Exploration and Imitation for the Acquisition of Object-Action Complexes on Humanoids

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ARMAR-III in a Kitchen Environment

Limitations and shortcuts

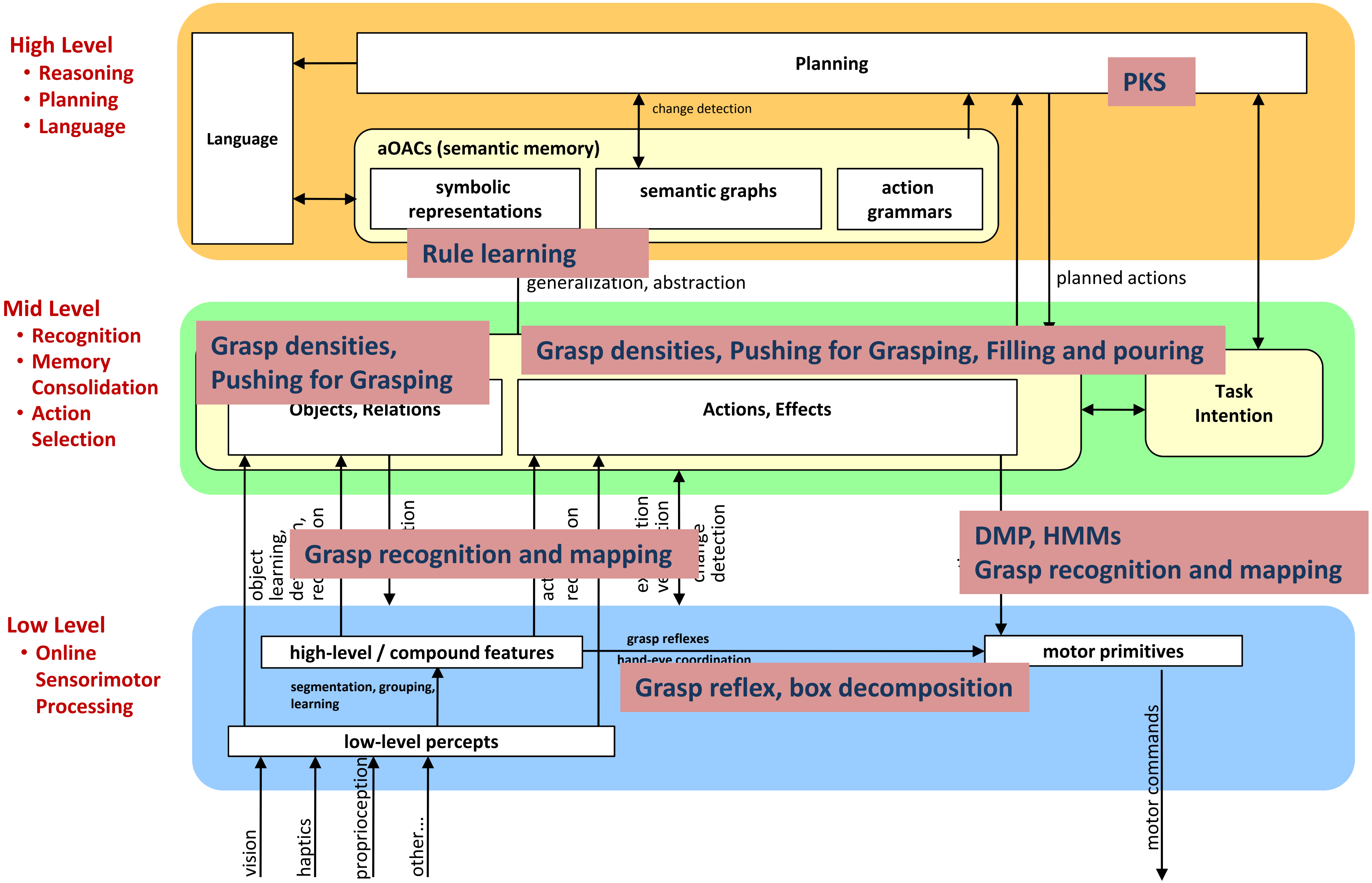
- Objects
  - Complete model knowledge (shape, color, texture)
  - Only visual representation is used

  - How to learn new objects?
  - How to acquire multi-sensory representations of objects?

- Actions
  - “engineering” approaches as place holders for learned primitive actions.

  - How to learn new actions?
  - How to adapt actions to new situations?
  - How to chain different actions to achieve complex tasks?

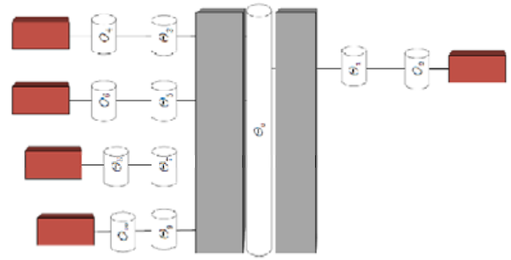
Underlying Control Architecture



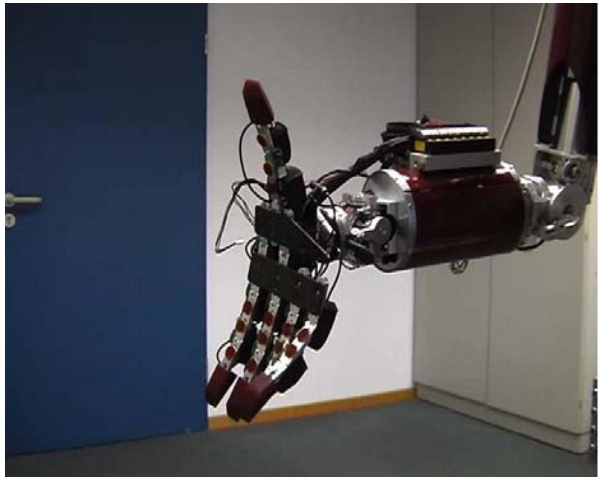
In this talk

- Autonomous Exploration:
  - Visually-guided haptic exploration
  - Visual object exploration and search
- Coaching and Imitation
  - Learning from Observation
  - Goal-directed Imitation

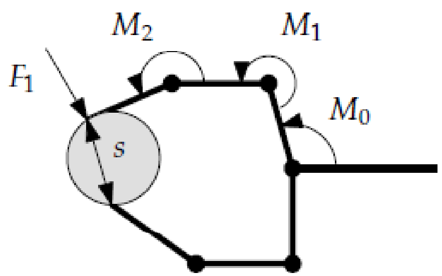
Hand: available skills



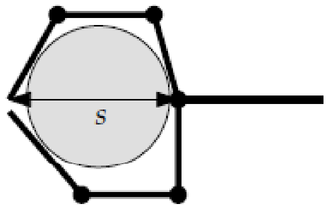
- Direct Kinematics
- Inverse Kinematics
- Position/force control



- Detection of contact and “objectness”
- Assessment of object deformability



Precision grasps:
Distance between
fingertips

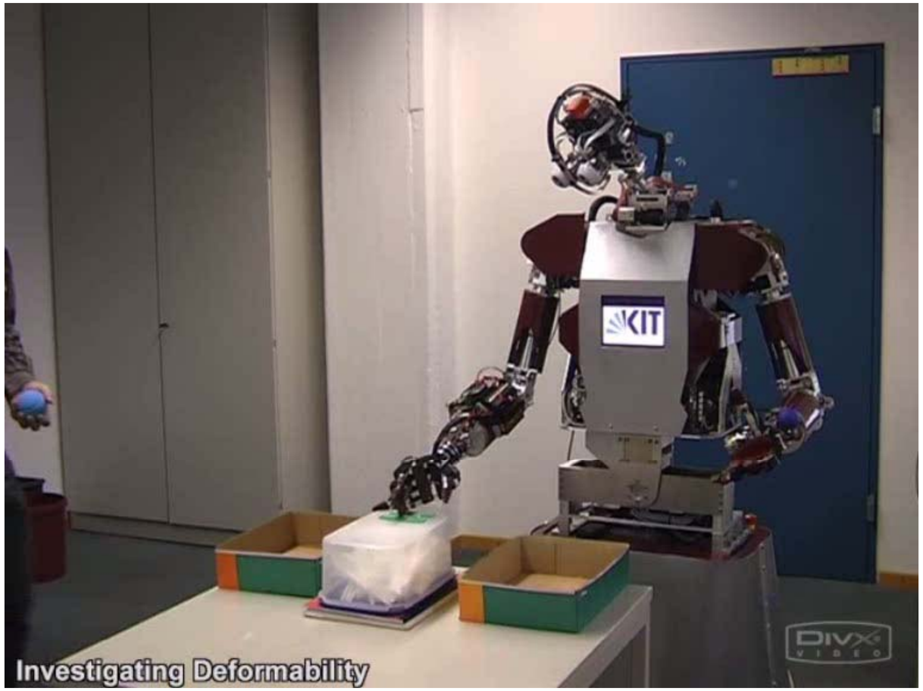


Power grasps:
Distance between
fingertips and palm

Multisensorial object exploration

- Fusion of tactile, proprioceptive and visual sensor data with a five-fingered hand

Verification of object size

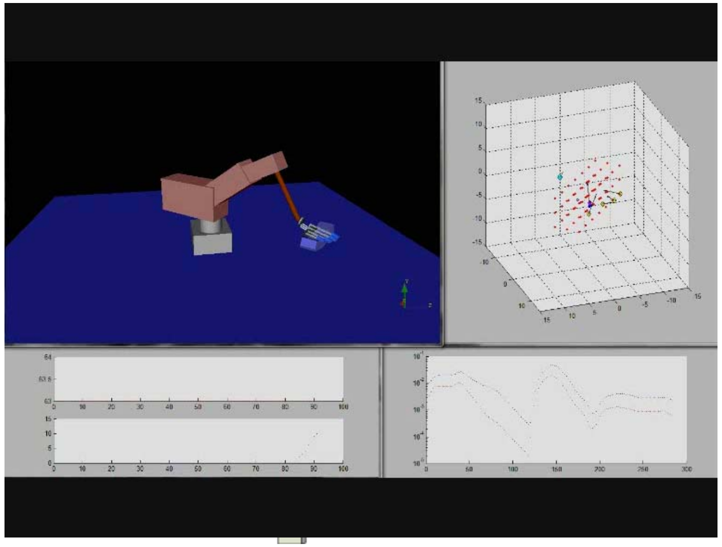


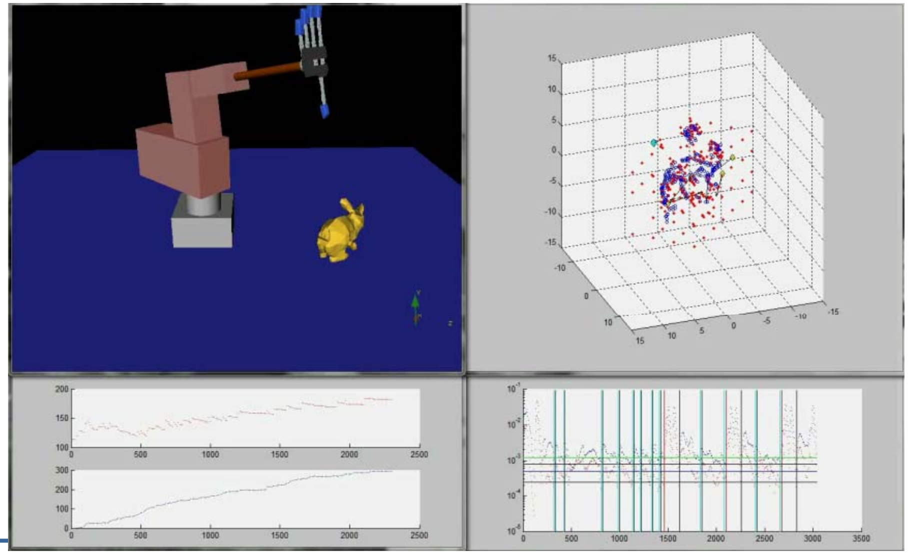
Verification of object deformability

Tactile Object Exploration

- Potential field approach to guide the robot hand along the object surface
- Oriented 3D point cloud from contact data
- Extract faces from 3D point cloud
  - Geometric feature filter pipeline
    - Parallelism
    - Minimum face size
    - Mutual visibility
    - Face distance

→ Association between objects and actions (grasps) → Symbolic grasps (grasp affordances)

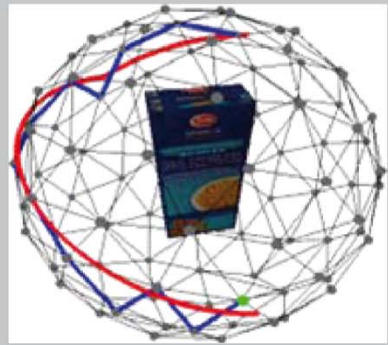




Active Visual Object Exploration and Search

Exploration

Representation

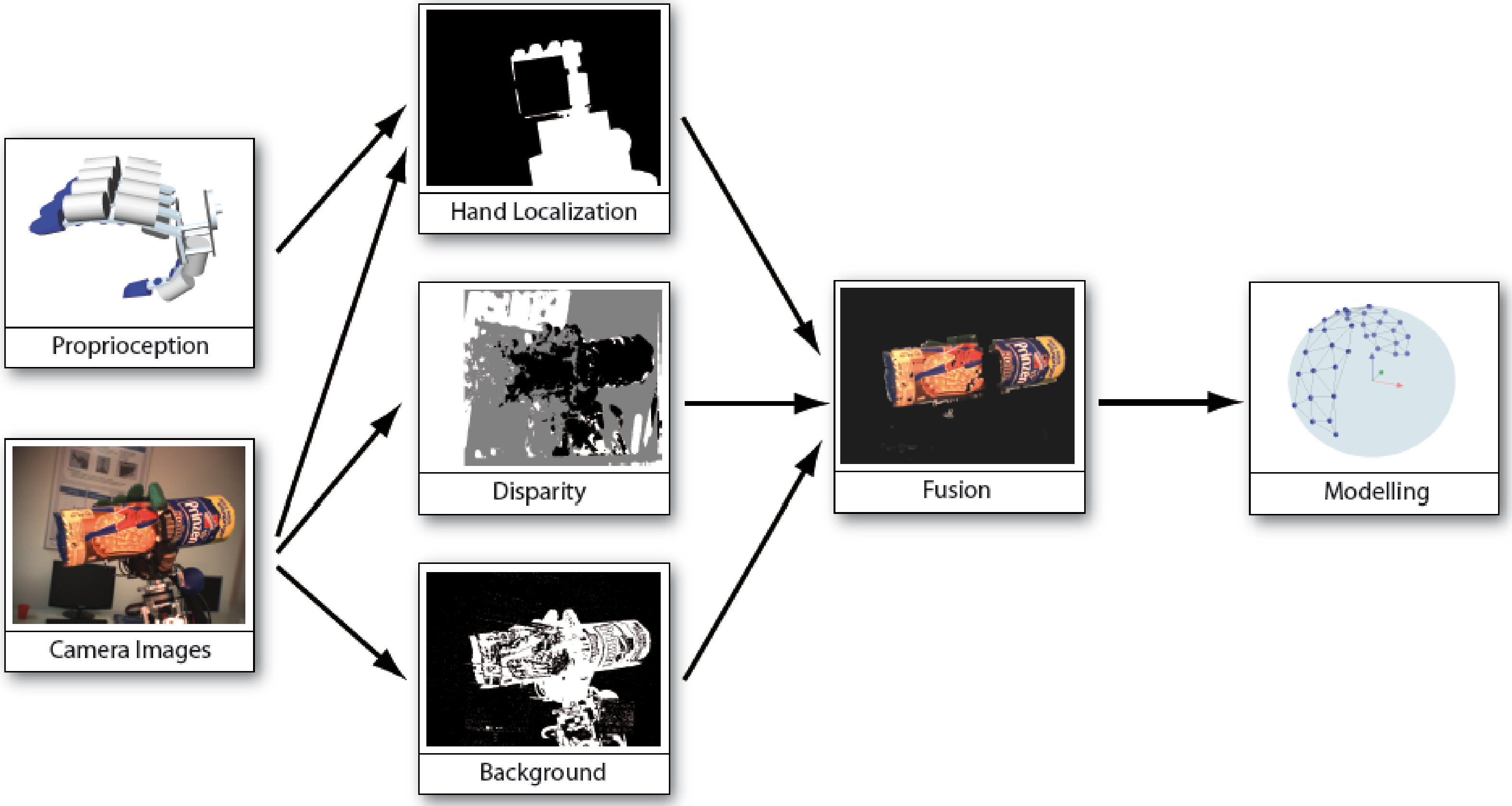


Visual Search

- Generation of visual representations through exploration
- Application of generated representations in recognition tasks.

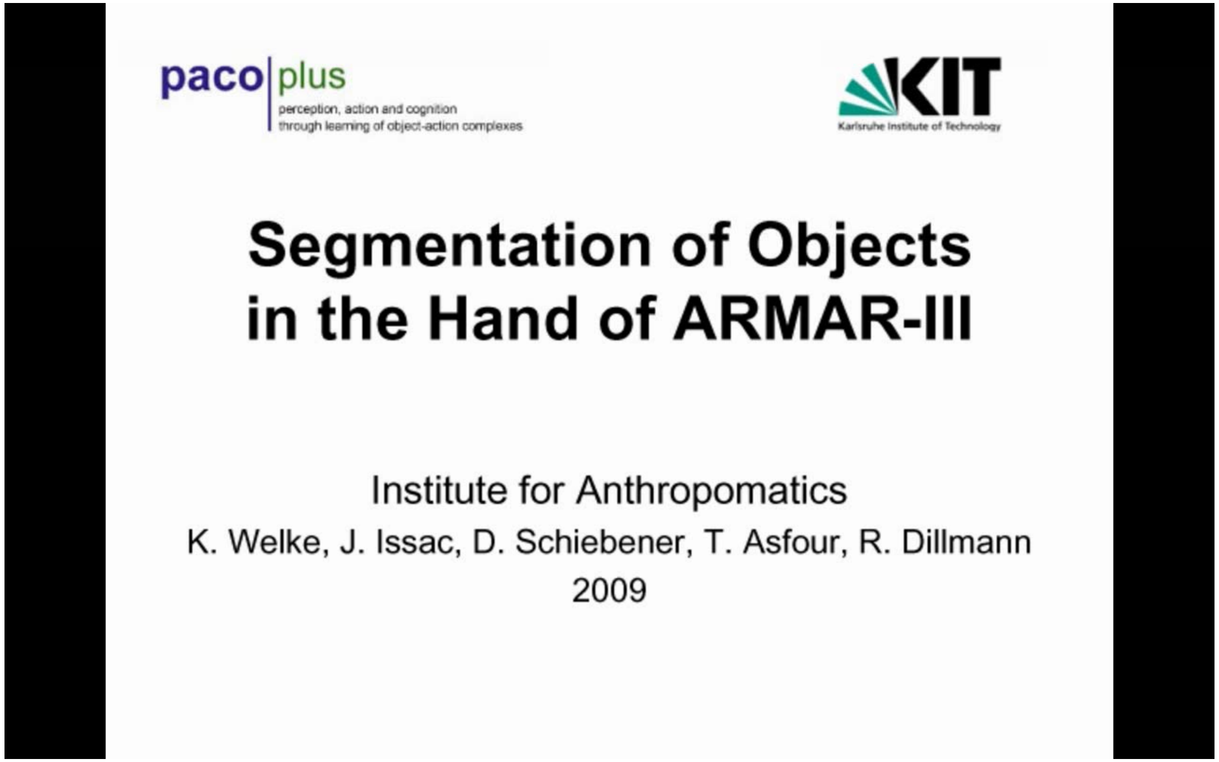
Active Visual Object Exploration

Exploration of unknown object

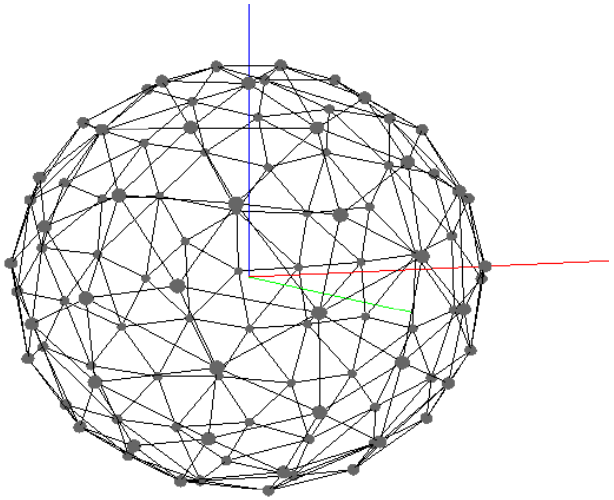


Exploration

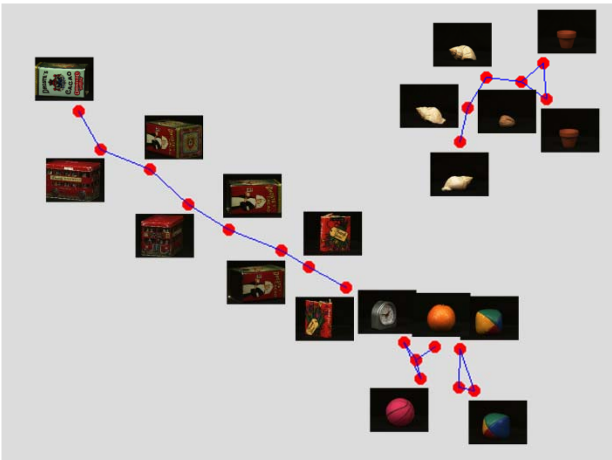
- Exploration of unknown object
  - Background-object and hand-object segmentation
  - Generation of different views through manipulation



Representation



- Aspect Graph
  - Multi-view appearance-based representation
  - Each node corresponds to one view
  - Edges describe neighbor relations



- Feature Pool
  - Compact representation of views with prototypes
  - Grouping based on visual similarity
  - Vector quantization through incremental clustering

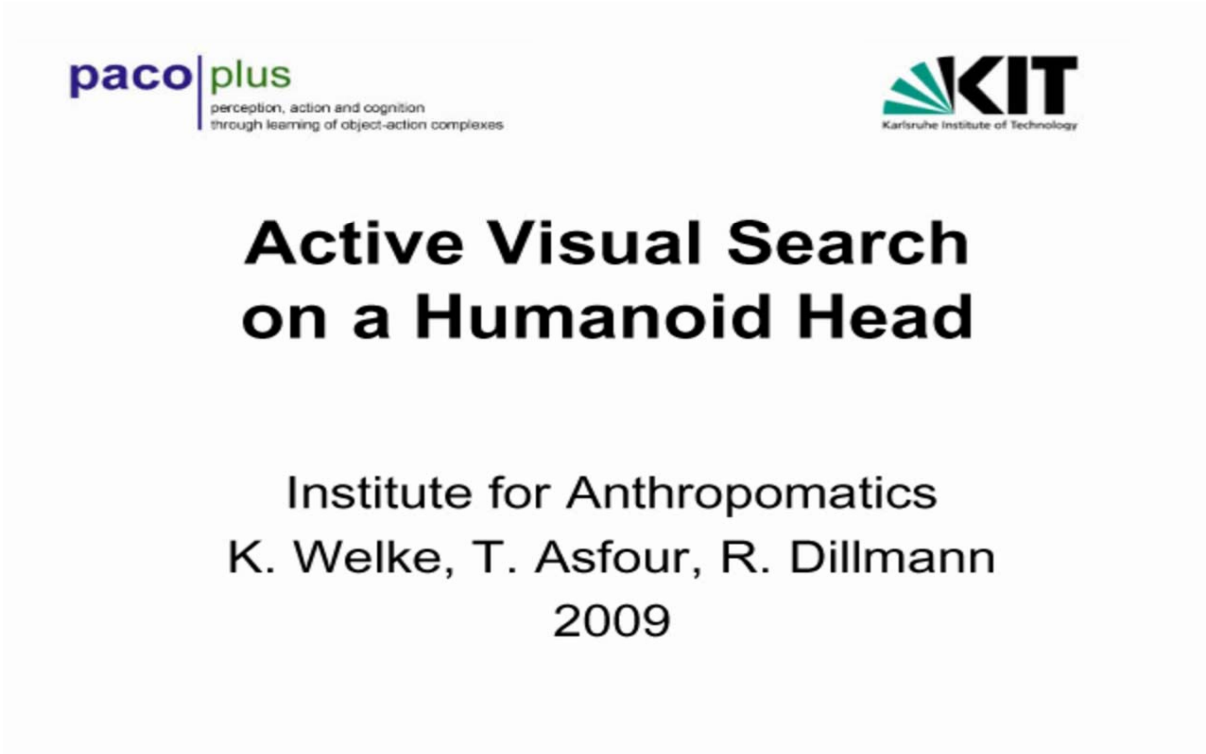
Active Visual Search

- Active Search

  Object search using perspective and foveal camera of Karlsruhe Humanoid Head

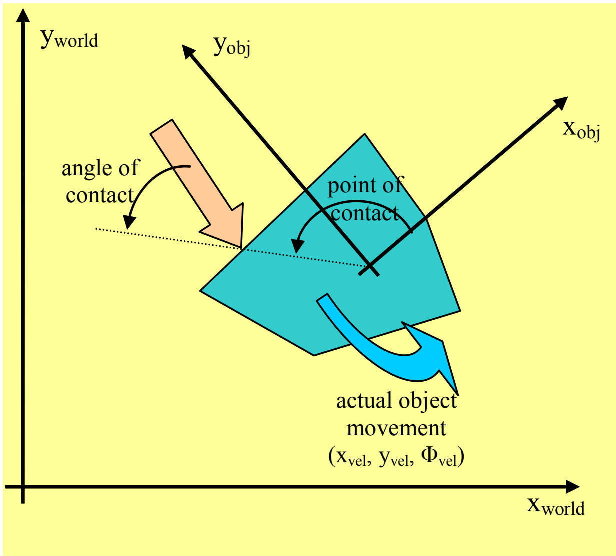
- Scene memory

  Integration of object hypotheses in an ego-centric representation



Learning by Autonomous Exploration: Pushing

- Learning of actions on objects (Pushing)
- Learning relationship between point and angle of push and the actual movement of an object



- Use the knowledge in order to find the appropriate point and angle of push in order to bring an object to a goal

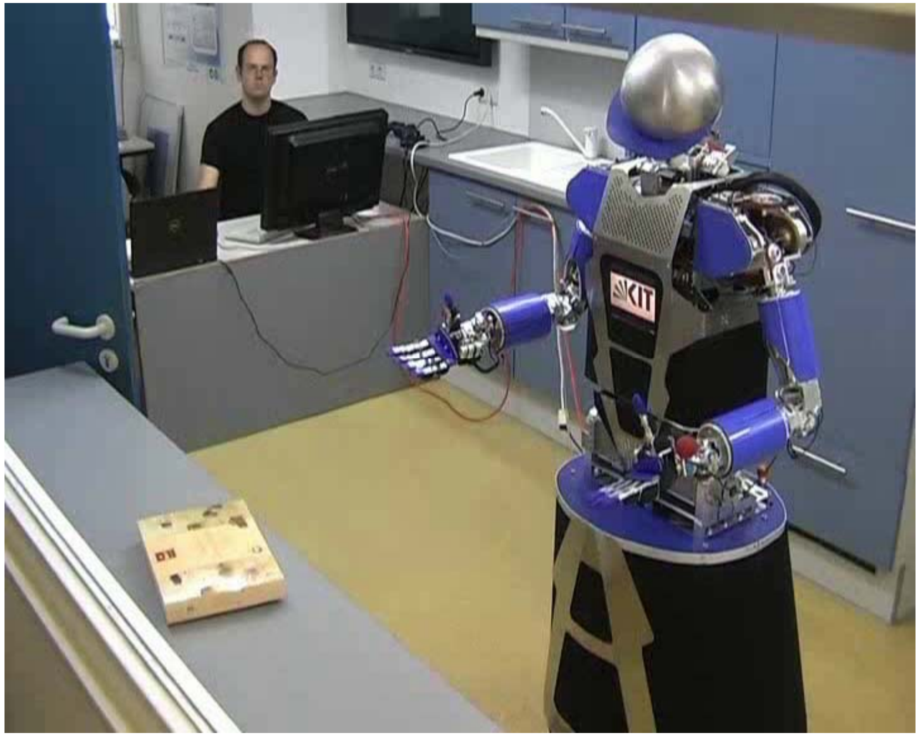
Pushing within the Formalized OAC concept

- Requirements:
  - Initial motor knowledge: the robot need to know how to move the "pusher" along straight lines
  - Assumed visual processing: segment and localize objects
- The pushing OAC oac^{push} learns the prediction function *updateT,* which is implemented as a feedforward neural network.
- This network represents a forward model for object movements that have been recorded with each pushing action.
- Learning by exploration

```
D = ∅;
while true do
    repeat
        a = SelectRandomMotion; bin(o); loc(o);
        expr = execute(push);
        if d(loc(o), loc(o)') > ε then
            D = D ∪ {expr};
            updateM(expr);
        end
    until enough data collected ;
    updateT(D);
end
```

Pushing for grasping

- Object independent pushing (generalization across objects).
- Learning relationship between point and angle of push and the actual movement of an object
- Direct association between the binarized object image and the response of the object with respect to the applied pushing action.
- Use the knowledge in order to find the appropriate point and angle of push in order to bring an object to a goal
- Pushing for grasping



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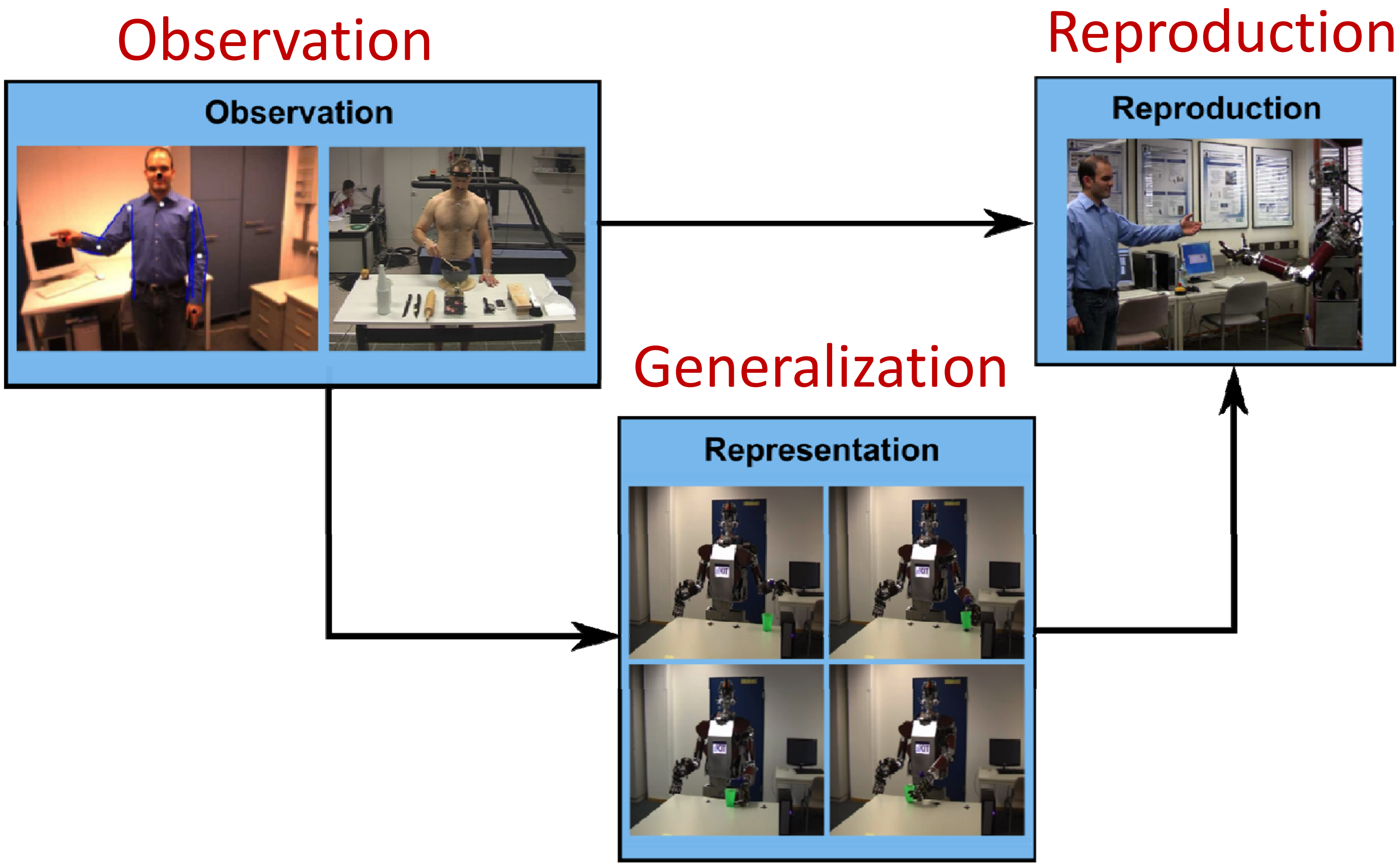
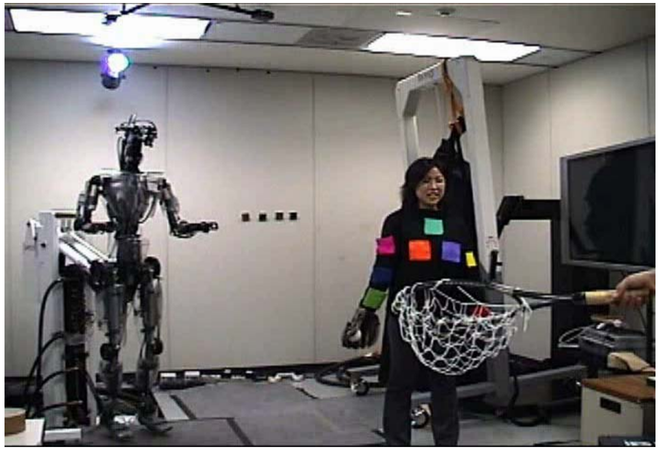
Observation, Reproduction, Generalization

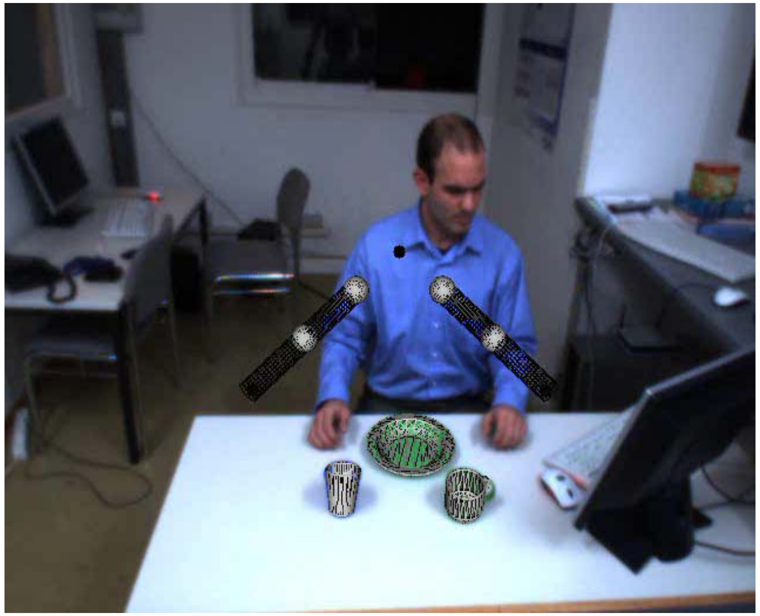


Build a library of motor primitives

Coaching



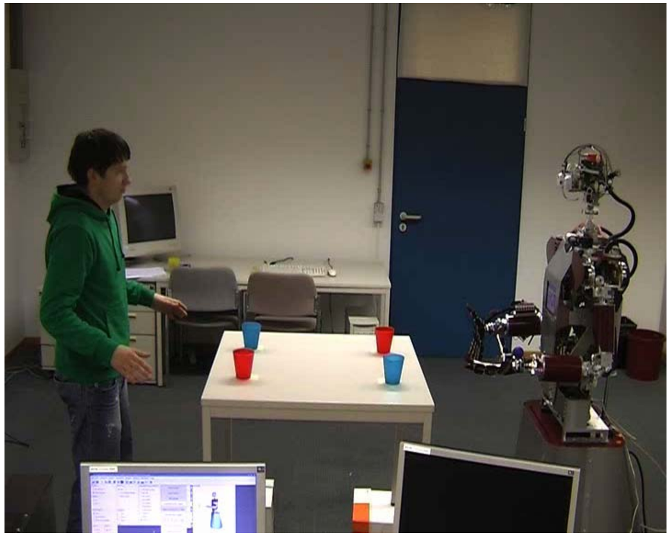
Markerless human motion tracking and object tracking

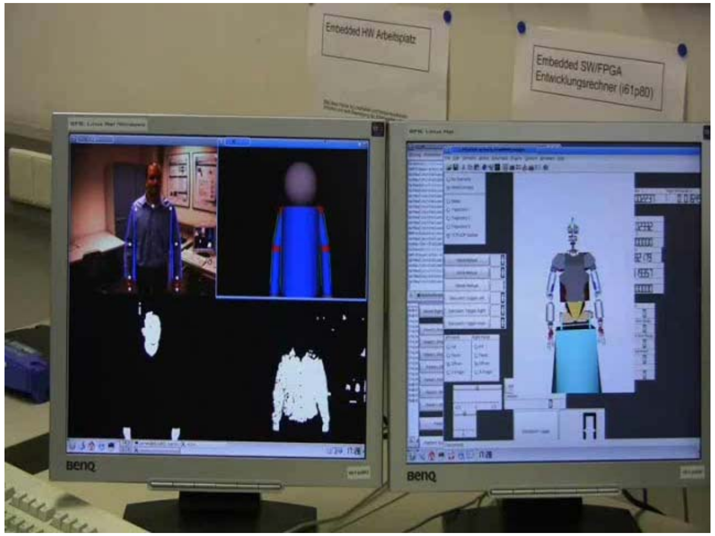


Guiding

Build a library of motor primitives

- Master Motor Map (MMM) as an interface for the transfer of motor knowledge between different embodiments





Action representation using DMPs

canonical system: $\tau\,\dot{u} = -\alpha\,u$

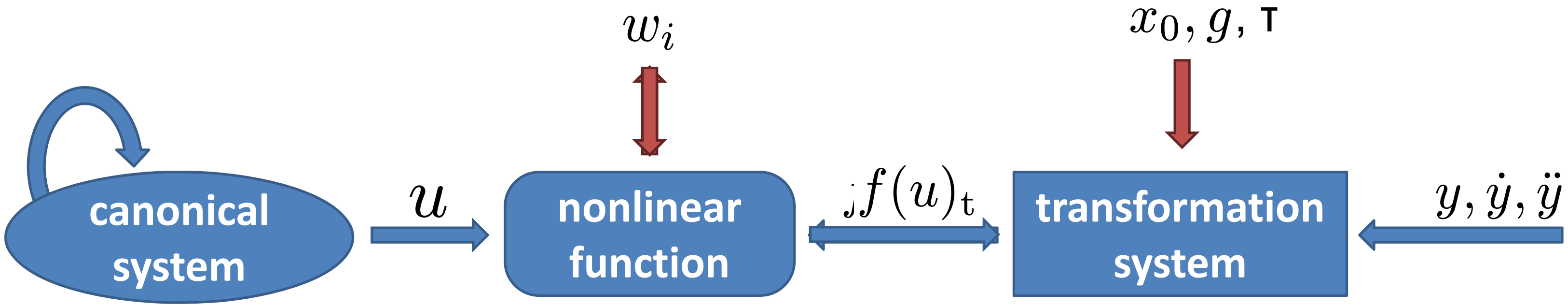
nonlinear function: $f(u) = \dfrac{\sum_i \psi_i(u)\,w_i\,u}{\sum_i \psi_i(u)}$ $\quad \psi_i(u) = e^{-h_i(u-c_i)^2}$

transformation system: $\tau\dot{v} = K(g-x) - Dv + (g-x_0)f$

$\tau\dot{x} = v$

Locally weighted learning

Gaussian process regression



Learning from multiple examples

- To relate actions to goals, we need to observe more than one movement
  - Example movements $\mathbf{M}_i$ encoded by a sequence of trajectory points $\{\mathbf{p}_{ij}, \mathbf{v}_{ij}, \mathbf{a}_{ij}\}$ at times $\{t_{ij}\}$, $j = 1, \ldots, n_i$.
  - Associated goals (query points) $\mathbf{q}_i$.

Parameters to be estimated

- To generate a new control policy, we need to estimate the DMP parameters w, g, and τ as a function of parameters q that characterize the task

$$\mathbf{F}:\mathbf{q}\rightarrow\begin{bmatrix}\mathbf{w}\\ \mathbf{g}\\ \tau\end{bmatrix}$$

- Gaussian process regression to associate the query points with the goal of an action, frequency and timing.

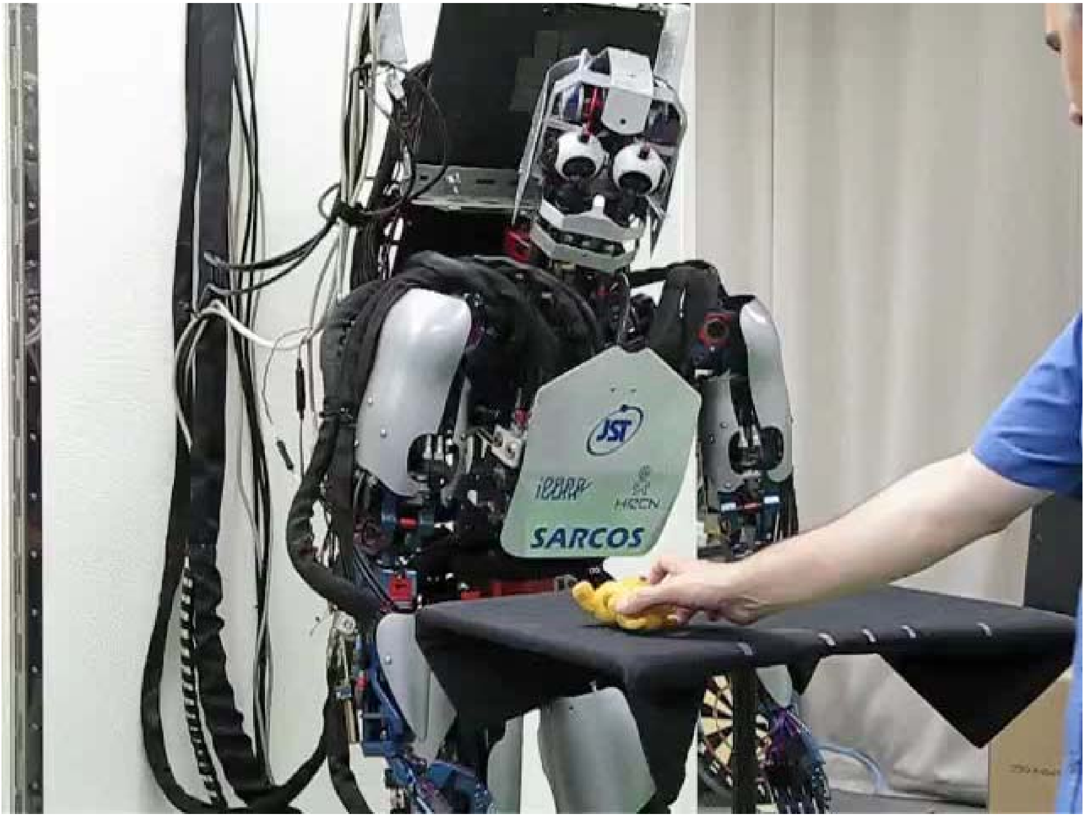
Parameters to be estimated

- To generate a new control policy, we need to estimate the DMP parameters **w, g**, and τ as a function of parameters **q** that characterize the task

$$\mathbf{F} : \mathbf{q} \rightarrow \begin{bmatrix} \mathbf{w} \\ \mathbf{g} \\ \tau \end{bmatrix}$$

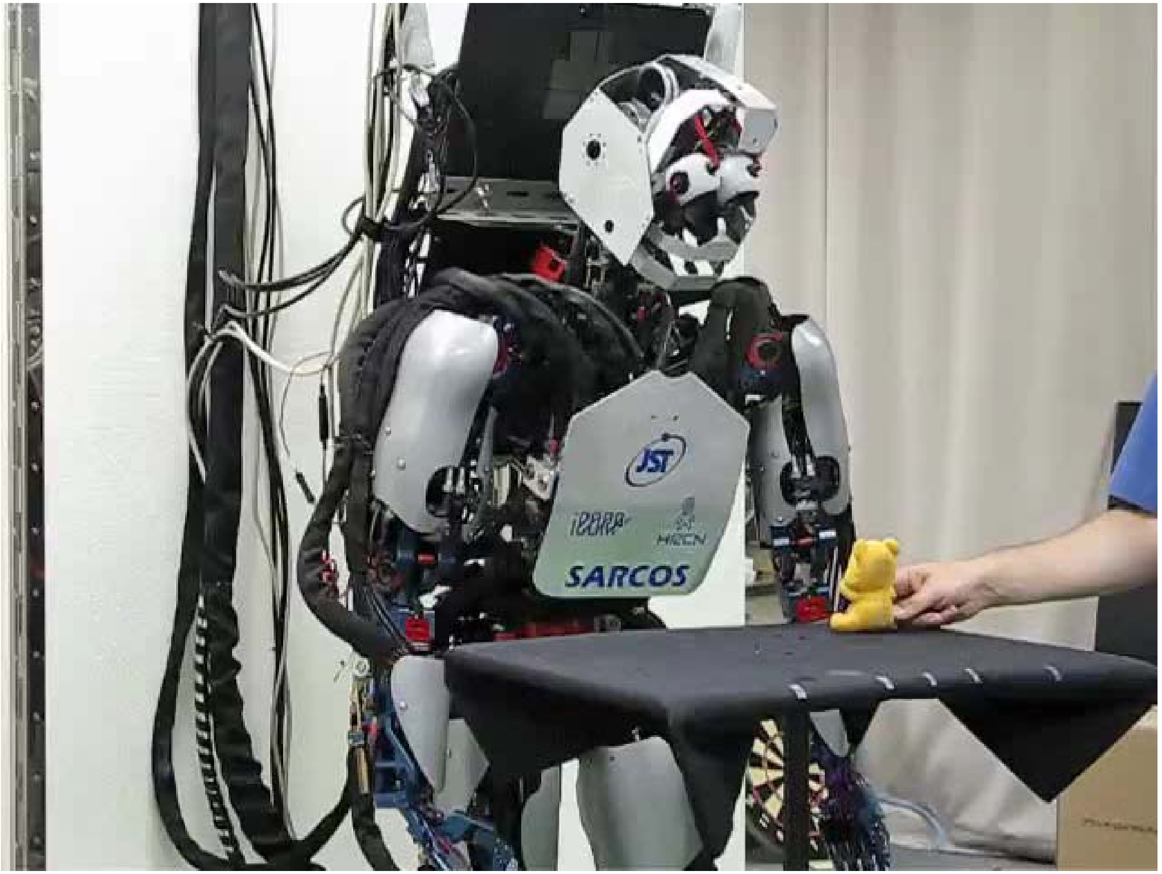
- Locally weighted regression to estimate the shape parameters at new situations.

Reaching and active vision



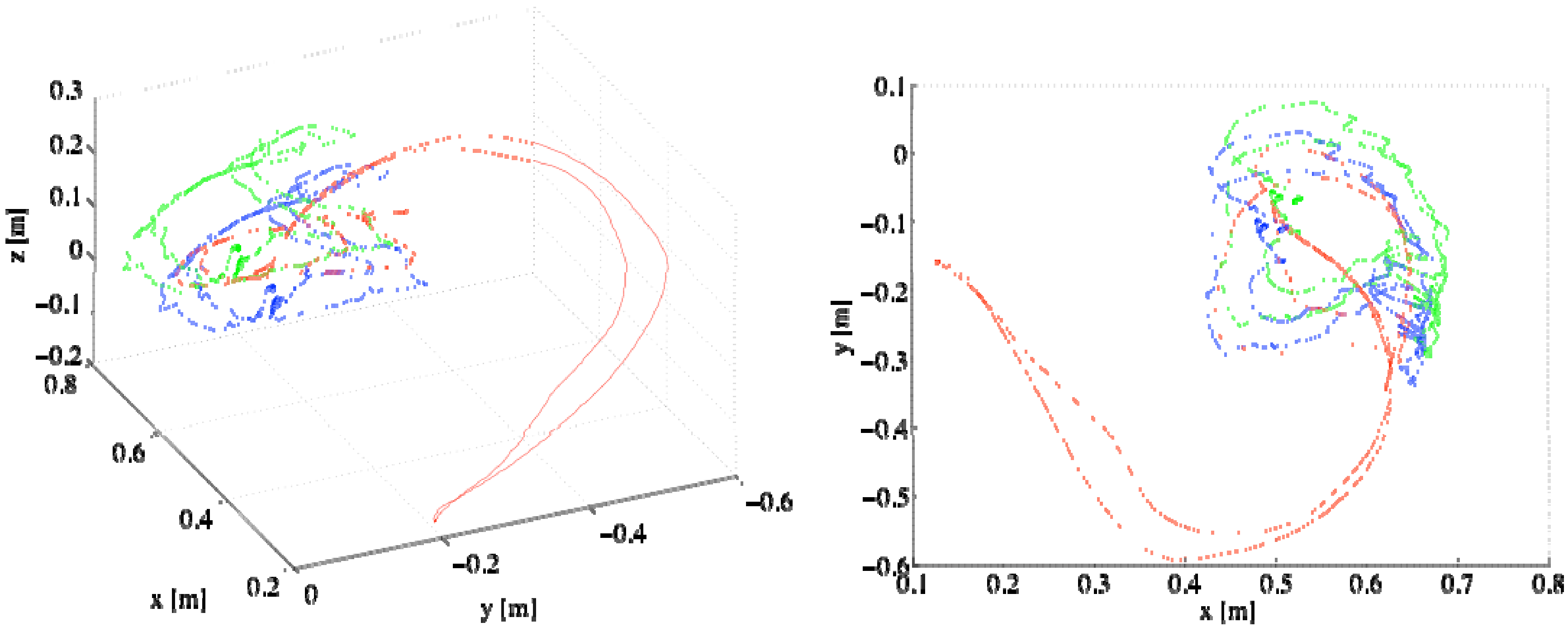
- 3-D active vision; errors corrected by GPR.
- No knowledge about the kinematics assumed; kinematics of the goal configuration learned from the data.
- Generated DMPs avoid the table.

Perceptual feedback



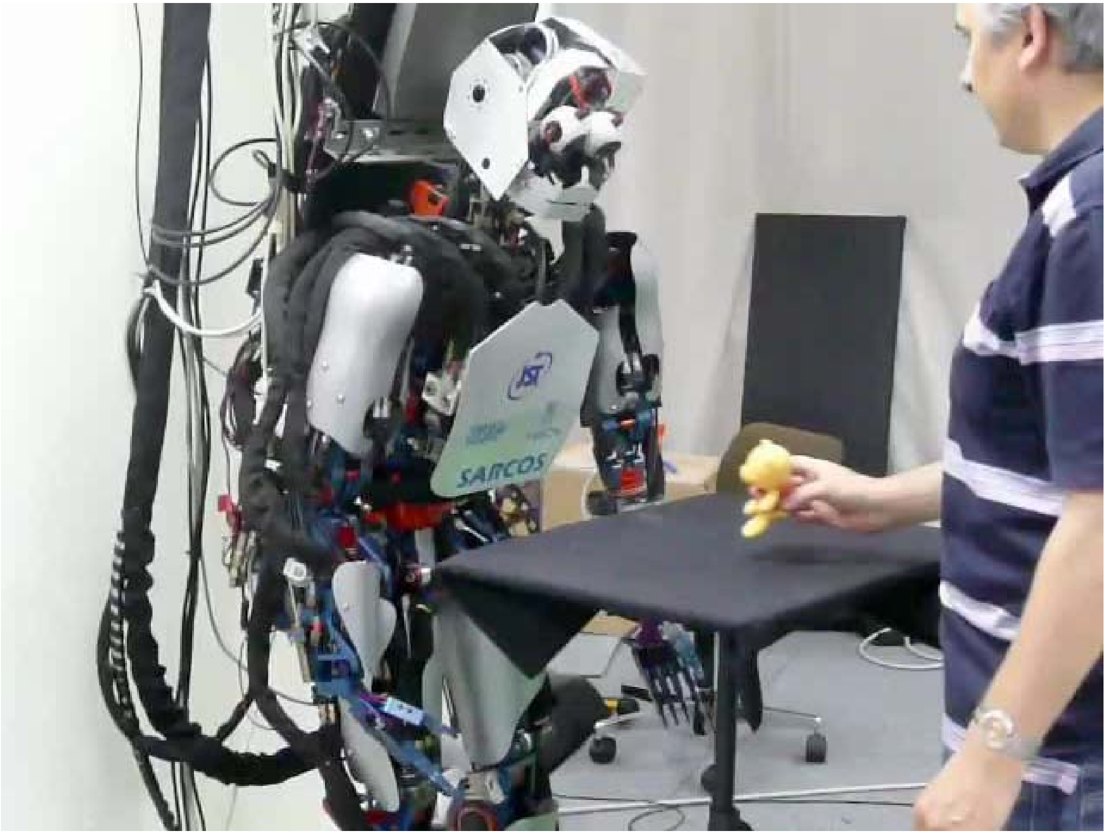
The properties of DMPs allow us to easily modify the final reaching position on-line.

Accuracy for reaching and grasping



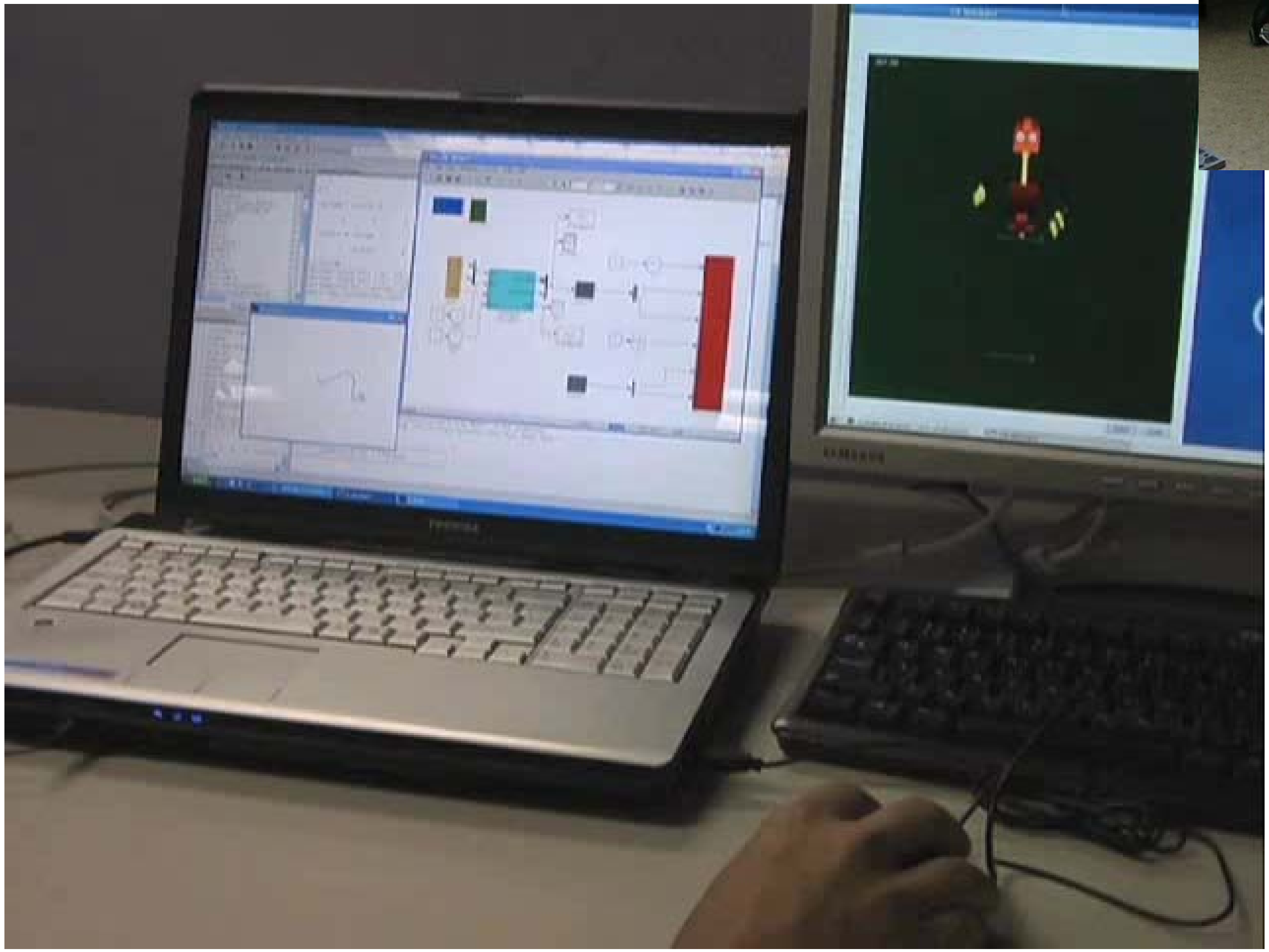
- Difference between the means: [1.6, 4.2, 7.6] cm.
- Systematic modeling errors are successfully corrected.

Grasping



It was not necessary to track the hand to correct modeling errors (vision + kinematics).

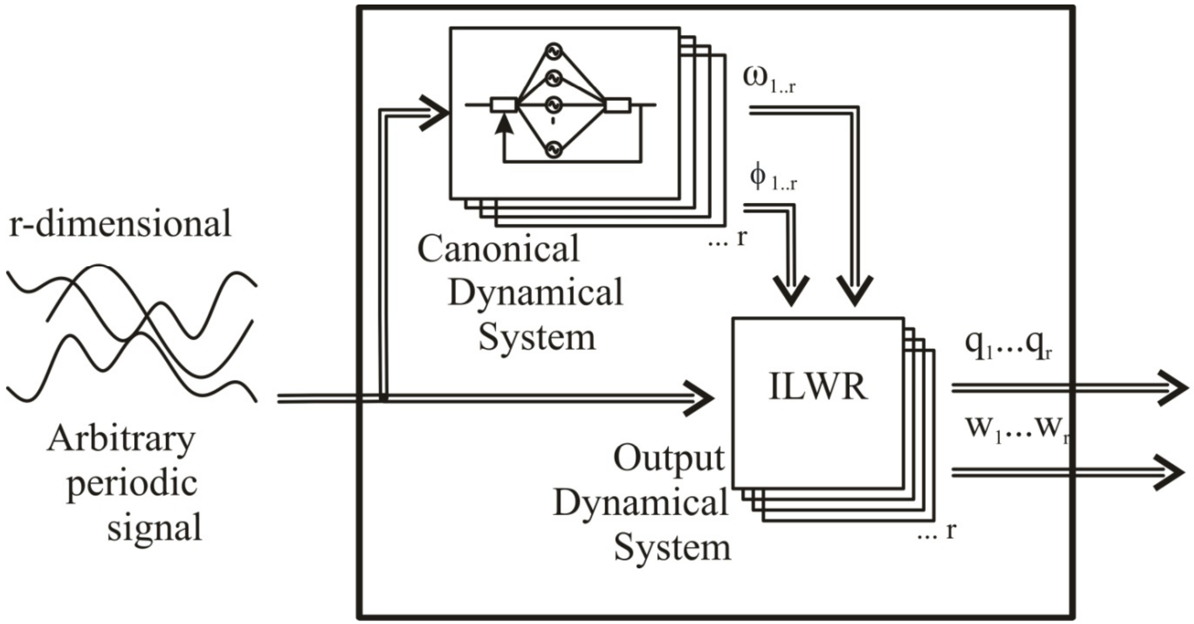
Coaching periodic motion



- The first system that does not need the frequency to be specified beforehand.
- The system allows training with the teacher in the control loop.

Periodic movements

- Extract the frequency and learn the waveform.
- **Adaptive Frequency Oscillators** for frequency extraction.
- Incremental regression for waveform learning **– Dynamic Movement Primitives.**



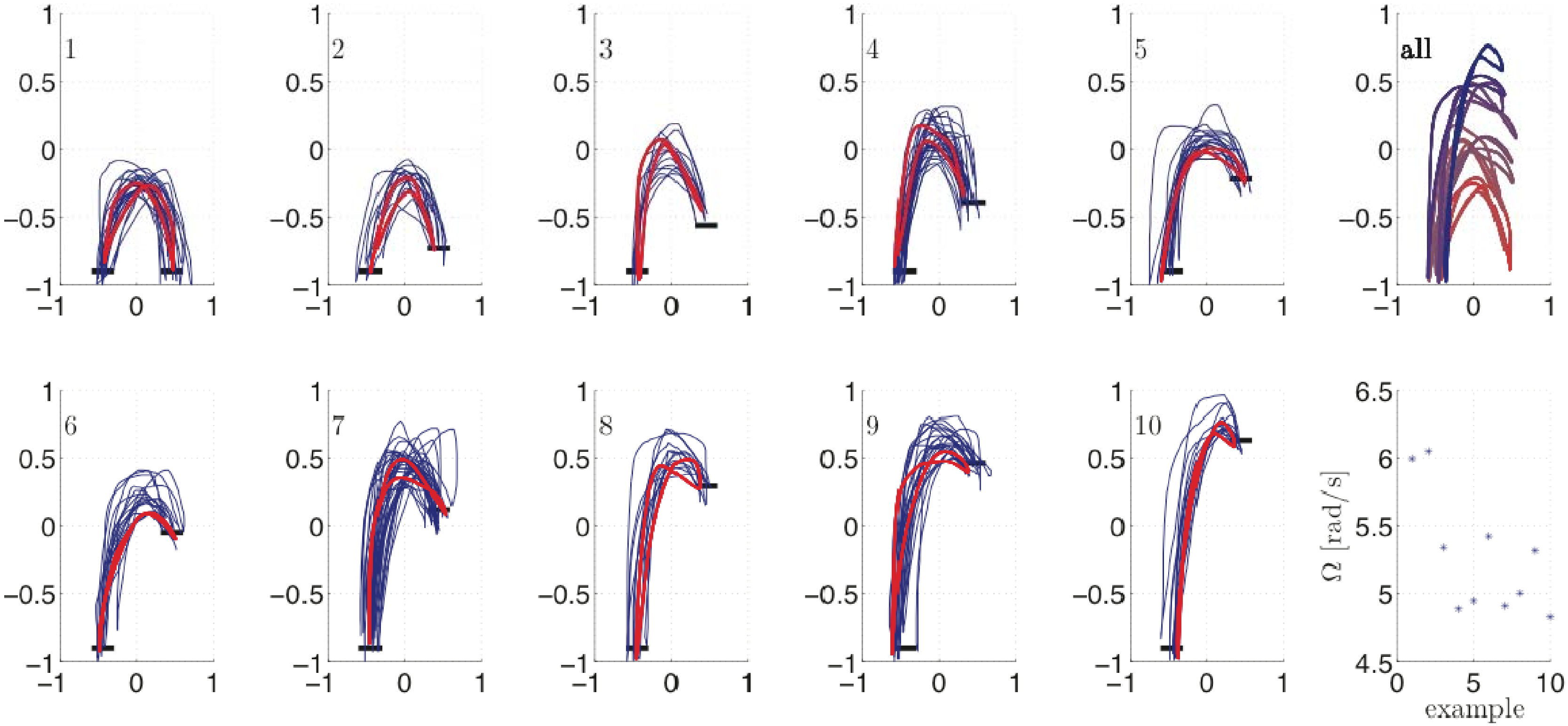
Generalization of Periodic Movements

- The data needs to be first processed to obtain the optimal frequency for each example motion.
- To match the phases between the training trajectories, each example trajectory must end in the same configuration.
- When using recursive learning with a forgetting factor, we need to ensure that we parse all examples with the matching phases.

Periodic movements: Wiping

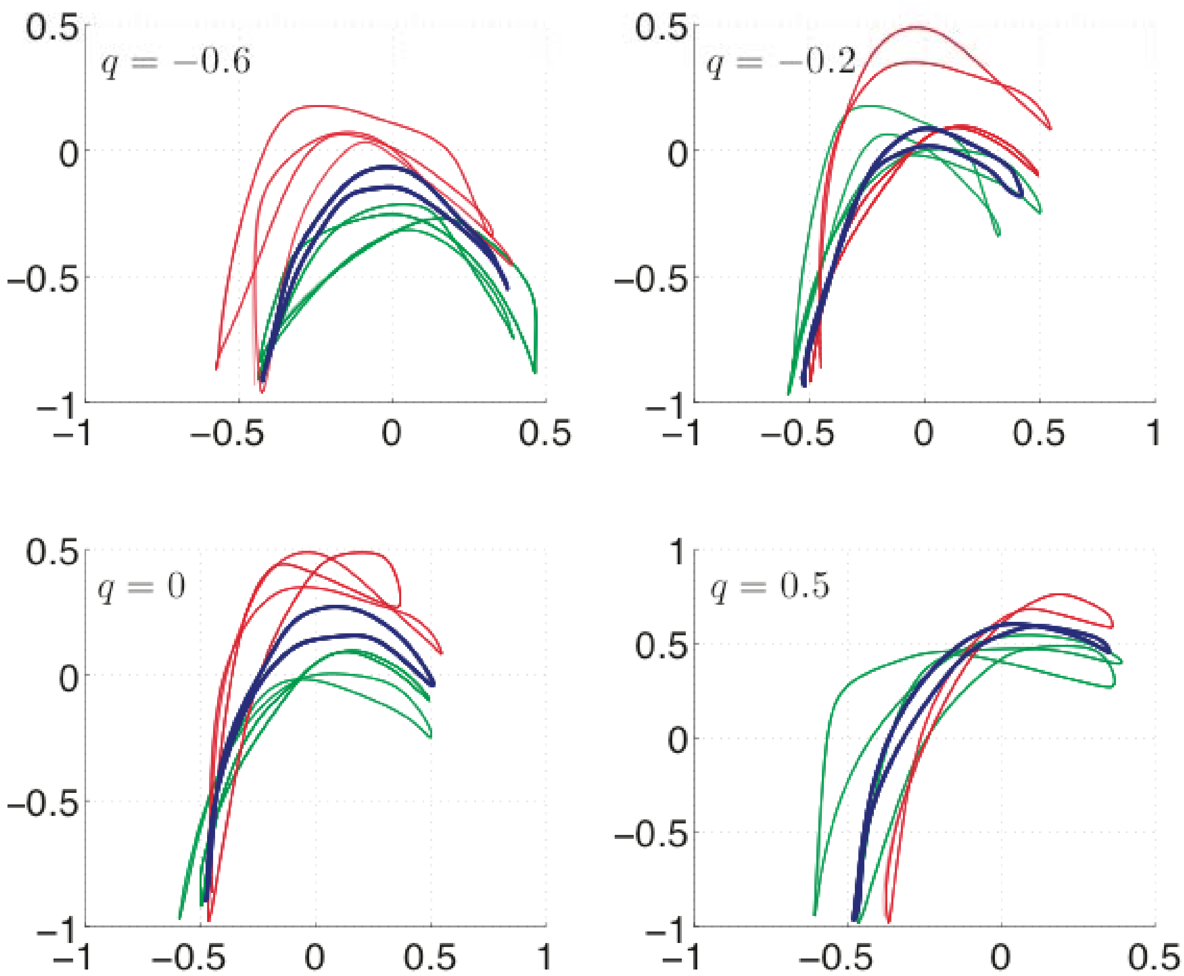
Training

Training Data

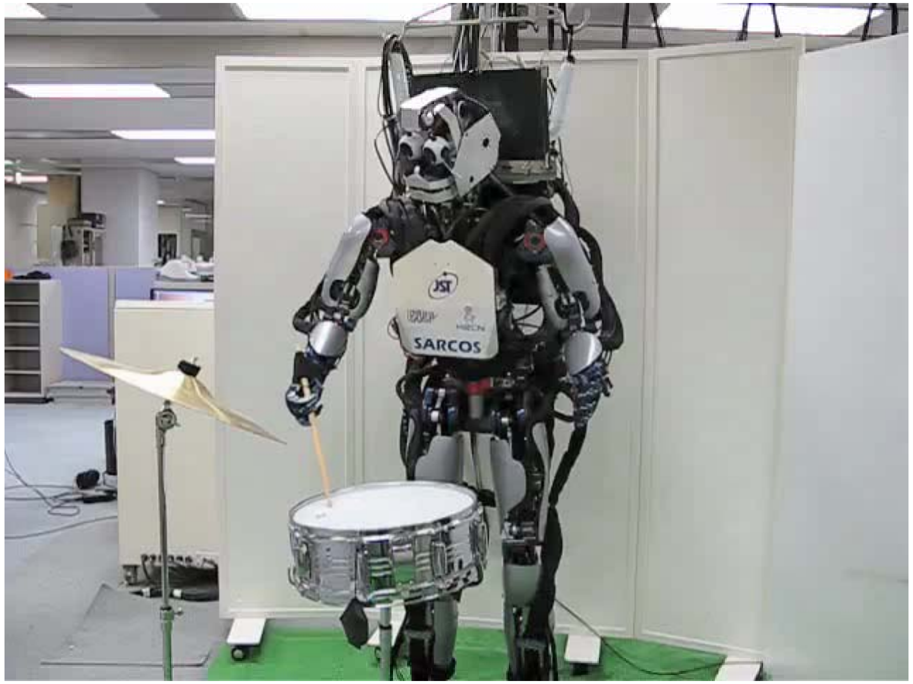


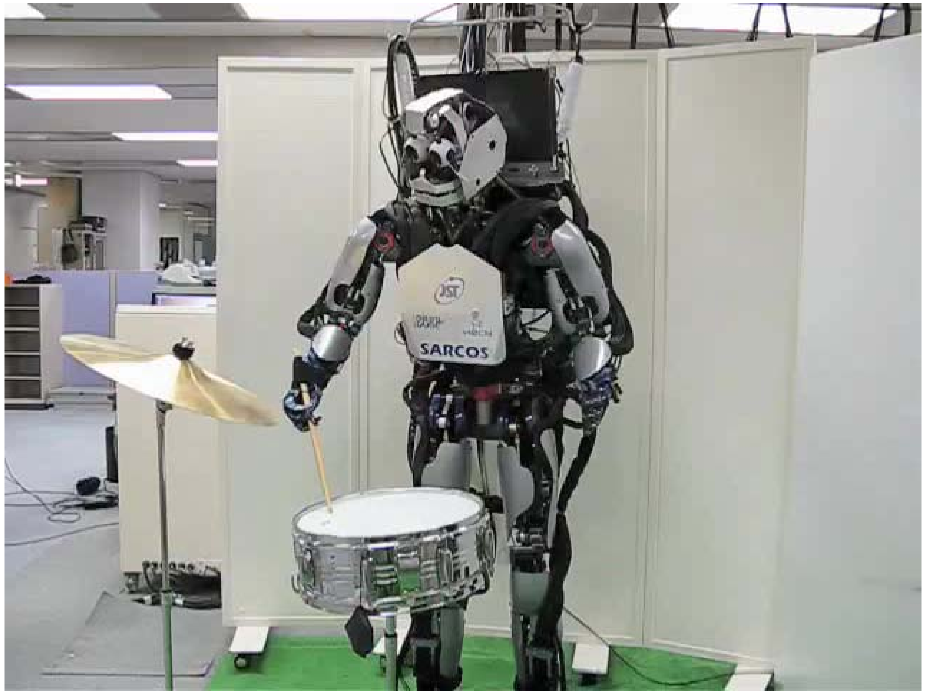
The frequencies need to be estimated when acquiring the data.
Height difference is used as a query parameter.

Generalization Performance



Changing the Height of the Drums





Sequencing of discrete DMPs

- On-line learning of DMPs for
  - Reach
  - Transport
  - Retreat

- Associating semantic information with DMPs

→ sequencing of movement primitives

→ planning

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Perception, Action and Cognition through Learning of Object-Action Complexes

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