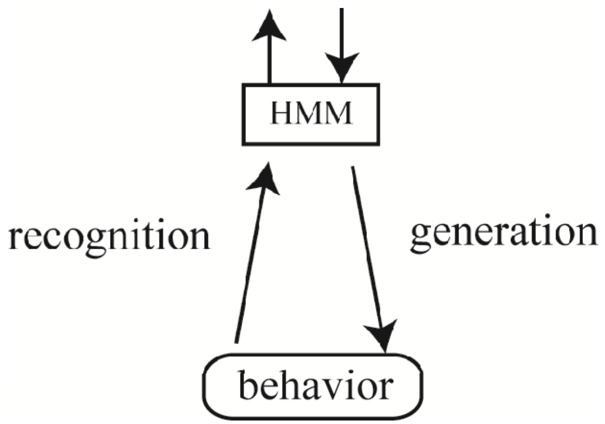
[Gallese et al.1996] [Rizzolatti et al. 1996].

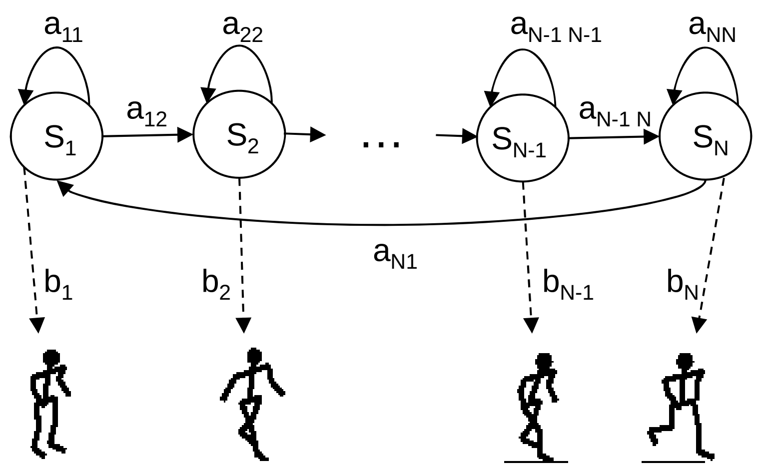
Programming by Demonstration

Mathematical formulation of Mirror Neurons

- Mimesis Model
- Probabilistic representation for spatiotemporal data
- Learning, recognition, generation (a bidirectional computational model)
- Mimesis from partial observation

  [Lee and Nakamura IJRR 2010]





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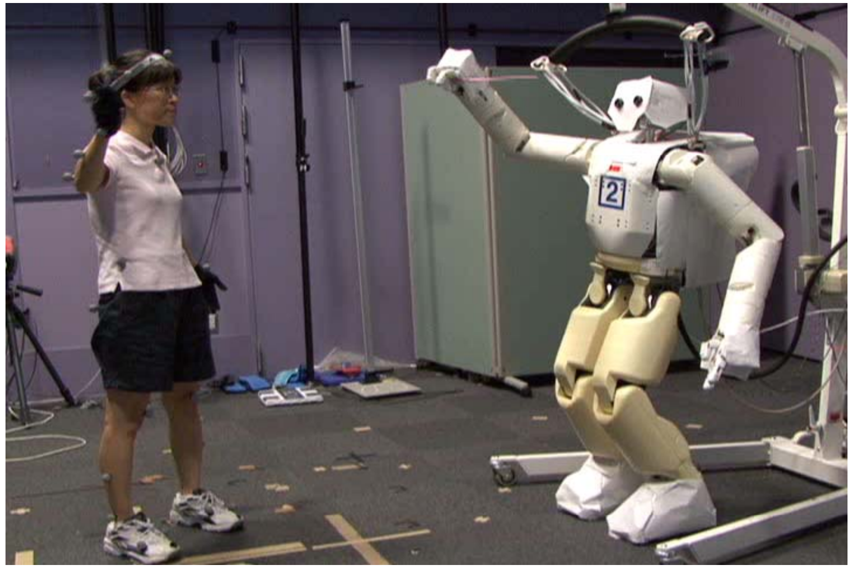
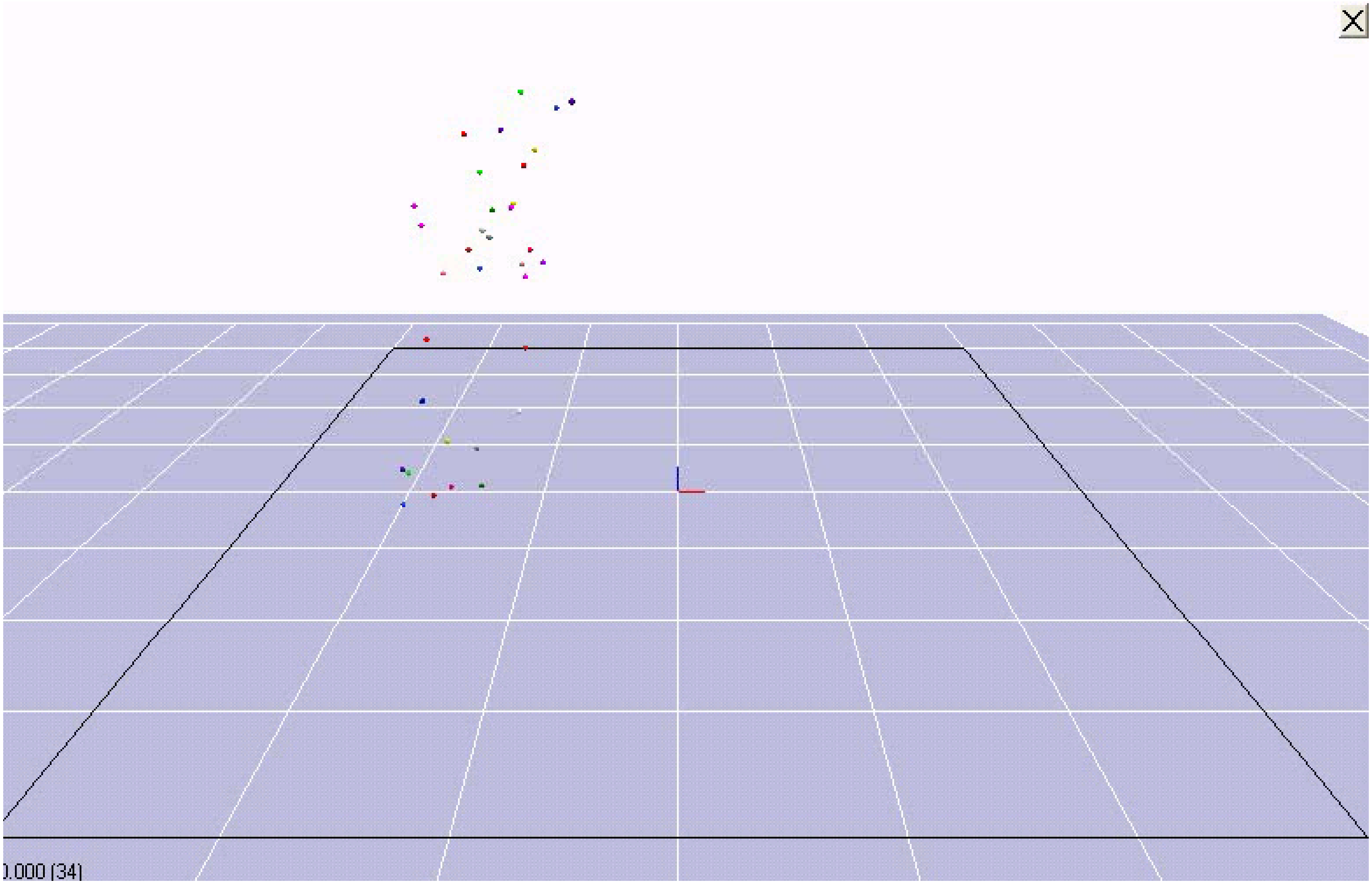


[Lee and Nakamura IJRR 2010]

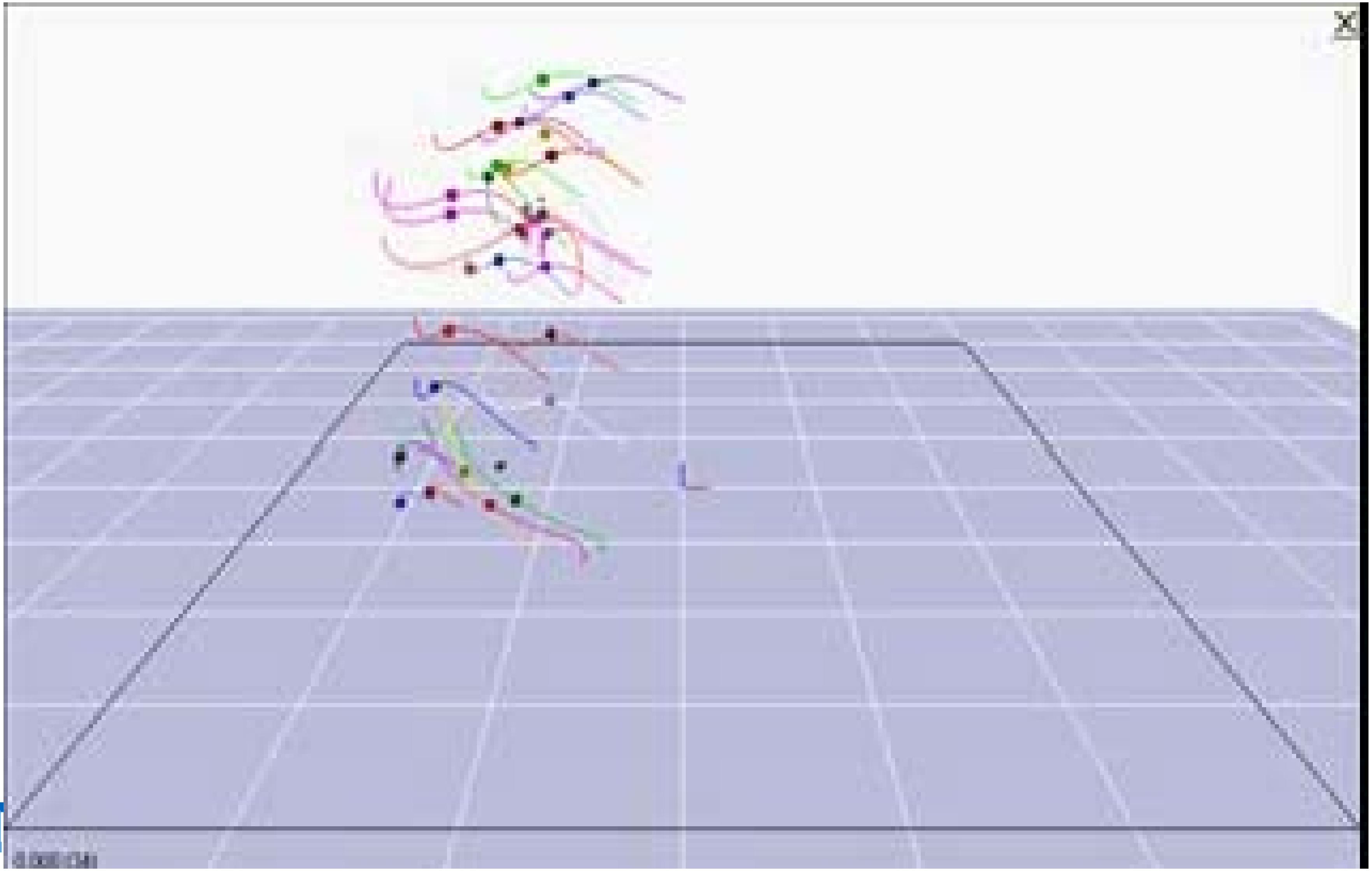
Motion Recostruction from Monocular Vision

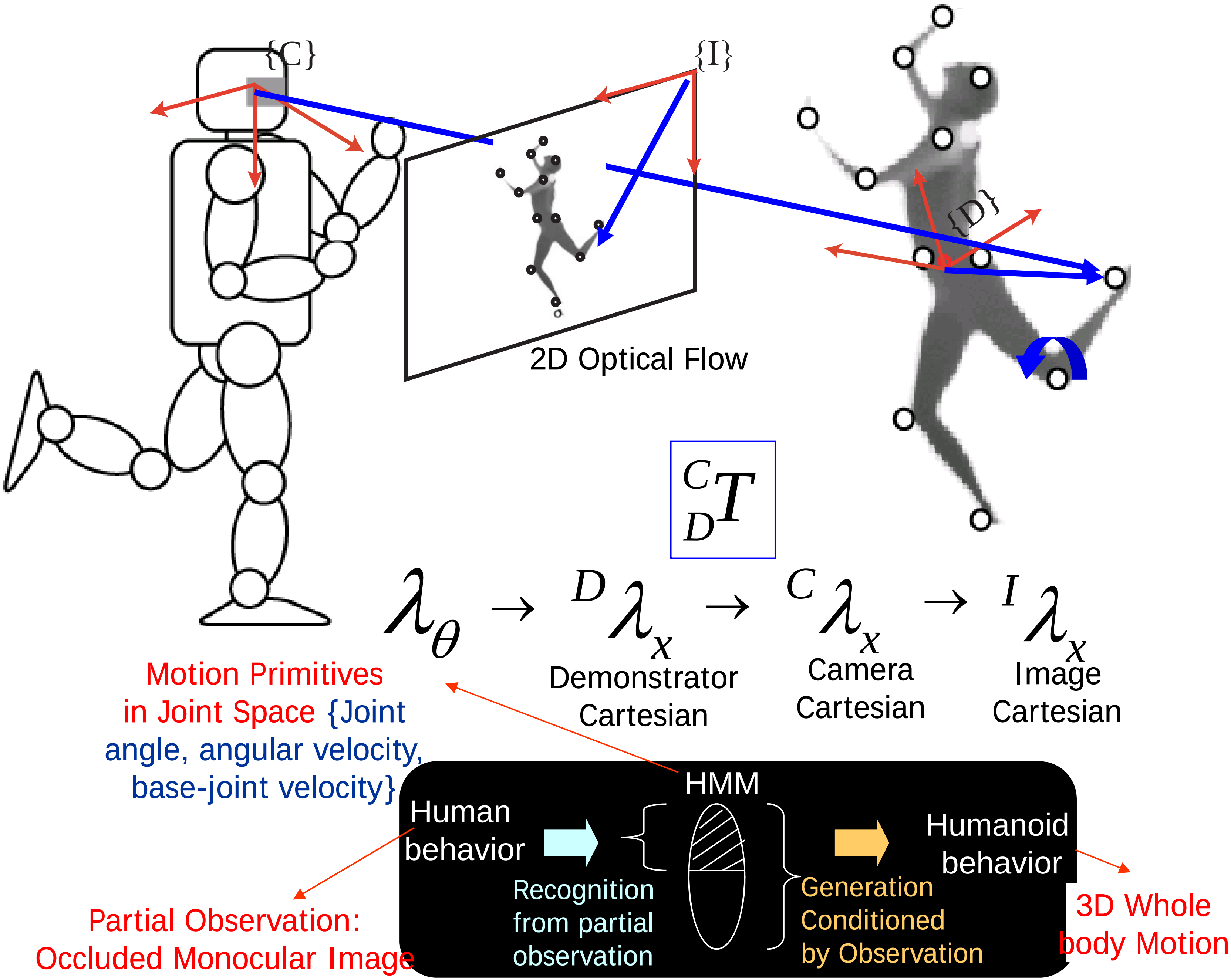


Recognition from Optical Flow

Biological Movement [Johansson 1975]

→ Aim to recognize and recover the motion from the optical flow of feature points




{C}
{I}
2D Optical Flow
{D}
$^{C}_{D}T$
$\lambda_\theta \rightarrow {}^{D}\lambda_x \rightarrow {}^{C}\lambda_x \rightarrow {}^{I}\lambda_x$
Motion Primitives in Joint Space {Joint angle, angular velocity, base-joint velocity}
Demonstrator Cartesian
Camera Cartesian
Image Cartesian
HMM
Human behavior
Recognition from partial observation
Generation Conditioned by Observation
Humanoid behavior
Partial Observation: Occluded Monocular Image
3D Whole body Motion

Motion Recostruction from Monocular Vision

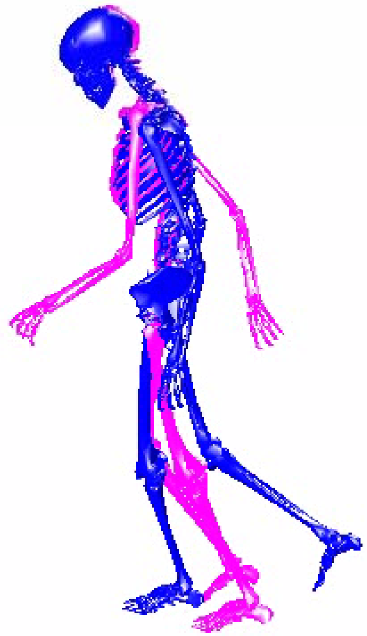
[Lee and Nakamura IROS 2007]

Human perception of biological movements

- Activity recognition
  - 6 motions
- Motion Capturing 56DOF

magenta : True Model

blue: Recovered Model



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Grasping Skill Learning from Motion and Force Data

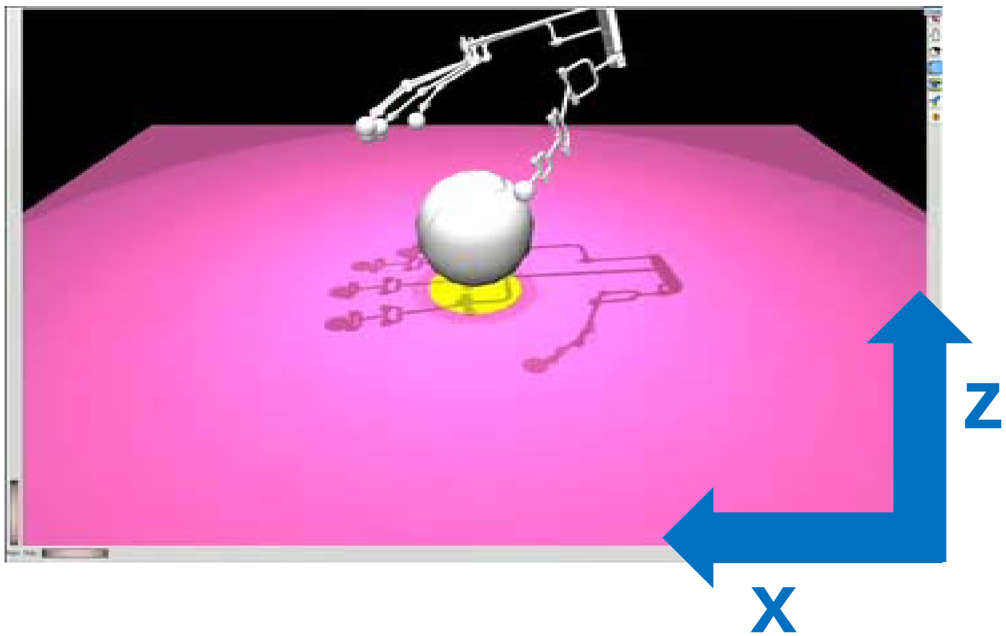
- Learning grasping skills from motion and force patterns
- Teleoperation using Cyberglove, Flock of Birds, & Cybergrasp (Haptic Feedback)

Grasping Skill Reproduction

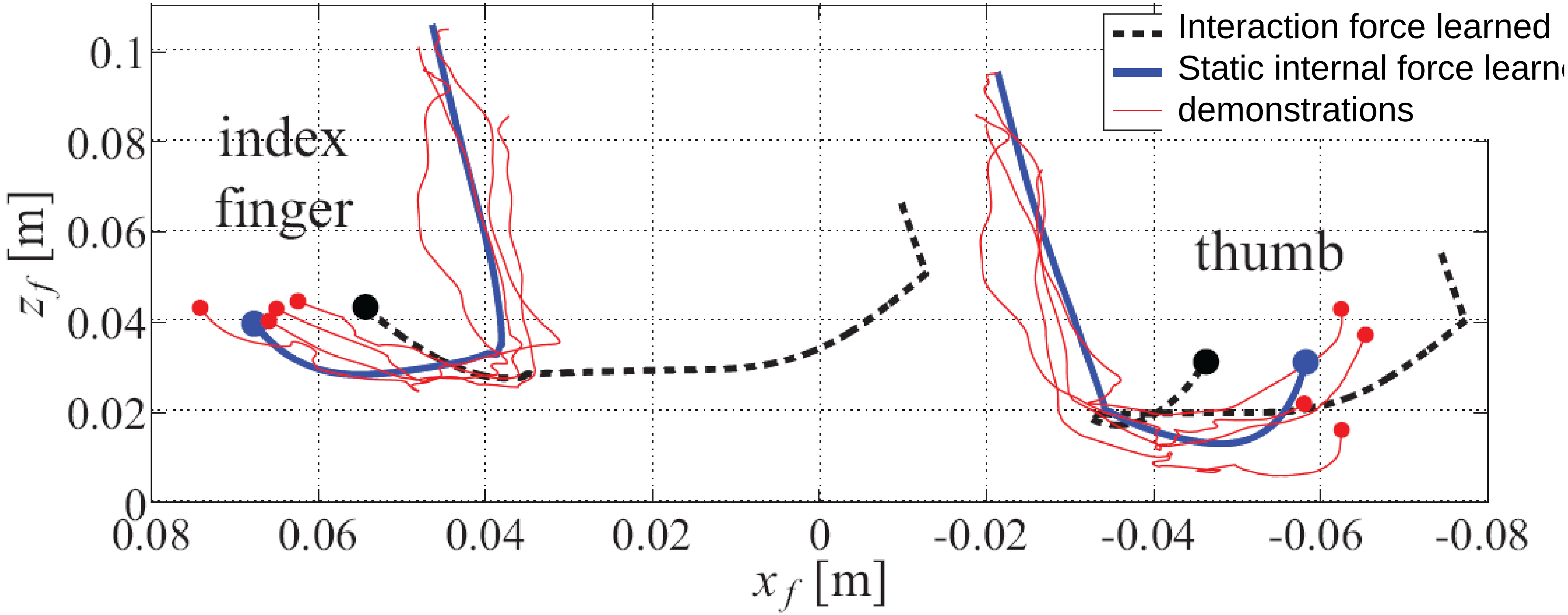
- Parallel position (PD) and force (PI) control

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \tau - J^T f$$

$$\tau = k_p e_p + k_d \dot{e}_p + J^T \{ f_d + k_f \int e_f \, dt \}$$



Learning Interaction vs. Internal Forces

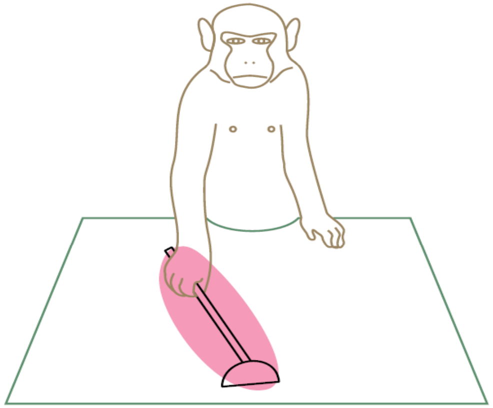


Generalization Capability: Radius

r[cm]	max(f^{in})[N]		$\overline{f}^{in}$[N]		ΔT[ms]	
3.6	3.21	-*	3.20	-*	28	-*
4.0	**3.21**	**5.41**	**3.20**	**5.10**	**11**	**209**
4.8	3.21	7.12	3.20	7.04	39	371
5.6	3.21	12.92	3.20	12.84	88	531
6.0	3.21	-*	3.20	-*	106	-*
Force control	ON	OFF	ON	OFF	ON	OFF

* unsuccessful grasping attempt

Transferring other manipulation skills



- Mechanism for Association of Whole Body Motion from Tool Knowledge
  - Tool in Body Schema [Maravita and Iriki 2004]
  - e.g. Distal-type neurons
  - [Lee et al IROS2008] [Kunori,Lee,NakamuraIROS2009]

- Learning interaction control policies
  - Dynamic movement primitives for parallel position and force control
  - Deformable objects, sculpting tasks
  - [Koropouli, Lee, Hirche, 2011 IROS]

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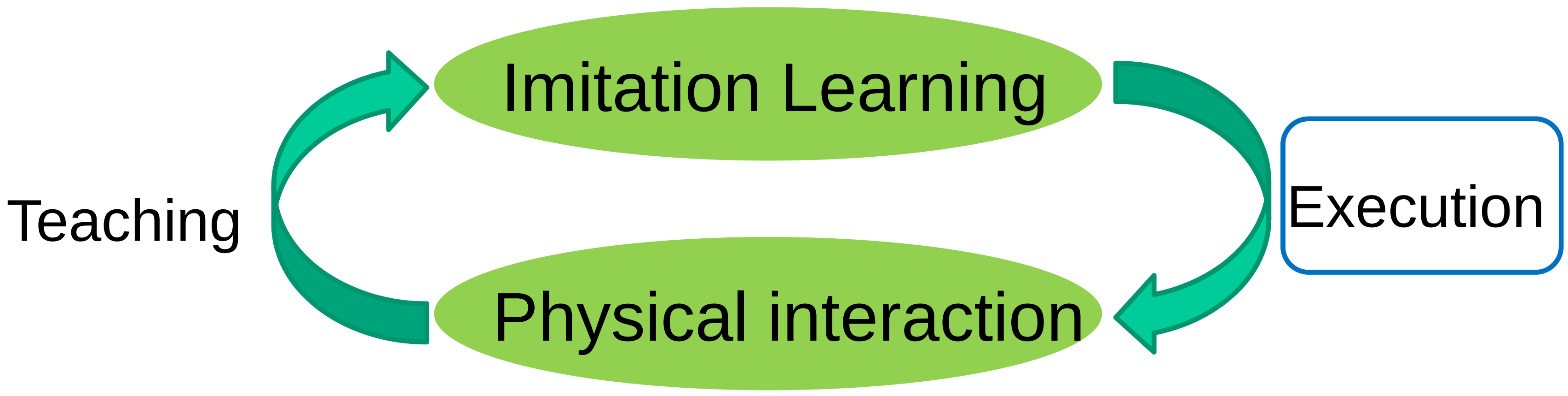
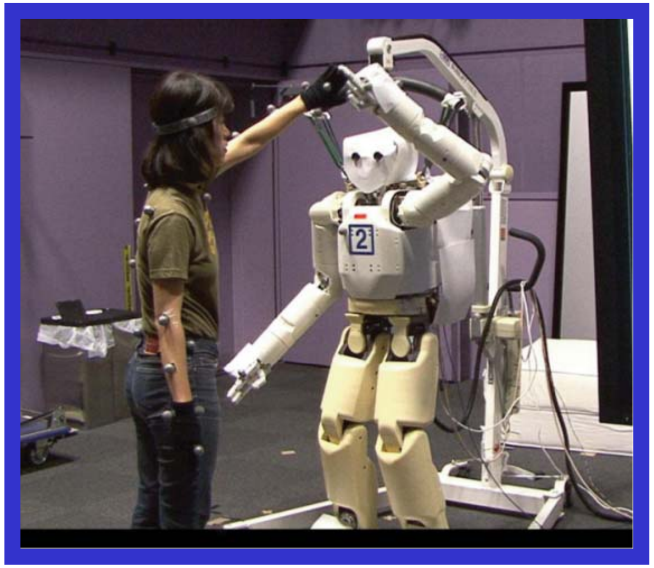
Simple Human Robot Interaction

AUTOMATICA 2010

Collaboration with Dr. Ott, Dr. Albu-Schaeffer, Haddadin, DLR



Mimetic Communication
[Lee et al IJRR 2010]



Motivation: Motion → Interaction

From the Movie “Terminator 2 Judgment Day”

Issues for pHRI:

✓Human motion imitation → Marker Control

✓Learn/Recognize/Generate Motion Primitives → Mimesis Model

✓Learn/Recognize/Generate Interaction Rules → Mimetic Communication Model

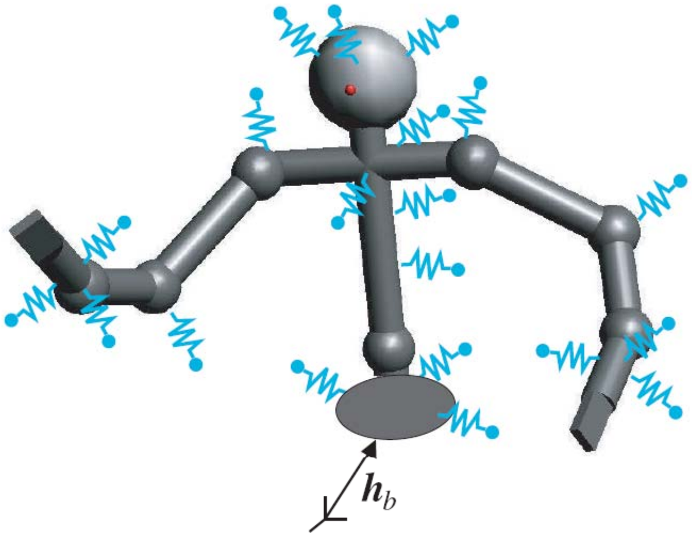
✓Contact transition → Real-time motion adaptation

✓Application : High-Five like interaction

Motion Imitation by Marker Control

Dynamics of the humanoid's upper body on a free-floating base body:

$$M(q)\begin{pmatrix}\ddot{q}\\ \ddot{x}\end{pmatrix}+C(q,\dot{q},\dot{x})\begin{pmatrix}\dot{q}\\ \dot{x}\end{pmatrix}=\begin{pmatrix}\tau\\ f\end{pmatrix}$$



Virtual Springs:

$$V_i(q,x)=\frac{1}{2}k_i\left\|r_{d,i}-r_i(q,x)\right\|^2$$

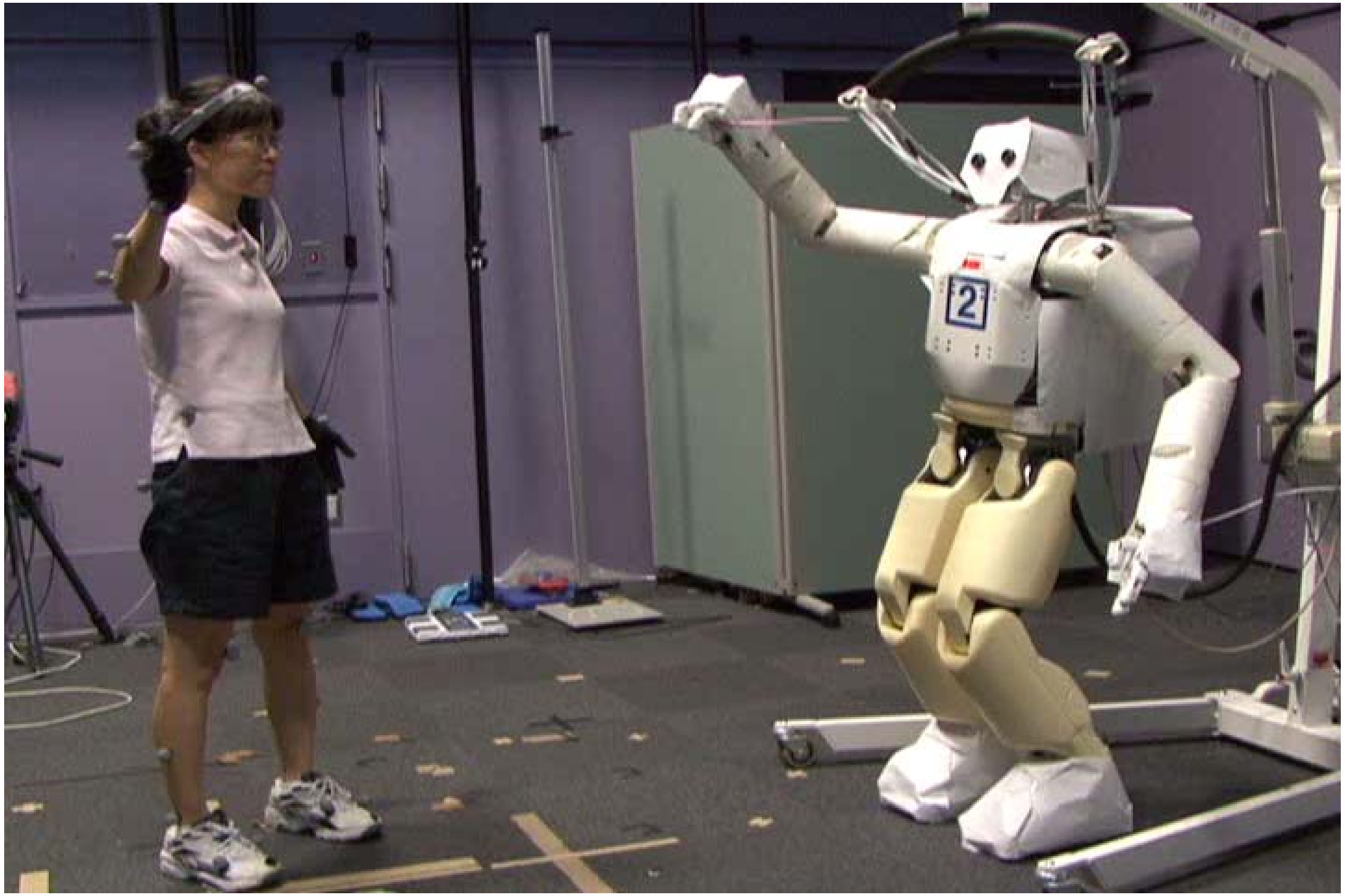
Measured marker position

Marker pos. of the simulation

$$\begin{pmatrix}\tau\\ f\end{pmatrix}=-D(q)\begin{pmatrix}\dot{q}\\ \dot{x}\end{pmatrix}+\sum_{\forall i\in M}k_iJ_i^T(q)(r_{d,i}-r_i(q,x))$$

Motion Imitation by Marker Control

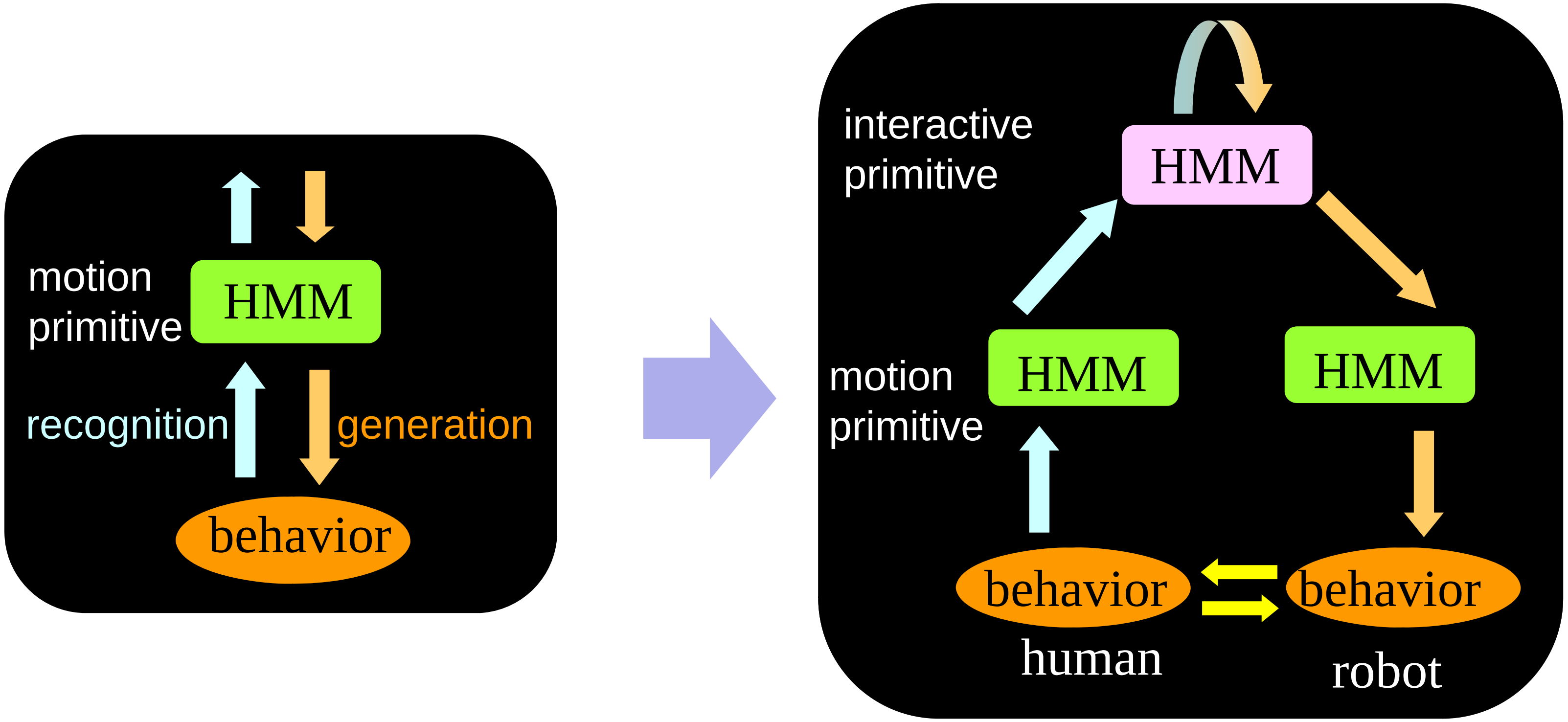
- Upper body Control: Marker trajectory following
- Lower body Control: Balancing, Hip orientation and Height following



[Ott, Lee, Nakamura, "Motion Capture based Human Motion Recognition and Imitation by Direct Marker Control", Humanoids 2008]

Full Body Motion Imitation

Motion Learning → Interaction Learning



Mimetic Communication Model

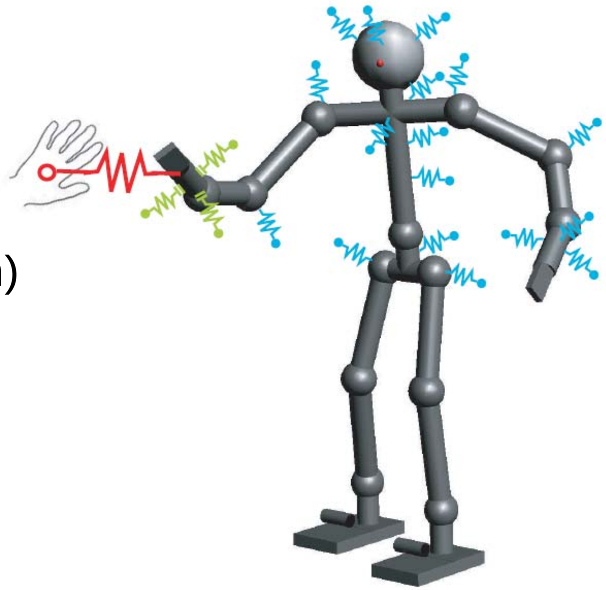
learning, recognition & generation of interaction primitives

- How to react to human’s action
- Contact location & timing

Physical Contact Establishment

- Adaptation of the robot's motion to the desired contact point in real-time:

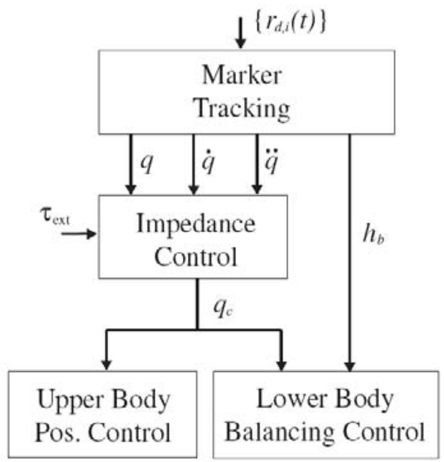
  1) Use additional spring (red) connected to the desired contact point.
  2) Project the forces of the hand's marker springs (green) into a subspace related to the hand orientation.



$$\begin{pmatrix}\tau\\ f\end{pmatrix} = -D(q)\begin{pmatrix}\dot{q}\\ \dot{x}\end{pmatrix} + \sum_{\forall i\in M\setminus H} k_i J_i^T(q)(r_{d,i}-r_i(q,x))$$
$$+\sum_{k=R,L} J_{h,k}^T(q)\begin{pmatrix}\boxed{\delta_k F_{h,k}+}(1-\delta_k)F_{w,k}\\ T_{w,k}\end{pmatrix}$$

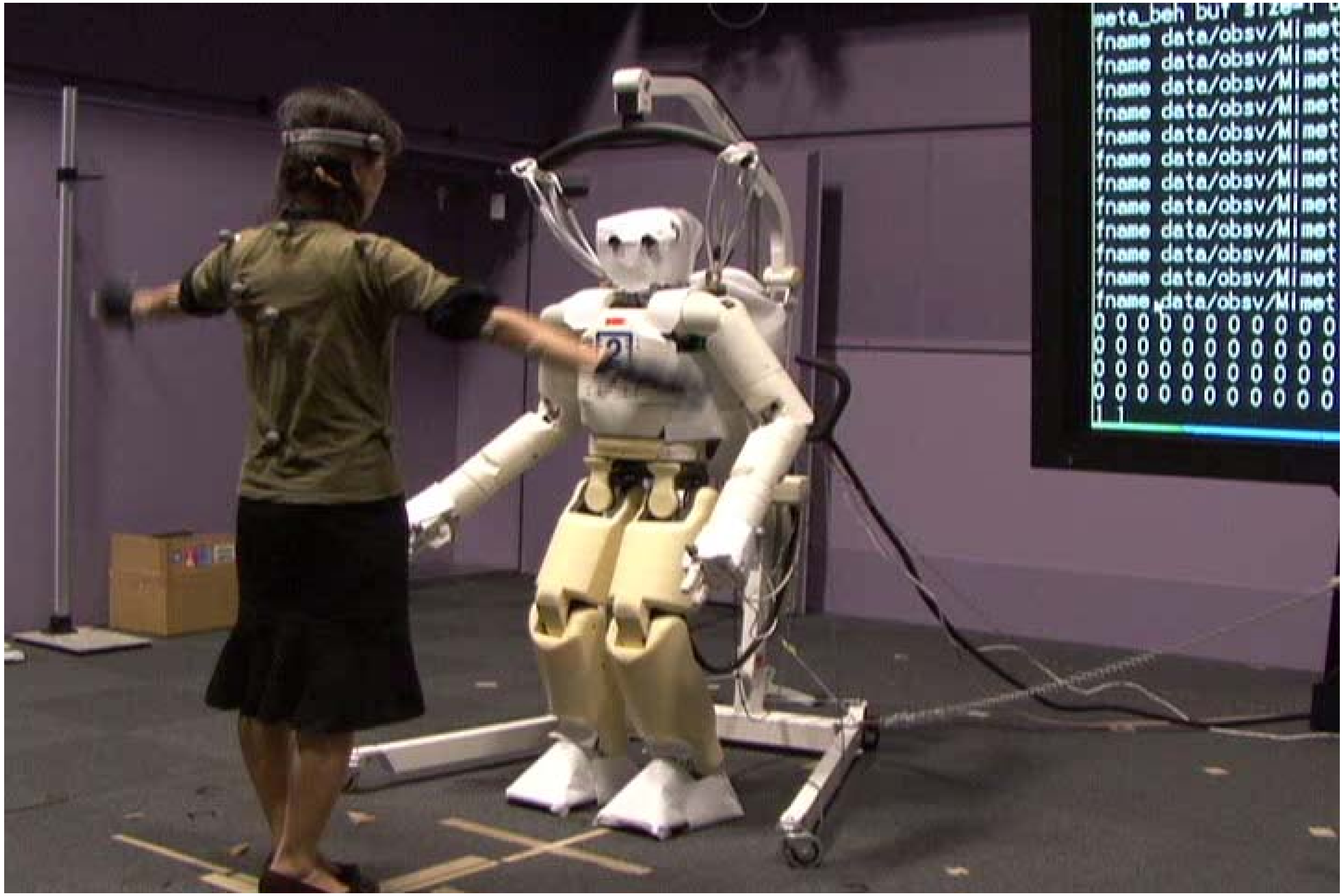
Distance information
→ smooth transition
contact/non-contact

- Position control → (Position based) Impedance control
  - ✓ Limiting the contact forces
  - ✓ Implementing "smooth" contact

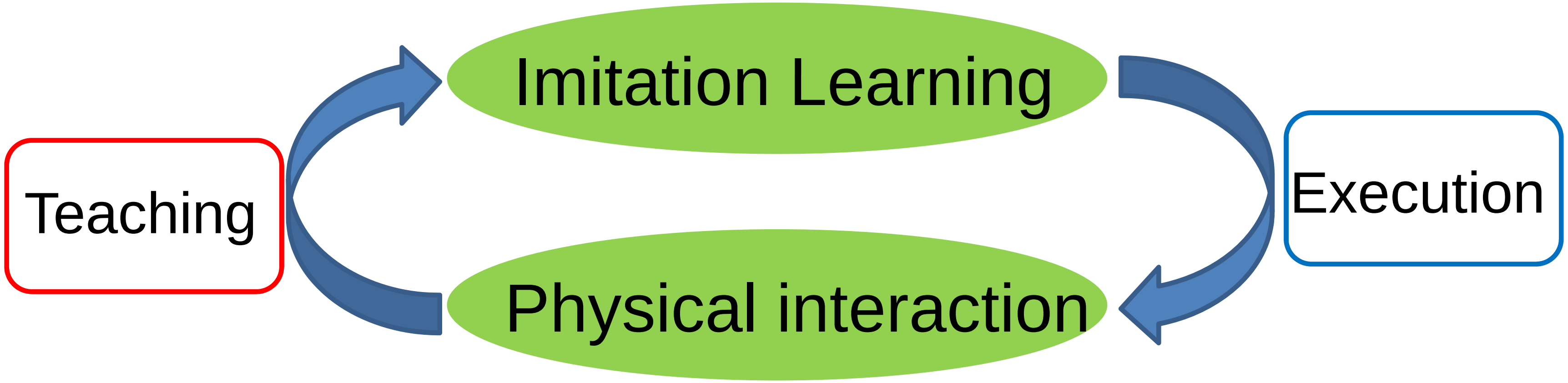


Experiments

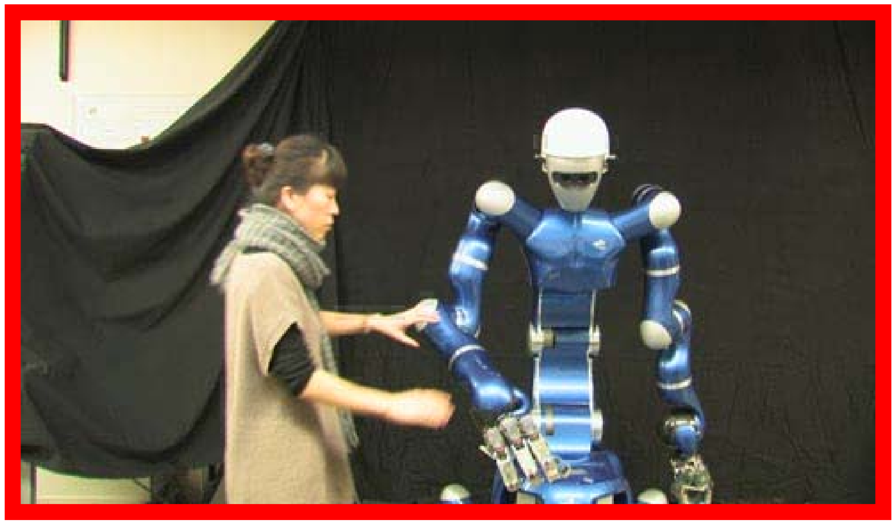
- 12 motion primitives and 8 interaction primitives
- Implementation to humanoid robot (38DOF), 30DOF is controlled.
- Position based Impedance Control to the Upper body



[Lee, Ott, Nakamura, ICRA 2009] [Lee, Ott, Nakamura, IJRR 2010]



Physical coaching
[Lee & Ott, Autonomous Robots 2011]



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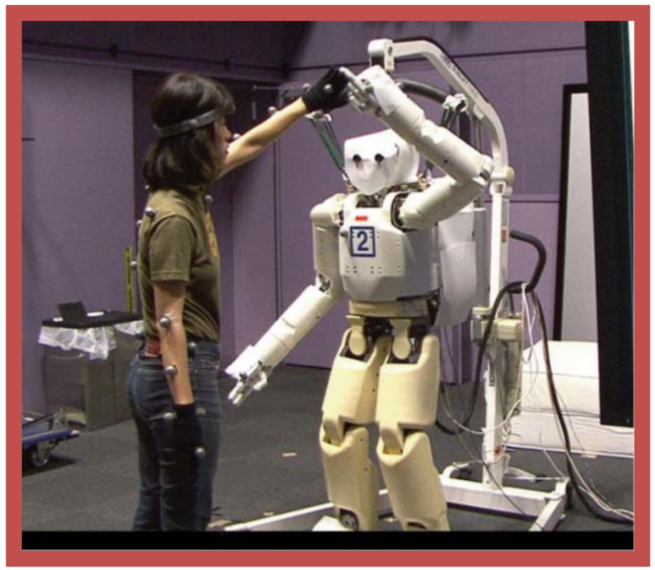
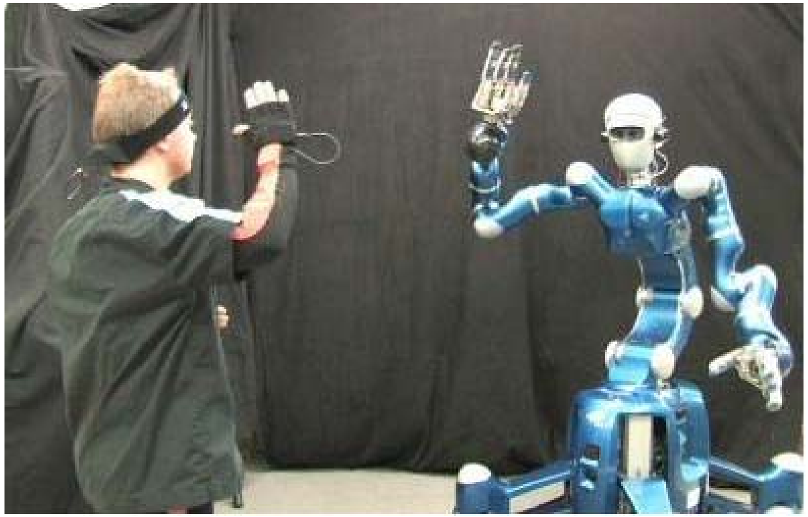
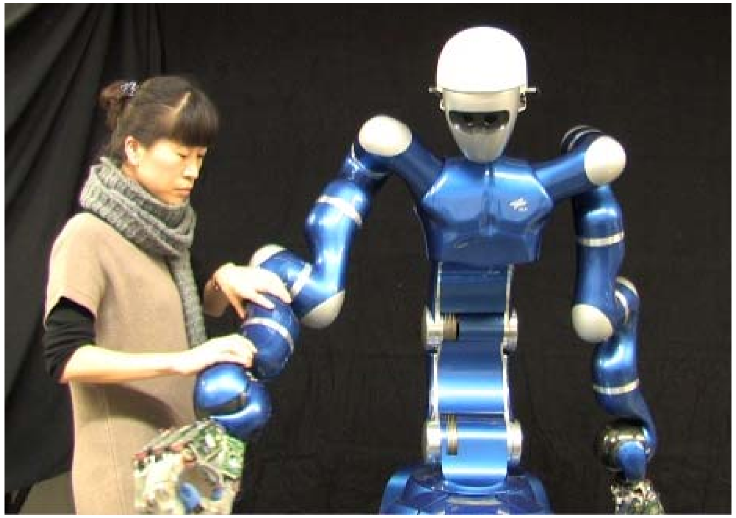
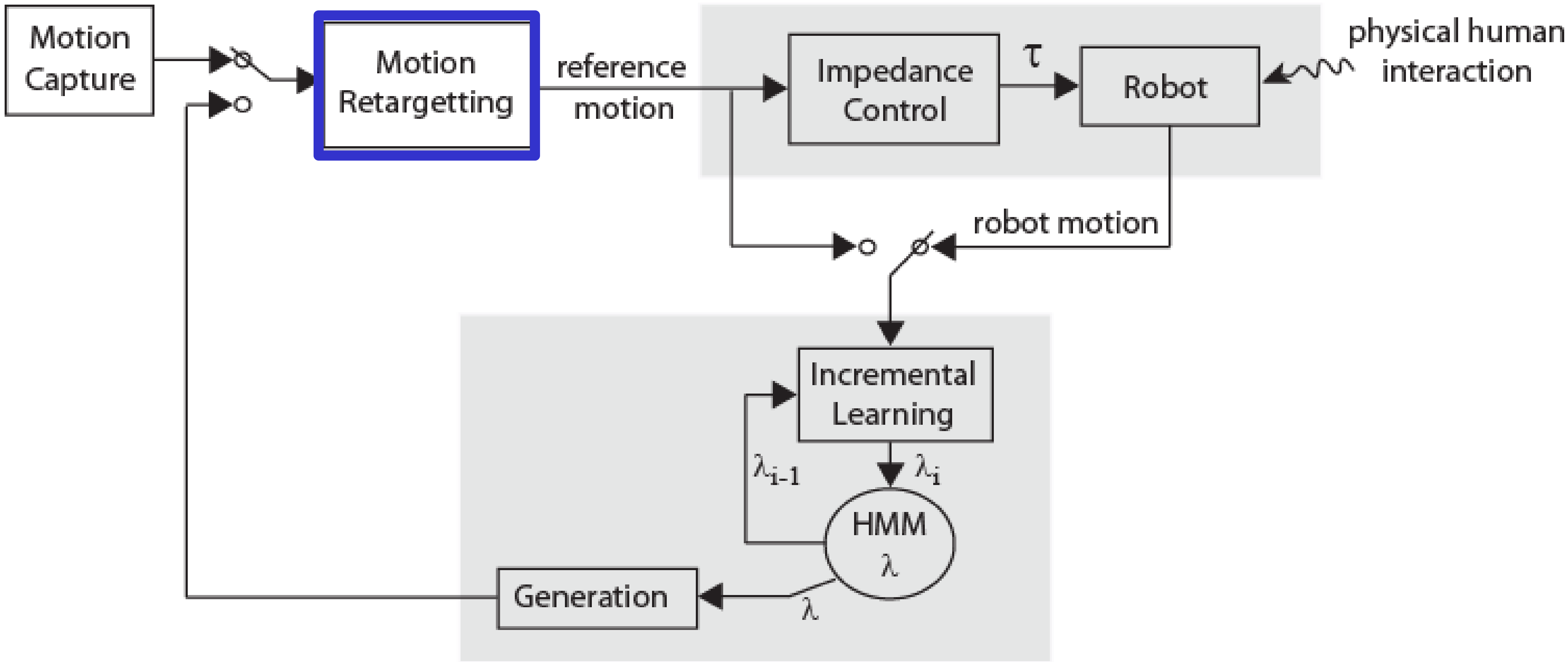
[Lee et al IJRR 2010]



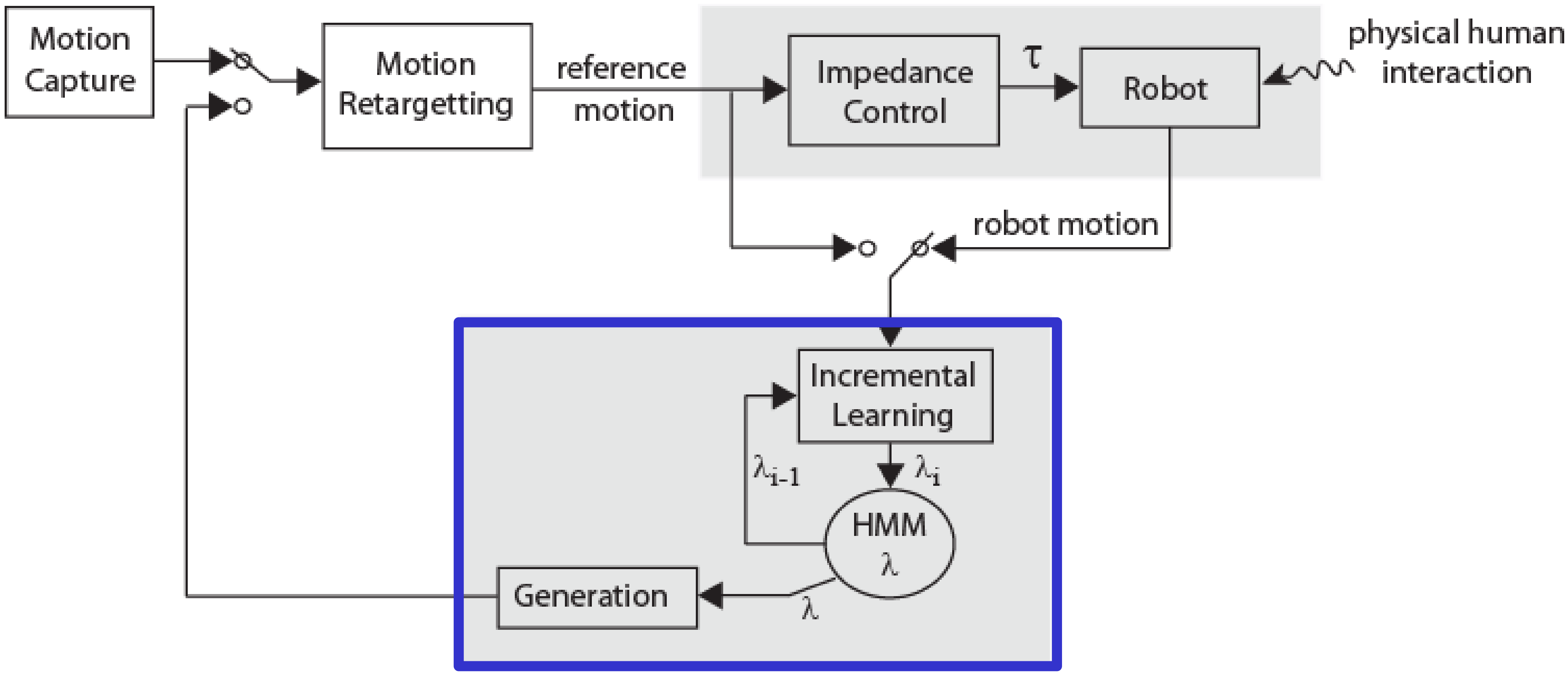
Demonstration Technique

Observational Demo		Kinesthetic Demo	
			
+	synchronized whole body motion	• Unsynchronized body motion • Accidental disturbance	−
−	correspondence problem	No correspondence problem	+

Overview



Motion Capture
Motion Retargetting
reference motion
Impedance Control
τ
Robot
physical human interaction
robot motion
Incremental Learning
λ_{i-1}
λ_i
HMM
λ
λ
Generation



Multi observations (reproduced & observed)

weighting factor

$$\pi_i = \sum_{e=1}^{E} \omega^e \gamma_i^e(1)$$

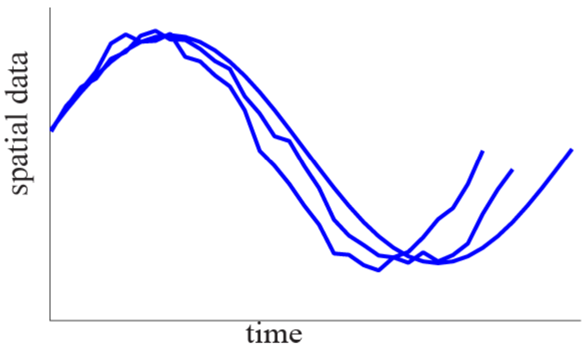
$$a_{ij} = \frac{\sum_{e=1}^{E} \omega^e \sum_{t=1}^{T_e-1} \xi_{ij}^e(t)}{\sum_{e=1}^{E} \omega^e \sum_{t=1}^{T_e-1} \gamma_i^e(t)}$$

$$\sum_{e=1}^{E} \omega^e = 1$$

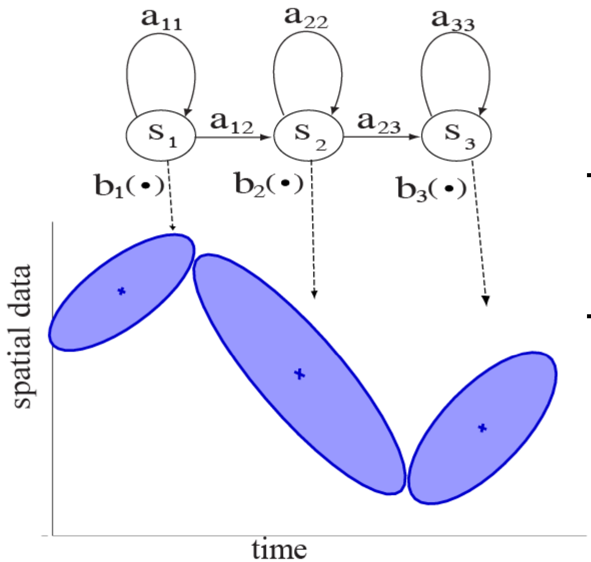
$${}^s\mu_i = \frac{\sum_{e=1}^{E} \omega^e \sum_{t=1}^{T_e} \gamma_i^e(t)\, {}^s o^e(t)}{\sum_{e=1}^{E} \omega^e \sum_{t=1}^{T_e} \gamma_i^e(t)}$$

$${}^s\Sigma_i = \frac{\sum_{e=1}^{E} \omega^e \sum_{t=1}^{T_e} \gamma_i^e(t)({}^s o^e(t) - {}^s\mu_i)({}^s o^e(t) - {}^s\mu_i)^T}{\sum_{e=1}^{E} \omega^e \sum_{t=1}^{T_e} \gamma_i^e(t)}$$

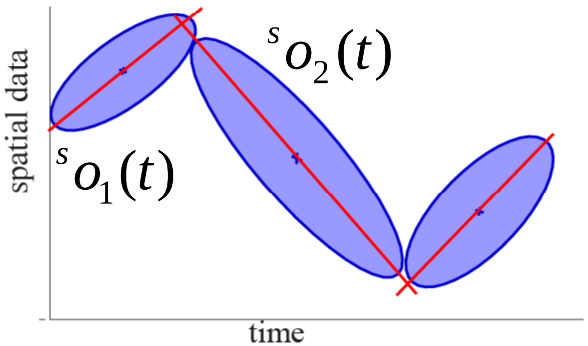
Motion Primitives



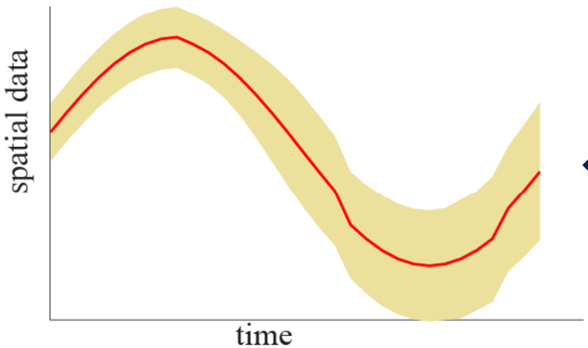
Data



HMM



Gaussian regression



- No preprocessing for learning & recognition
- Correlation of temporal & spatial data

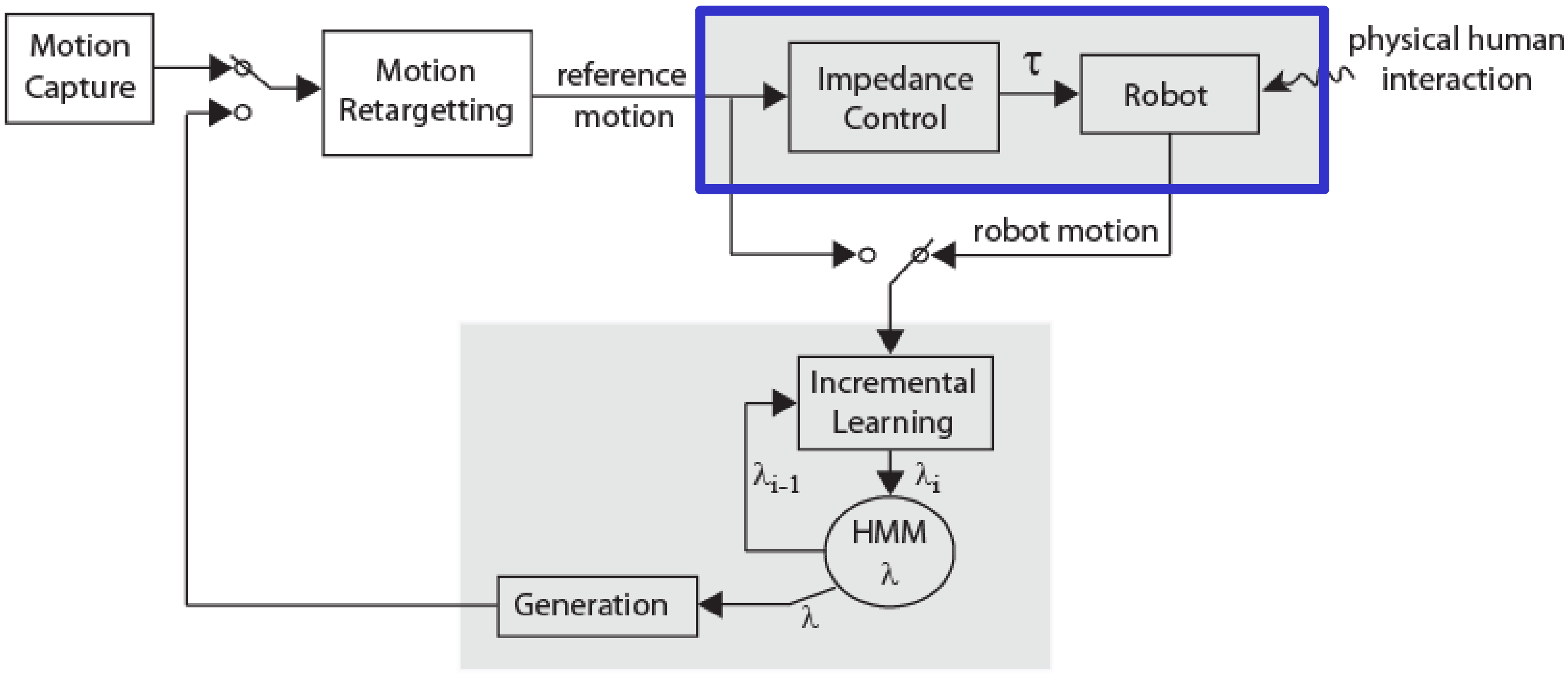
$$T = {}^{t}\mu_N + \frac{-3+\sqrt{1+48\,{}^{t}\Sigma_N}}{4}$$

$$\zeta_i(t) = P(q_t = S_i \mid {}^{t}O, \lambda)$$

$${}^{s}o(t) = \sum_{i=1}^{N} \zeta_i(t)\,{}^{s}o_i(t)$$

$${}^{s|t}\Sigma(t) = \sum_{i=1}^{N} \zeta_i(t)\,{}^{s|t}\Sigma_i(t)$$

- No slower filter for smoothing trajectory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robot motion
Incremental Learning
λi-1
λi
HMM
λ
Generation
λ

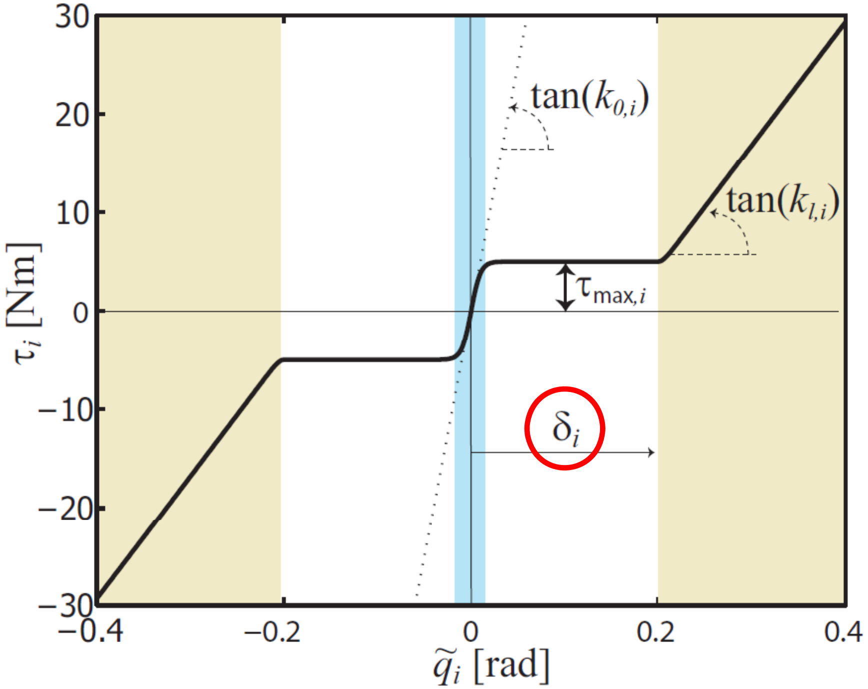
Compliant Control

Requirements

1. Precise tracking in free motion for motion primitive generation
2. Compliant interaction with low stiffness during teaching
3. Refinement tube: Limit the allowed deviation from the motion primitive

Integration into customized impedance controller

$$\tau = g(q) + M(q)\ddot{q}_d + C(q,\dot{q})\dot{q}_d - D\dot{\tilde{q}} - s(\tilde{q})$$

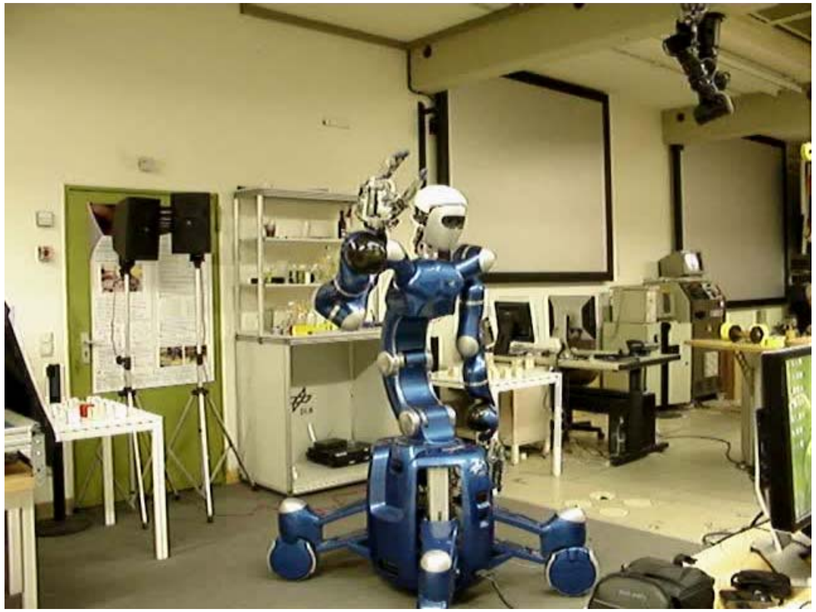


$$\delta = 3\sqrt{^{s|t}\Sigma(t)} + \varepsilon$$

Experiments – Physical Coaching

Impedance Control and Motion Refinement Tube

Without tube

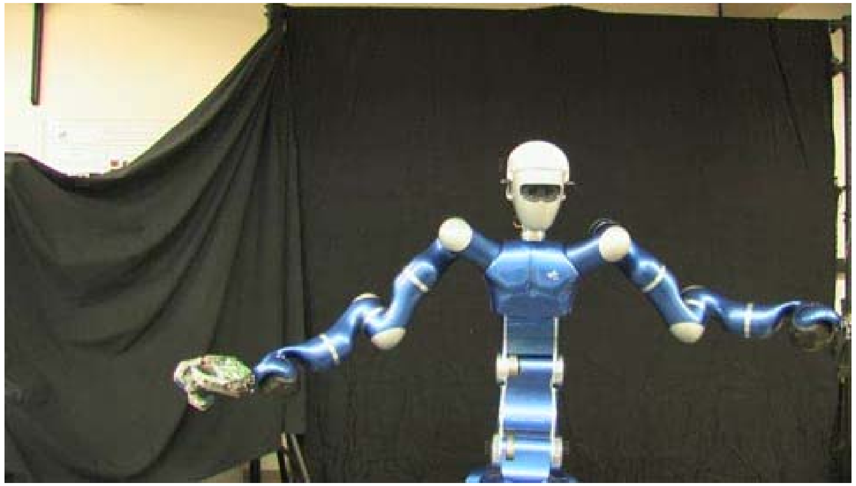


Undesired accidental disturbance

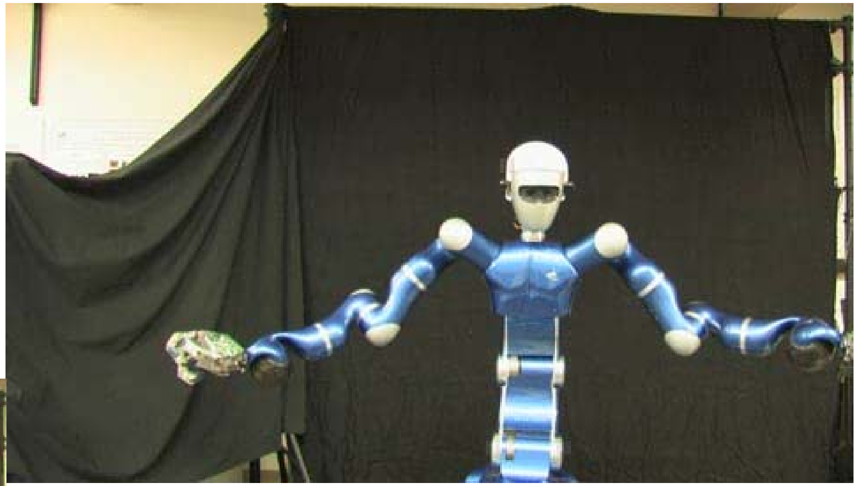
With tube

Guide for easy physical coaching

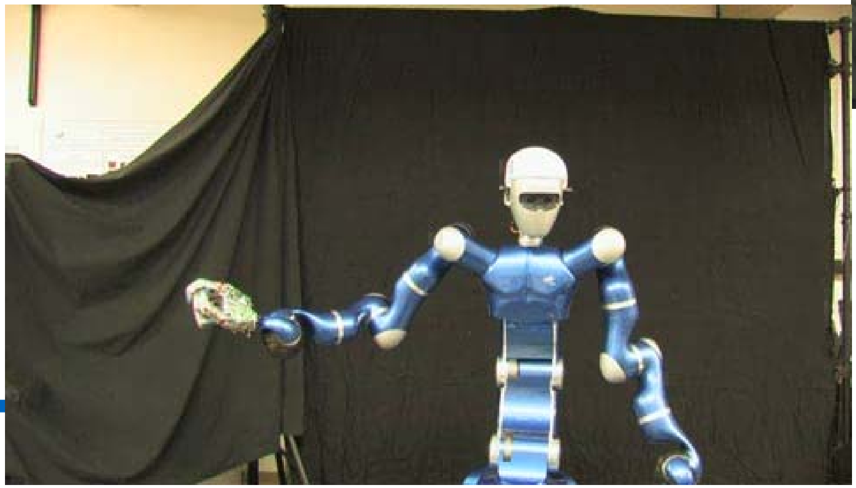
Incremental Refinement



Motion Retargeting from human body motion

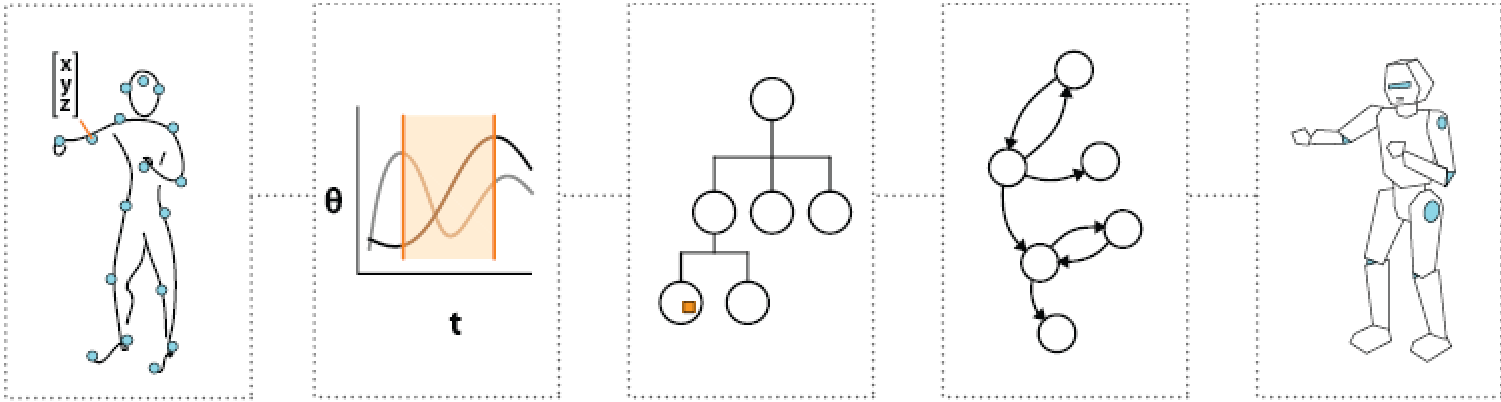


Motion Refinement by Kinesthetic Coaching



Refined Robot Motion

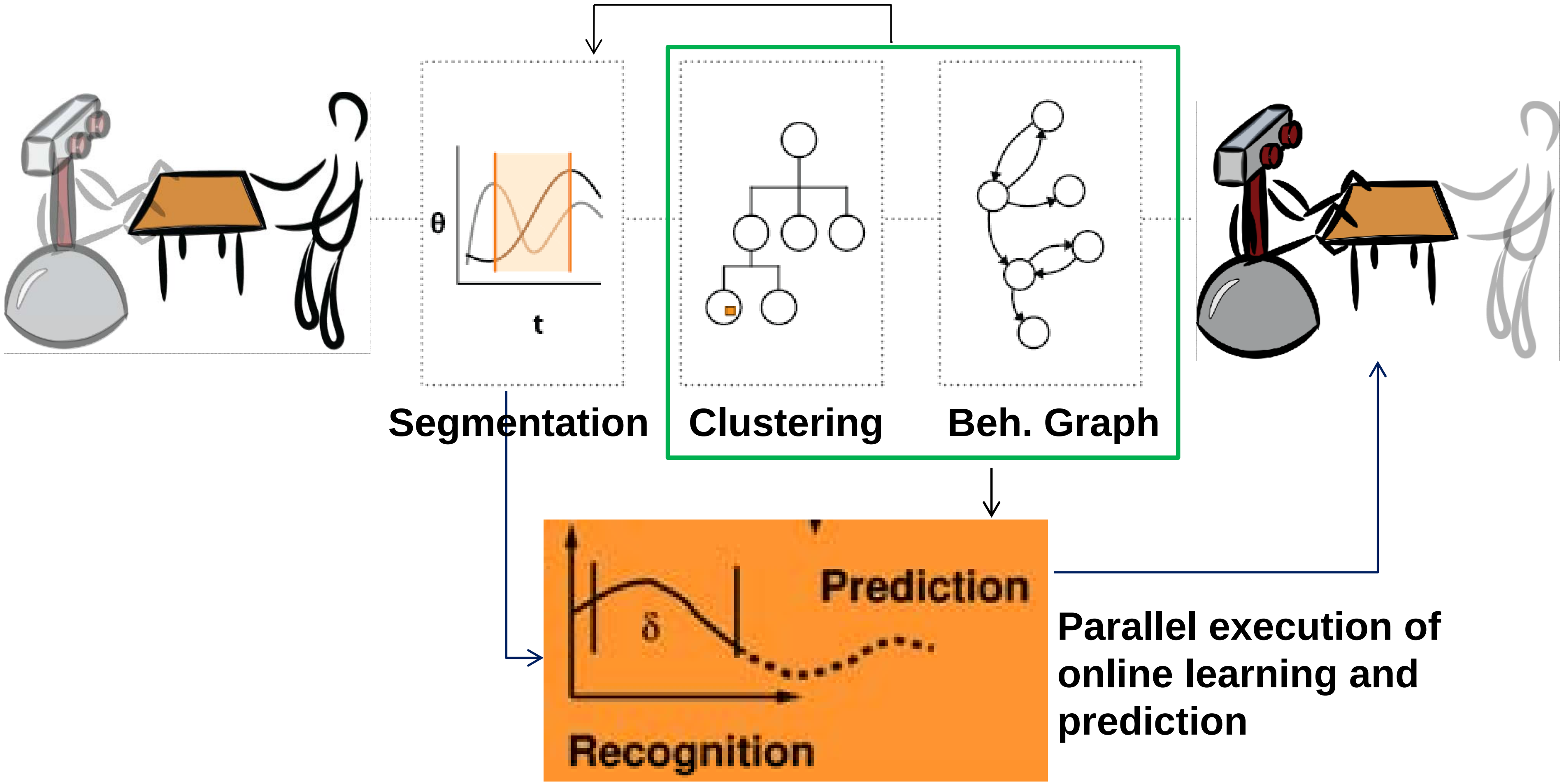
Incremental Learning : Unsupervised Segmentation and Clustering



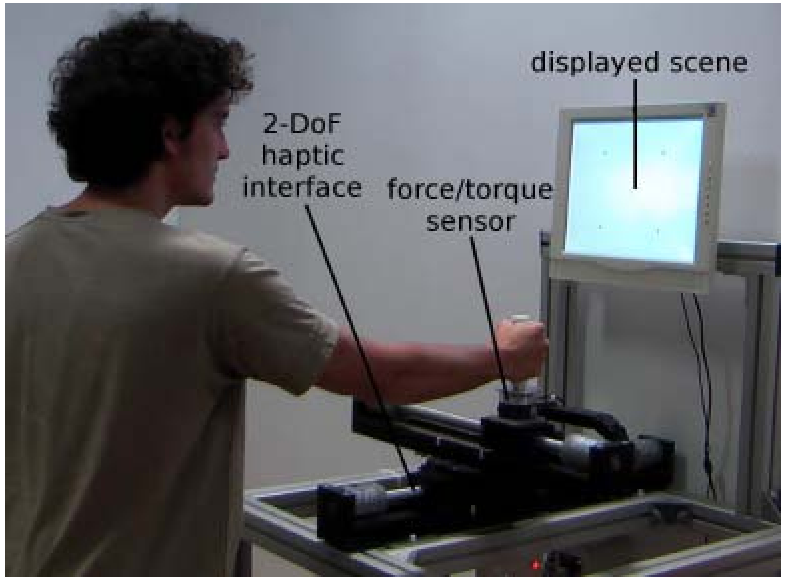
Segmentation **Clustering** **Beh. Graph**

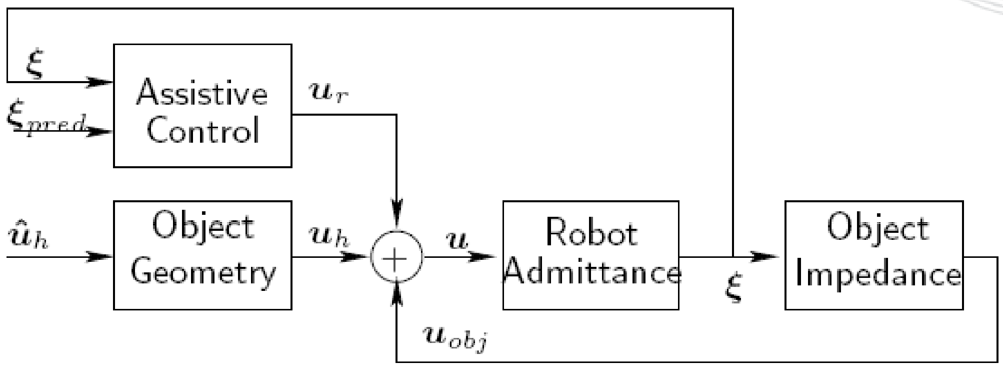
[Kulic, Lee, Ott, Nakamura, IJRR 2011]

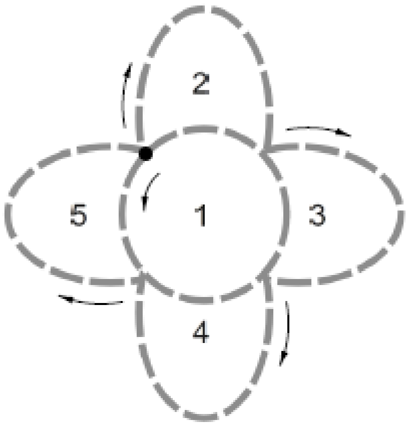
Parallel Learning, Prediction, Execution



Experiment in 2D Virtual Scenario

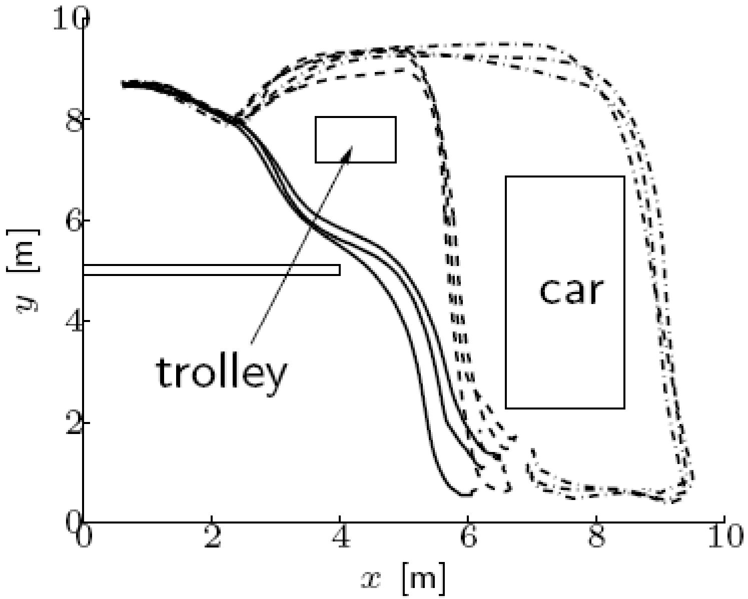






- 2D virtual scenario
- No initial knowledge
- As learning proceeds, prediction starts
- Robot behavior is changed from “passive follower” to “load sharing”

Experiment



Risk Sensitive Stochastic Optimal Control for Haptic Assistance
[Medina, Lee, Hirche, ICRA 2012]

$$\gamma(\theta) = -2\theta^{-1} \ln \mathbb{E}[\exp^{-\frac{1}{2}\theta J}]$$

$$\text{where } J = \sum_{k=1}^{T} \boldsymbol{z}_k^{\mathrm{T}} Q \boldsymbol{\Sigma}_{\xi_{pred,k}}^{-1} \boldsymbol{z}_k + \boldsymbol{u_r}_k^{\mathrm{T}} R \boldsymbol{u_r}_k$$

Conclusion

Movements

• mirror neuron → mimesis model
• self vs others : motion skills learning & recognition

Manipulation

• grasping skills from position and force patterns

Pysical HRI

• learning pHRI tasks (give-me-five)
• physical coaching for incremental learning
•Human intention recogntiion for collaboration

SAPHARI

Safe and Autonomous Physical Human-Aware Robot Interaction

SEVENTH FRAMEWORK PROGRAMME

Thank you
for your attention

Additional Questions?
Email: dhlee@tum.de

Acknowledgement

www.cotesys.org