Humanoid Grasping and Manipulation

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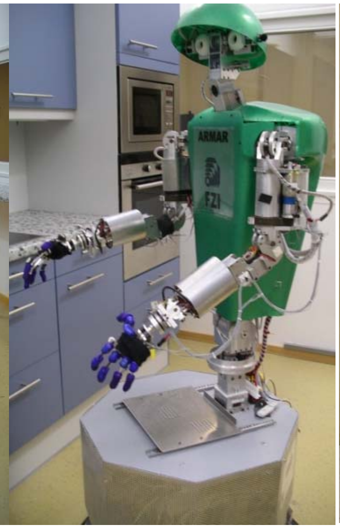


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Three key questions

- Grasping and manipulation in human-centered and open-ended environments
- Learning through Observation of humans and imitation of human actions
- Interaction and natural communication

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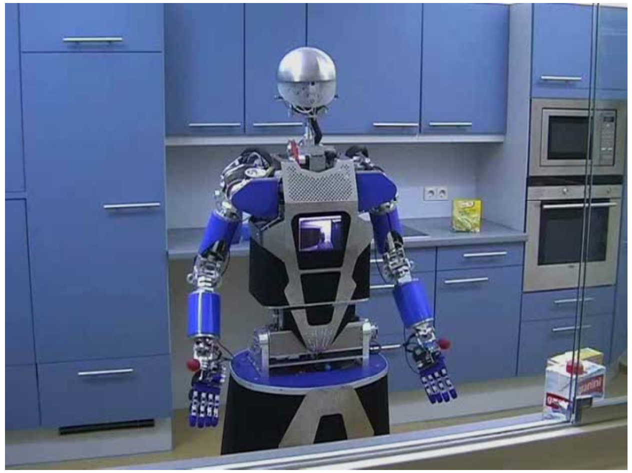
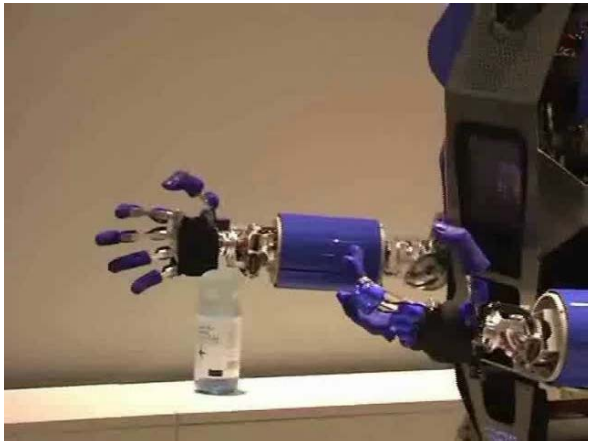
Humanoid Robot ARMAR-III

- 7 DOF head with foveated vision
  - 2 cameras in each eye
  - 6 microphones
- 7-DOF arms
  - Position, velocity and torque sensors
  - 6D FT-Sensors
  - Sensitive Skin
- 8-DOF Hands
  - Pneumatic actuators
  - Weight 250g
  - Holding force 2,5 kg
- 3 DOF torso
  - 2 Embedded PCs
  - 10 DSP/FPGA Units
- Holonomic mobile platform
  - 3 laser scanner
  - 3 Embedded PCs
  - 2 Batteries

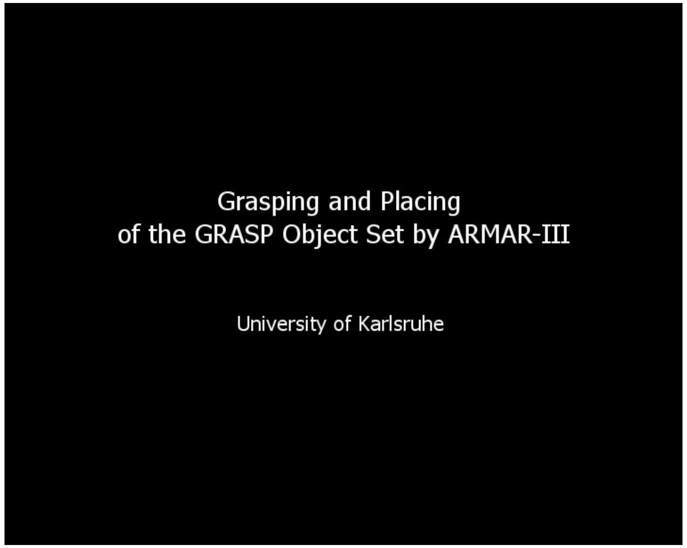




Fully integrated autonomous humanoid system

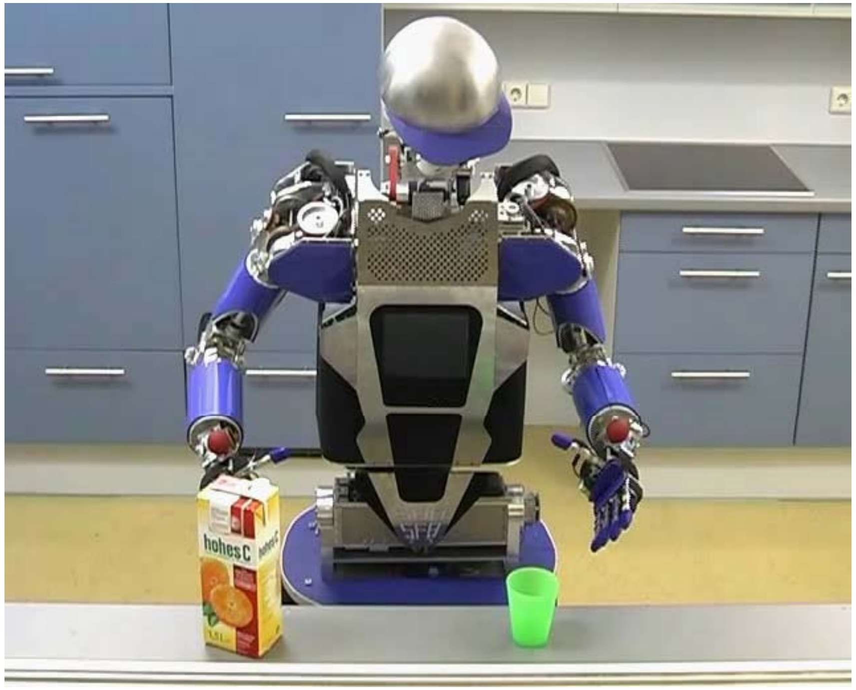
Integrated implementation

- Vision-based grasping
- Object recognition and localization
- Combining force and vision for opening and closing door tasks
- Hybrid position/force control
- Vision-based self-localisation
- Audio-visual tracking and localization
- Multimodal human-robot dialogs
- Speech recognition for continuous speech
- Learning new objects, persons and words

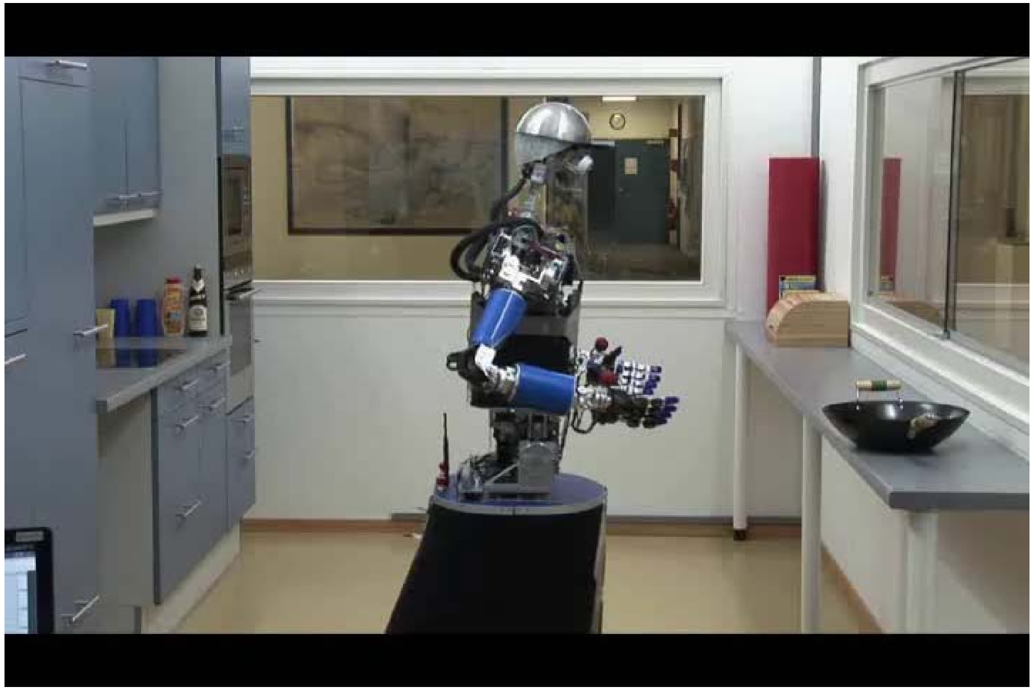


Bimanual grasping and manipulation

- Stereovision for object recognition and localization
- Visual Servoing for dual-hand grasping
- Zero-force control for teaching of grasp poses

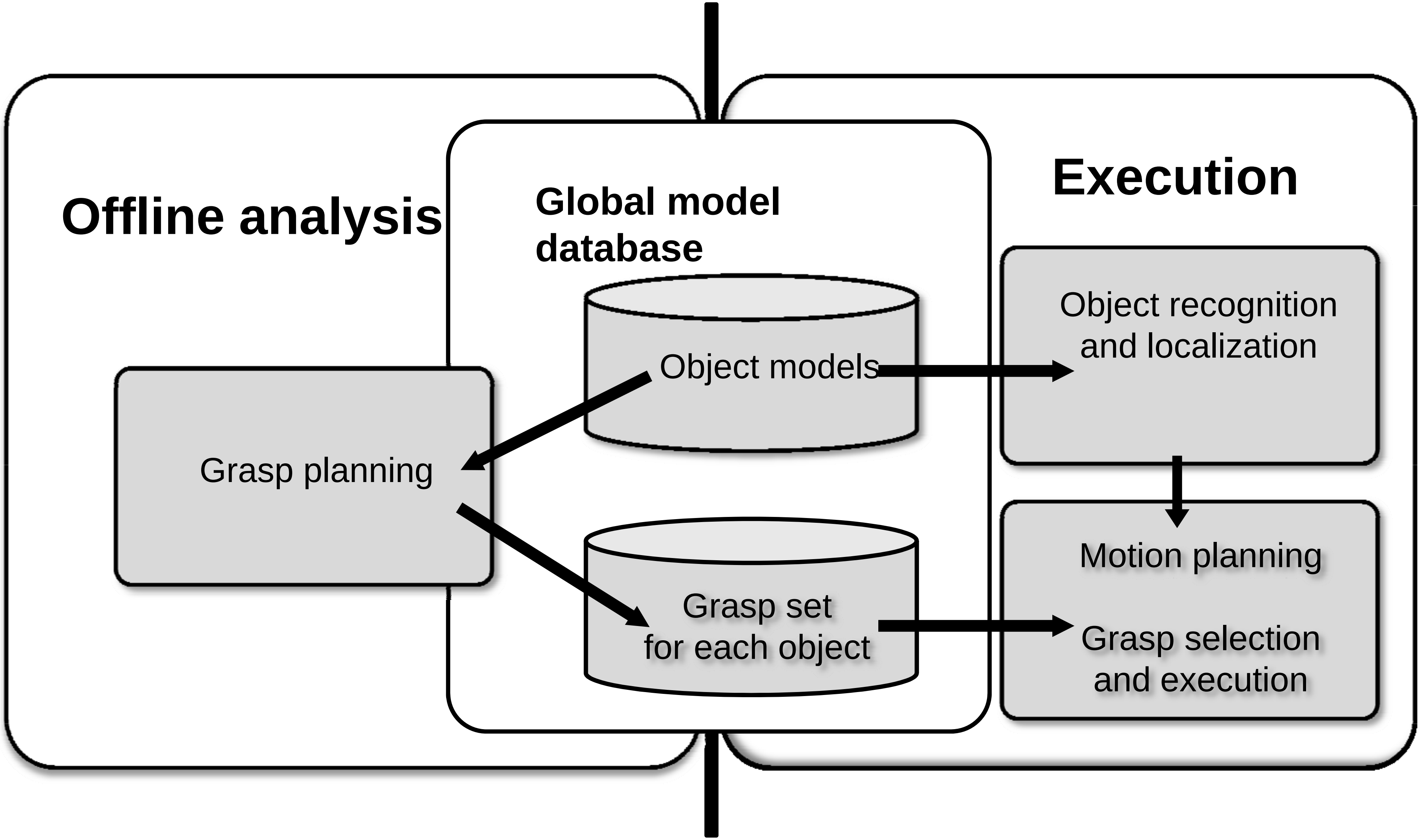


Loosely coupled dual-arm tasks



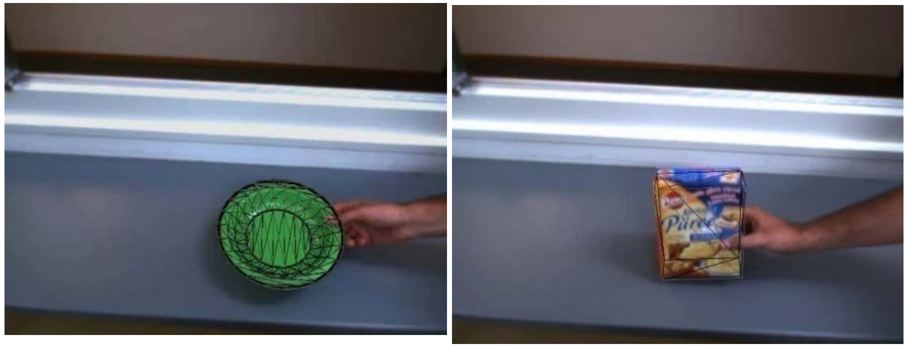
Tightly coupled dual-arm tasks

Grasping known objects: System architecture



Object recognition and localization

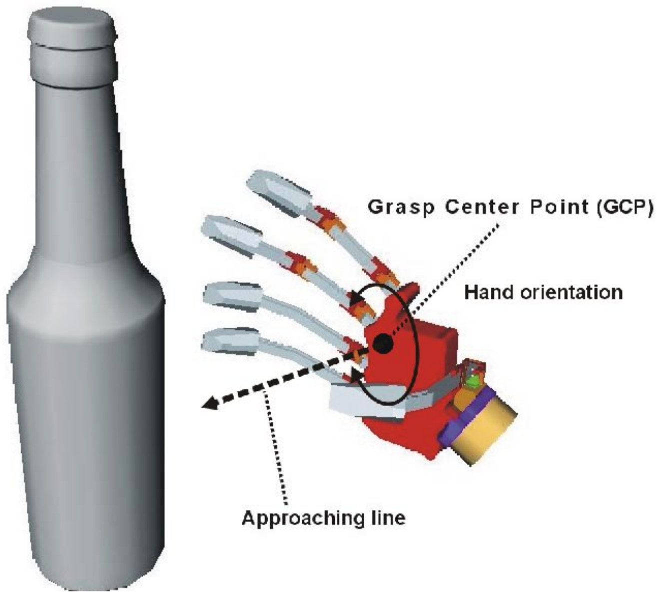
- Colored objects (IROS 2006, IROS 2009)
  - Segmentation by color
  - Appearance-based recognition using a global approach
  - Model-based generation of view sets
  - Combination of stereo vision and stored orientation information for 6D pose estimation
- Textured objects (Humanoids 2006, IROS 2009)
  - Recognition using local features
  - Calculation of consistent features with respect to the pose of the object using the Hough transform
  - 2D-localization using image point correspondences
  - 6D pose estimation using stereo vision



Correspondences between learned view and view in scene

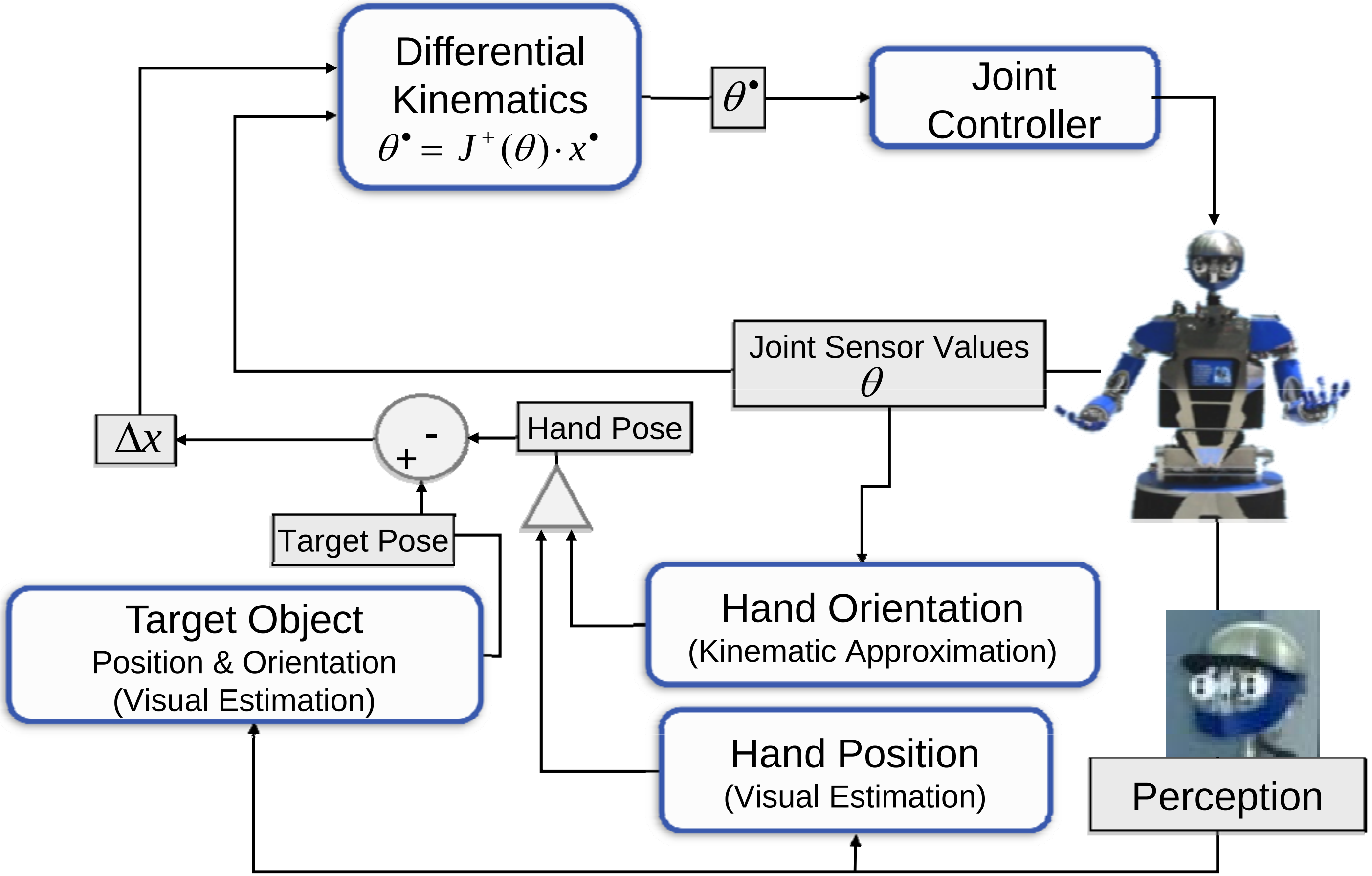
Grasping known objects: Offline grasp analysis

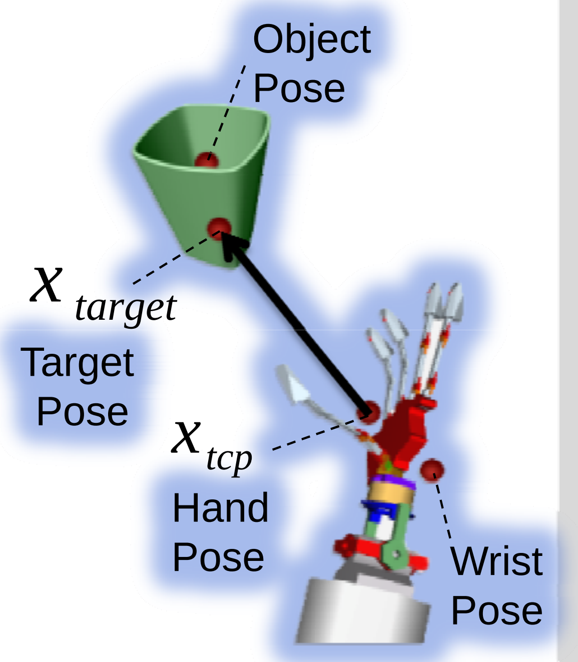
- Feasible grasps for every object are computed offline and stored together with the object models.
- A grasp is defined by:
  - Grasp type
  - Grasp starting point
  - Approaching direction
  - Hand orientation
- Simulation environment: GraspIt!



Hook *Cylindrical* *Spherical* *Pinch* *Tripod*

Position-based Visual Servoing





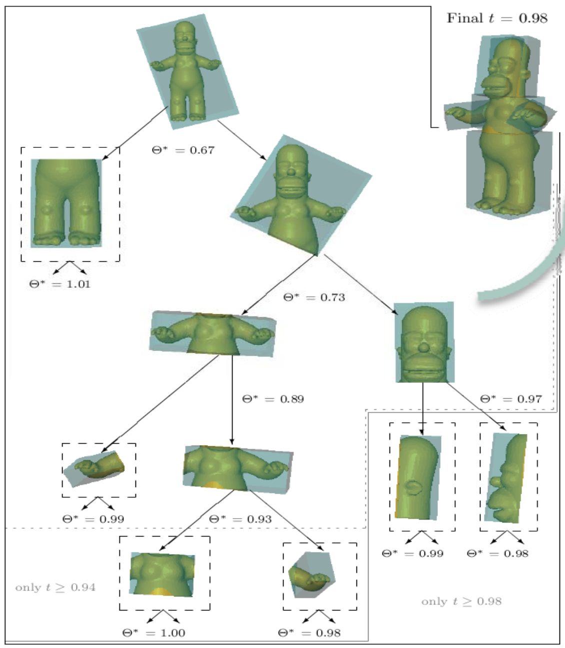
$$\theta^{\bullet} = J^{+}(\theta) \cdot x^{\bullet}$$

$$\partial^{t} = x^{t}_{vision} - x^{t}_{kinematic}$$

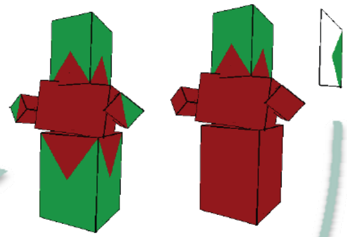
$$x^{t+1}_{tcp} = x^{t+1}_{kinematic} + \partial^{t}_{tcp}$$

Grasping Known Objects: A Box-Based Approach

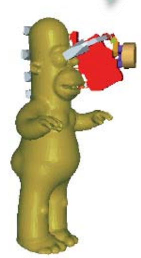
- Object shape approximation through Box Decomposition [Huebner et al. 2008]
- Grasp hypothesis generation on objects, evaluated in GraspIt! – part based grasping :



Shape Approximation



Heuristical Selection (Geometric Reduction & Grasp Quality Learning)



Final grasp for the task "show object"

Joint work with Danica Kragic and Kai Huebner, KTH, Sweden

Limitations and shortcuts

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

  - How to grasp unknown objects?
  - How to learn objects representations?
  - How to acquire multi-sensory representations of objects?

- Actions
  - Kinematic-based 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?

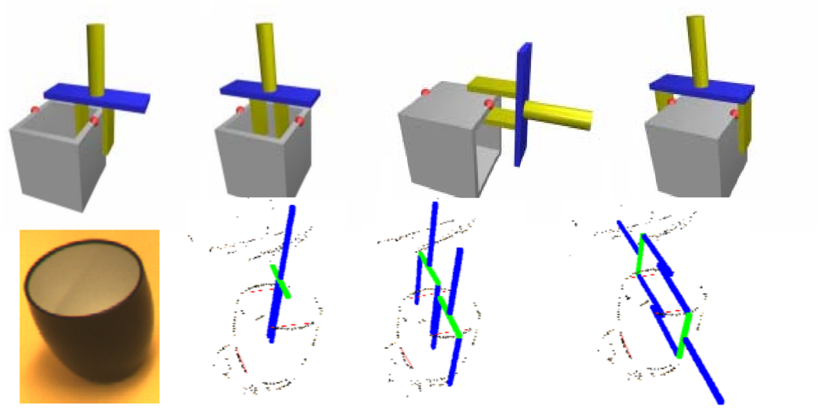
How to relax the limitations?

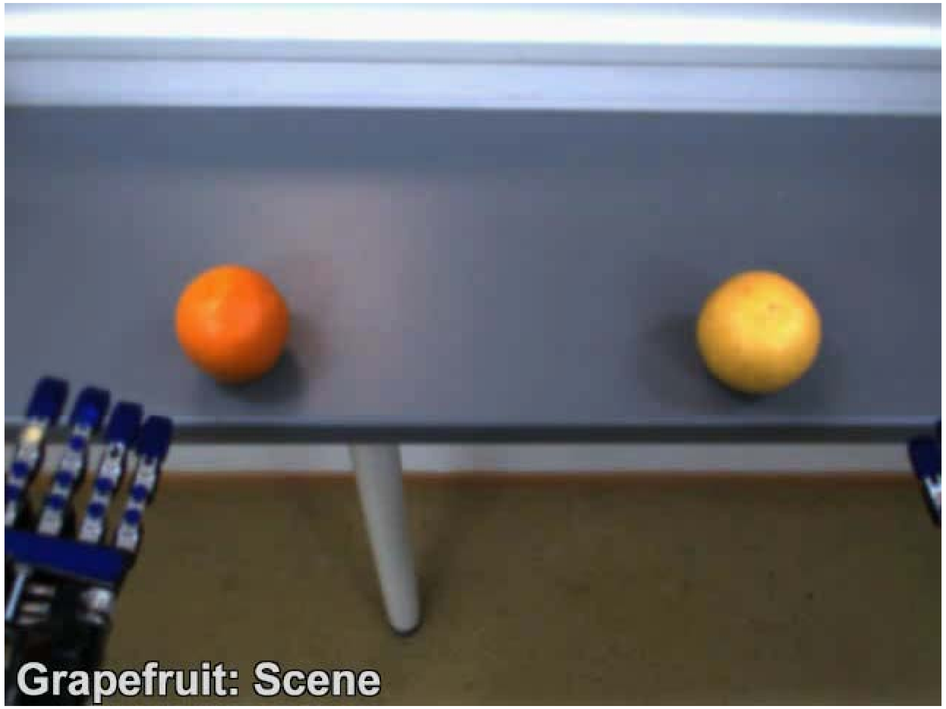
- Autonomous Exploration
  - Grasping unknown objects
  - Learning actions on objects (Pushing for grasping)
  - Visually-guided haptic exploration

- Coaching and Imitation
  - Learning from observation and goal-directed Imitation

Grasping unknown objects

- Co-planarity relation between visual entities define potential grasping affordances
- Surprising result: A success rate between 30-40% is already achievable by such a simple mechanisms.
  - One reason is high level mechansism for hypotheses rejections through motion planning
- There is an *autonomous success evaluation* based on force/haptic information
  - Collision, no success, unstable, stable

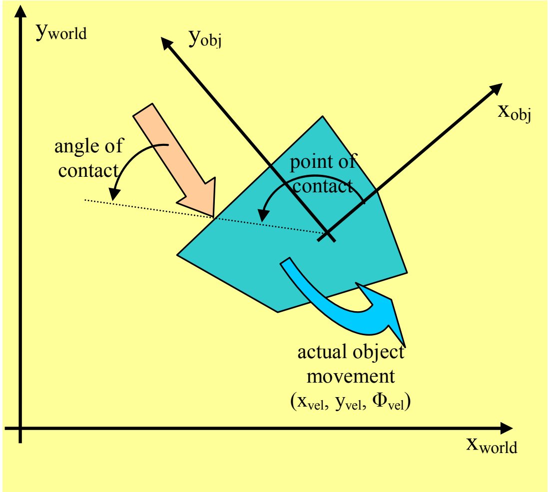


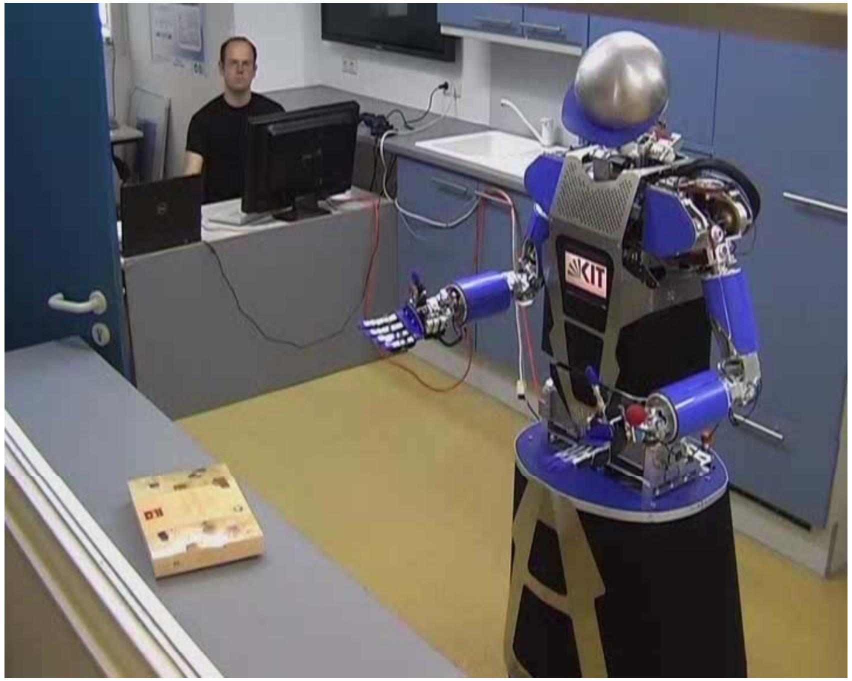


Joint work with Norbert Krüger and Mila Popovic, University of Southern Denmark

Learning of actions on objects

- Pushing for grasping
- 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



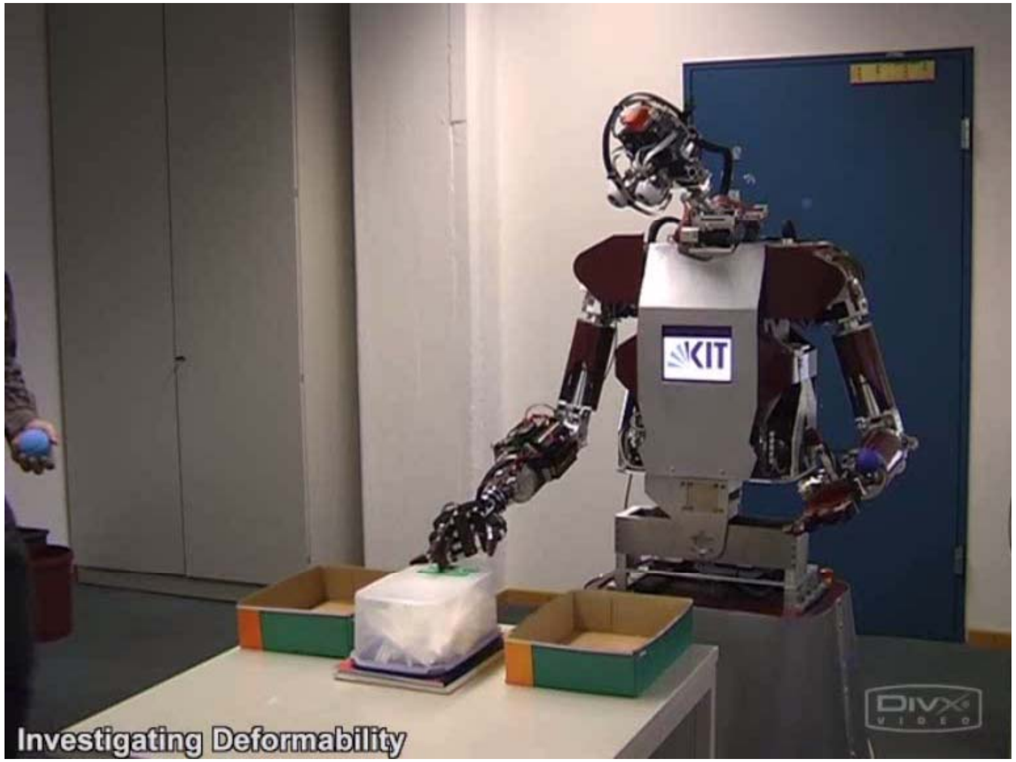


Joint work with Damir Omrcen and Ales Ude

Visually-guided haptic exploration

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

Verification of object size



Verification of object deformability

How to relax the limitations?

- Autonomous Exploration
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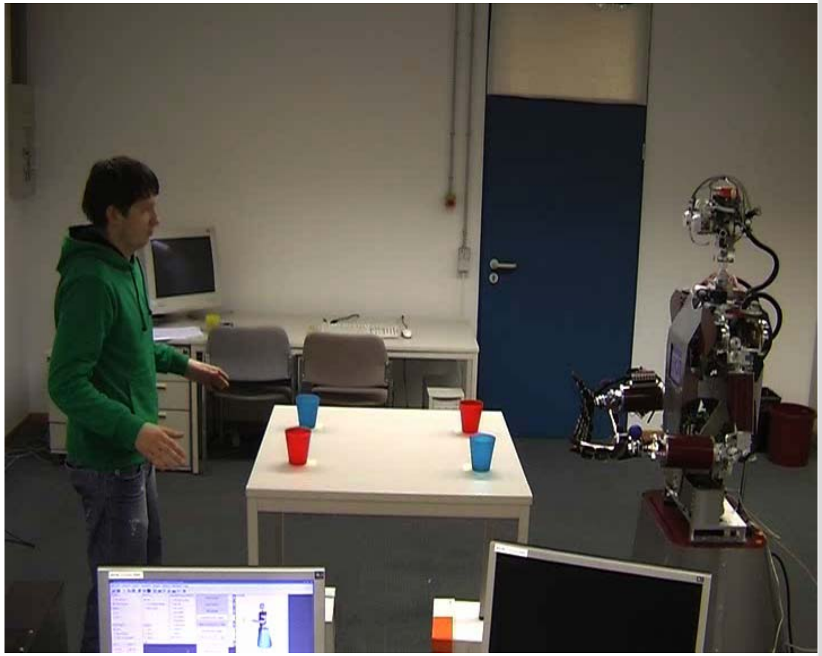
Learning from Observation

- Library of motor primitives
  - Markerless human motion tracking
  - Object tracking
- Master Motor Map (MMM) as an interface for the transfer of motor knowledge between different embodiments
- Action representation
  - Dynamic movement primitives for generating discrete and periodic movements
  - Adaptation of dynamic systems to allow sequencing of movement primitives
  - Associating semantic information with DMPs
  - → sequencing of movement primitives
  - → Planning



Learning from Observation

- Periodic movements: Wiping
  - Extract the frequency and learn the waveform.
  - Incremental regression for waveform learning

Joint work with Andrej Gams and Ales Ude

- Human grasp recognition, mapping and reproduction

Joint work with Danica Kragic

Connecting High-level Task Planning to Execution

PKS planner (STRIPS-like planner)

Joint work with Ron Patrick and Mark Steedman, University of Edinburgh

Conclusions

Current work on humanoid grasping and manipulation in human-centered environments

- Grasping known objects
  - Appearance-based approaches
  - Shape-based approaches (box decomposition)
- Grasping unknown objects
  - 3D visual primitives (CoVis) → Grasp reflex
- Pushing for Grasping
  - pushing movements encoded by a neural network learned by exploration
- Learning from human observation
  - Action representations, which support adaption to novel situations

Thanks

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Thank you ...

... for your attention.

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