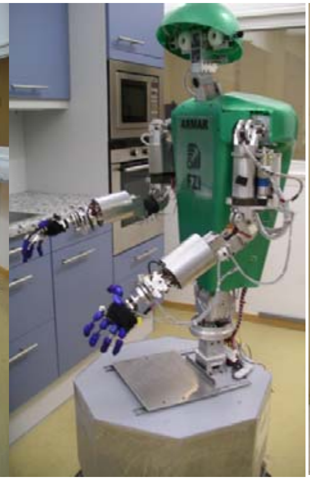
ShanghAI Lectures 2010
December, 16, 2010

Robots think with their hands

Tamim Asfour
Karlsruhe Institute of Technology, Institute for Anthropomatics, Germany

INSTITUTE FOR ANTHROPOMATICS, DEPARTMENT OF INFORMATICS






http://his.anthropomatik.kit.edu http://his.anthropomatik.kit.edu/english/65.php

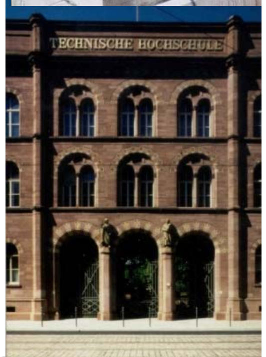
Where is Karlsruhe?

Surroundings

- Black Forest
- Baden-Baden
- Strasbourg
- Heidelberg
- Freiburg
- Stuttgart

University of Karlsruhe

- Founded 1825 as a polytechnical school, modeled after the *Ecole Polytechnique* in Paris.
- 1967 Renamed *Universität Fridericiana Karlsruhe (TH)*
- 11 Departments
- Famous teacher: Heinrich Hertz (1857-1894), Professor of Physics. Discovered electromagnetic waves. Basis for
  - radio transmission technology
  - modern information systems



Famous students

- Famous without studying
  - The first bicycle-like vehicle was the Laufmachine, invented by *Karl von Drais*. This bike had two in-line wheels and allowed to propel along with less effort than walking or running

- A well-known student
  - 1878 Karl Benz developed a two-cycle internal combustion engine and invented the differential drive (after becoming an engineer from the Polytechnikum)
  - 1885 he built a three-wheeled vehicle with an internal combustion engine
  - Today, DaimlerChrysler´s headquarter resides in Stuttgart.

Karlsruhe Institute of Technology (KIT)

- On October 01, 2009, the Karlsruhe Institute of Technology (KIT) was founded by a merger of Forschungszentrum Karlsruhe and Universität Karlsruhe
- KIT bundles the missions of both institutions:
  - A university of the state of Baden-Wuerttemberg with teaching and research tasks and
  - A large-scale research institution of the Helmholtz Association conducting program-oriented provident research on behalf of the Federal Republic of Germany.
- Three strategic fields: research, teaching, innovation
- One of the largest research and teaching institutions worldwide: About 8000 employees and annual budget of about EUR 700 million

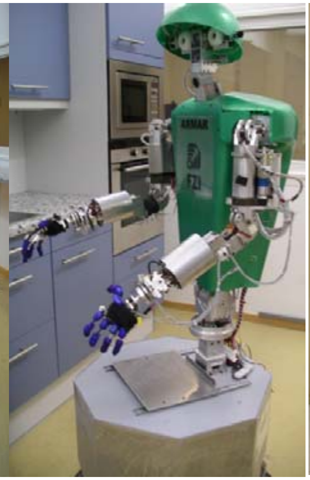
ShanghAI Lectures 2010
16. December 2010

Robots think with their hands

Tamim Asfour
Karlsruhe Institute of Technology, Institute for Anthropomatics
Humanoids and Intelligence Systems Lab

INSTITUTE FOR ANTHROPOMATICS, DEPARTMENT OF INFORMATICS






http://his.anthropomatik.kit.edu http://his.anthropomatik.kit.edu/english/65.php

Building Humanoids

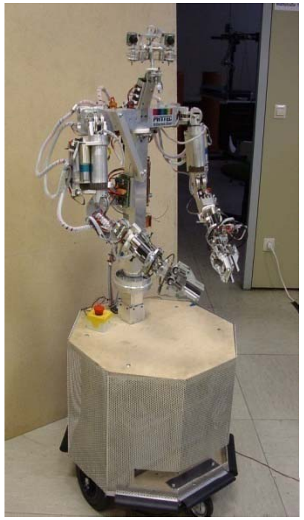
Building Humanoids = Building Human-Centered Technologies

- Assistants/companions for people in different ages, situations, activities and environments in order to improve the quality of life
- Key technologies for future robotic systems
- Experimental platforms to study theories from other disciplines

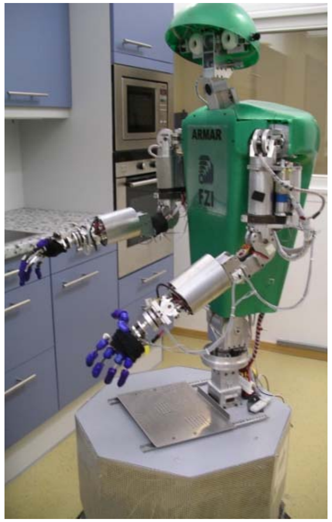
Ultimate goals

- 24/7 integrated complete humanoid robot systems able to act and interact in human-centered environments and to perform a variety of tasks
- Robots with rich sensorimotor capabilities as an indispensible requirement to implement cognitive capabilities in technical systems
- Reproducible complete humanoid systems in terms of mechanical design, mechantronics, hardware and software architecture
- Autonomous humanoid systems

Humanoid Robots @ KIT

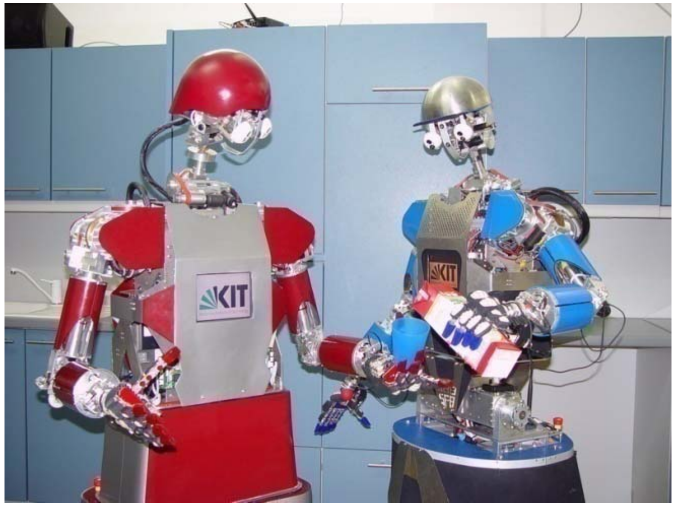


ARMAR, 2000



ARMAR-II, 2002

ARMAR-IIIa, 2006

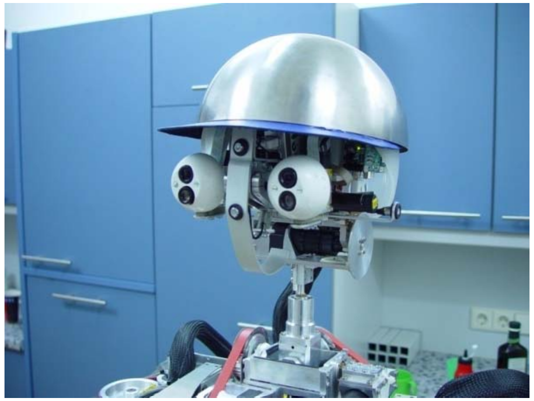


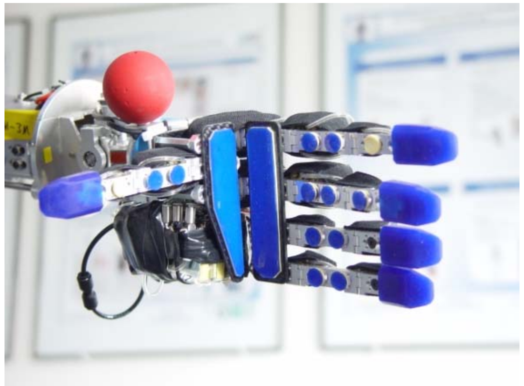
ARMAR-IIIb, 2008

- Collaborative Research Center 588: Humanoid Robots - Learning and Cooperating Multimodal Robots (SFB 588)
  - Funded by the German Research Foundation (DFG: Deutsche Forschungsgemeinschaft)
  - 2001 – 2012
  - http://www.sfb588.uni-karlsruhe.de/

ARMAR-IIIa and ARMAR-IIIb

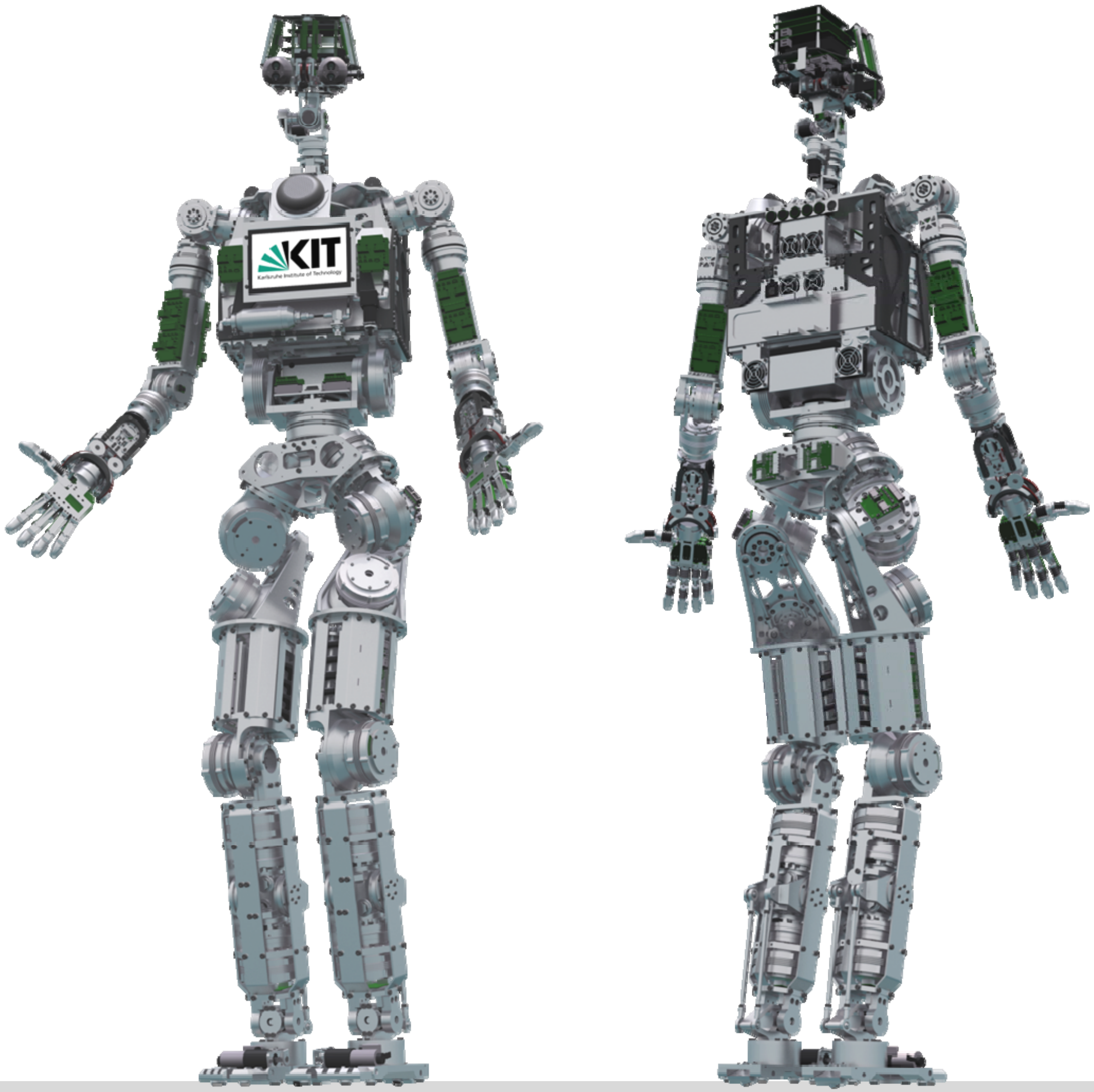
- 7 DOF head with foveated vision
  - 2 cameras in each eye
  - 6 microphones
- 7-DOF arms
  - Position, velocity and torque sensors
  - 6D FT-Sensors
  - Sensitive Skin
- 8-DOF Hands
  - Pneumatic actuators
  - Weight 250g
  - Holding force 2,5 kg
- 3 DOF torso
  - 2 Embedded PCs
  - 10 DSP/FPGA Units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





Fully integrated autonomous humanoid system

ARMAR-IV



- 63 DOF
- 170 cm
- 70 kg

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

© SFB 588, Karlsruhe Video

Interactive tasks in kitchen environment

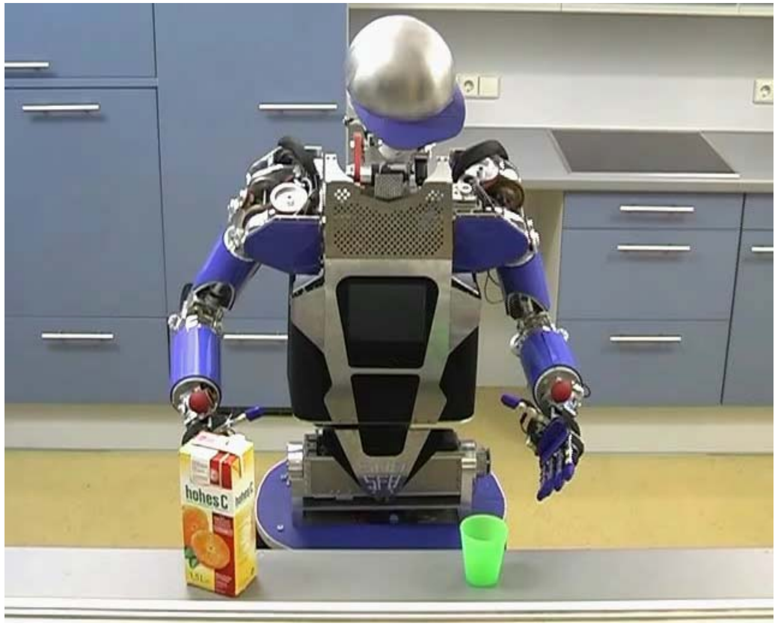
- Object recognition and localization
- Vision-based grasping
- Hybrid position/force control
- Vision-based self-localisation
- Combining force and vision for opening and closing door tasks
- Learning new objects, persons and words
- Collision-free navigation
- Audio-visual user tracking and localization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

Video

Bimanual grasping and manipulation

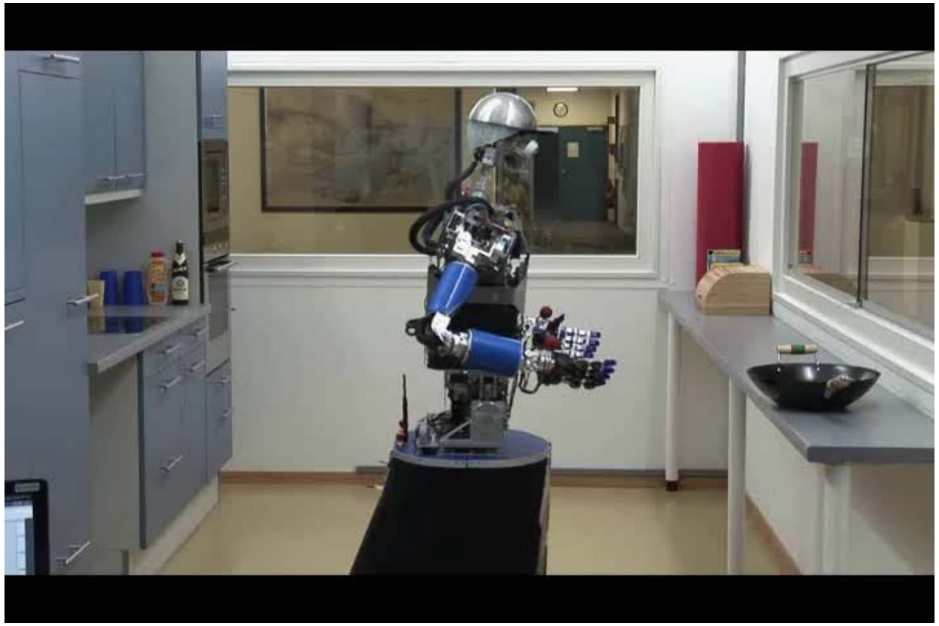
- Stereovision for object recognition and localization
- Visual Servoing for dual-hand grasping
- Zero-force control for teaching of grasp poses

Video



Loosely coupled dual-arm tasks

Video



Tightly coupled dual-arm tasks

Limitations and shortcuts

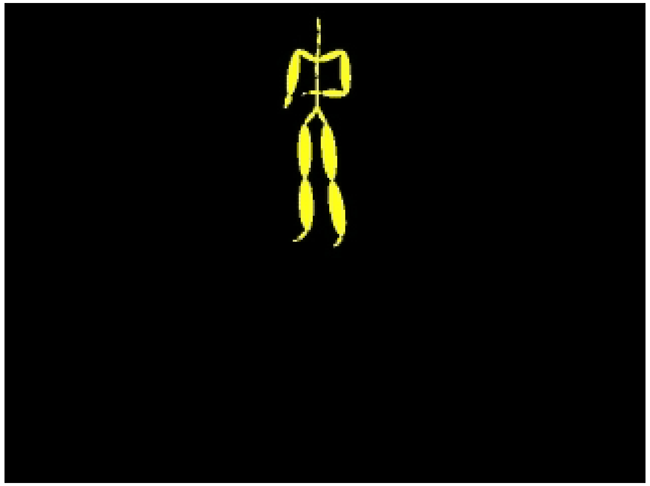
- Problem: Representational differences between high-level AI planning and low-level robotics/vision.
  - Continuous Robotics vs. Discrete AI Planning
  - Previous efforts have resulted in largely ad-hoc solutions.
- Claim: Object-Action Complexes (OACs) can be used as a "lingua franca" to bridge this representational divide.
  - Formalize the requirements for an artificial system to approach some level of cognitive complexity
  - Grounding of entities in the motor-sensory domain
  - Data structures, which can be used on all levels
- EU project PACO-PLUS: www.paco-plus.org

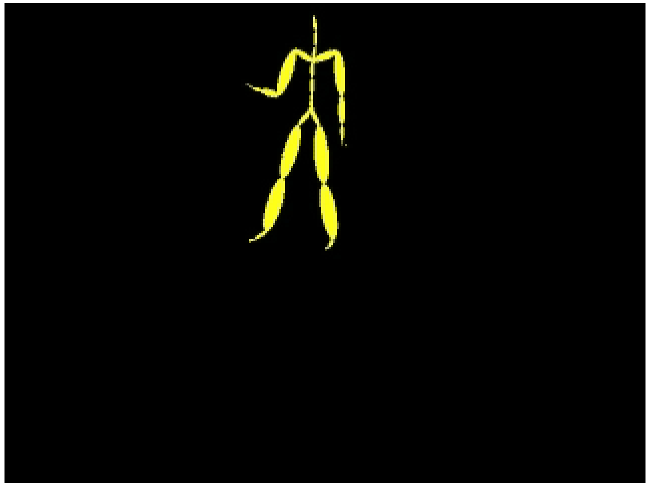
Main Paradigm

Videos

Objects and Actions are inseparably intertwined

- Visually based object recognition fails
- Visual information is sparse and limited
- Activity involving the object decreases the uncertainty about the object's nature considerably!





CMU Graphics Lab Motion Capture Database
http://mocap.cs.cmu.edu/

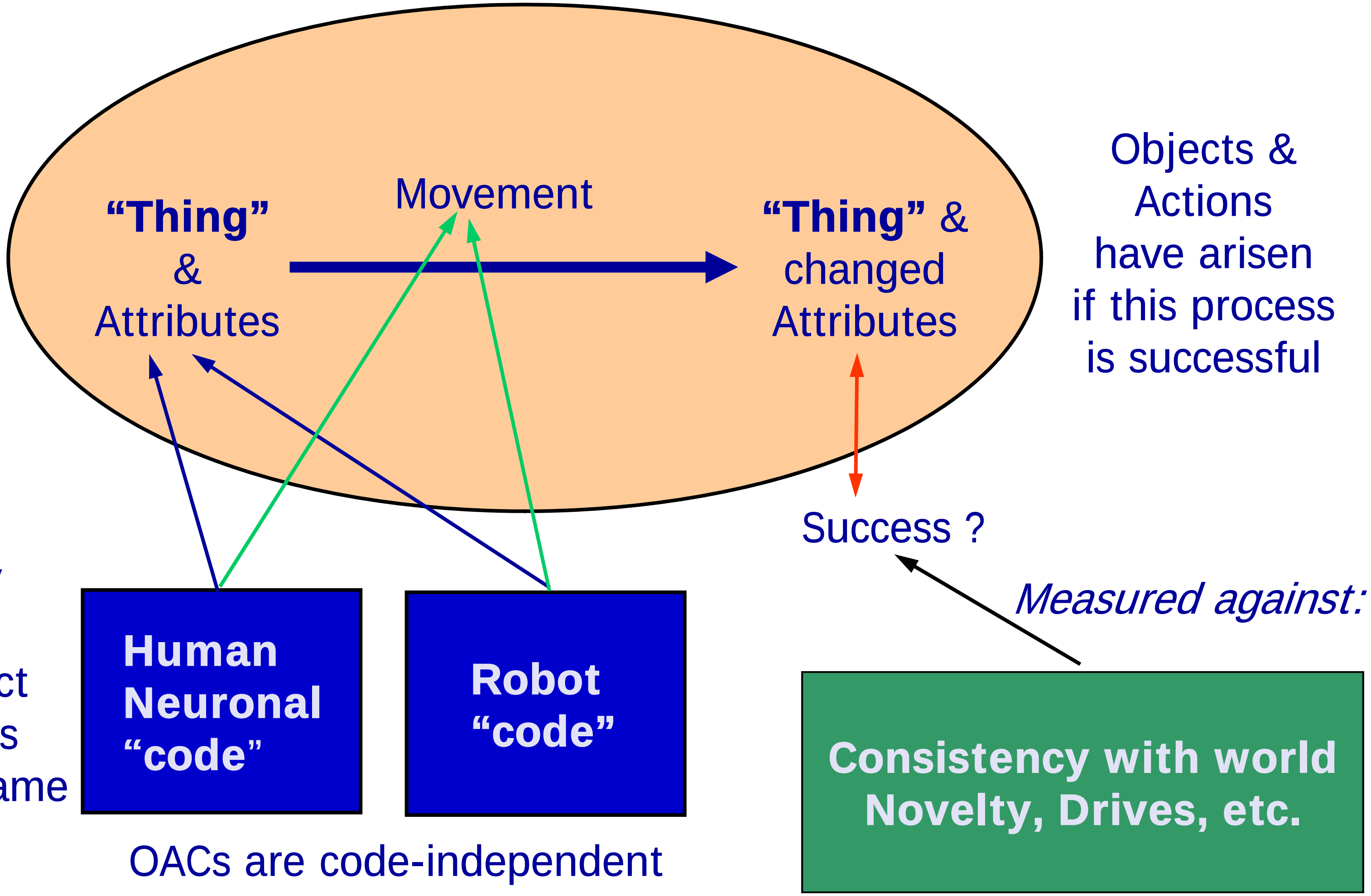
Intuitions on Object-Action Complexes

- Affordances (J.J. Gibson)
  - Objects affords actions

- Object-Action Complexes (OACs)
  - Actions define the meaning of Objects and
  - Objects suggest Actions

Object Perspective

OAC



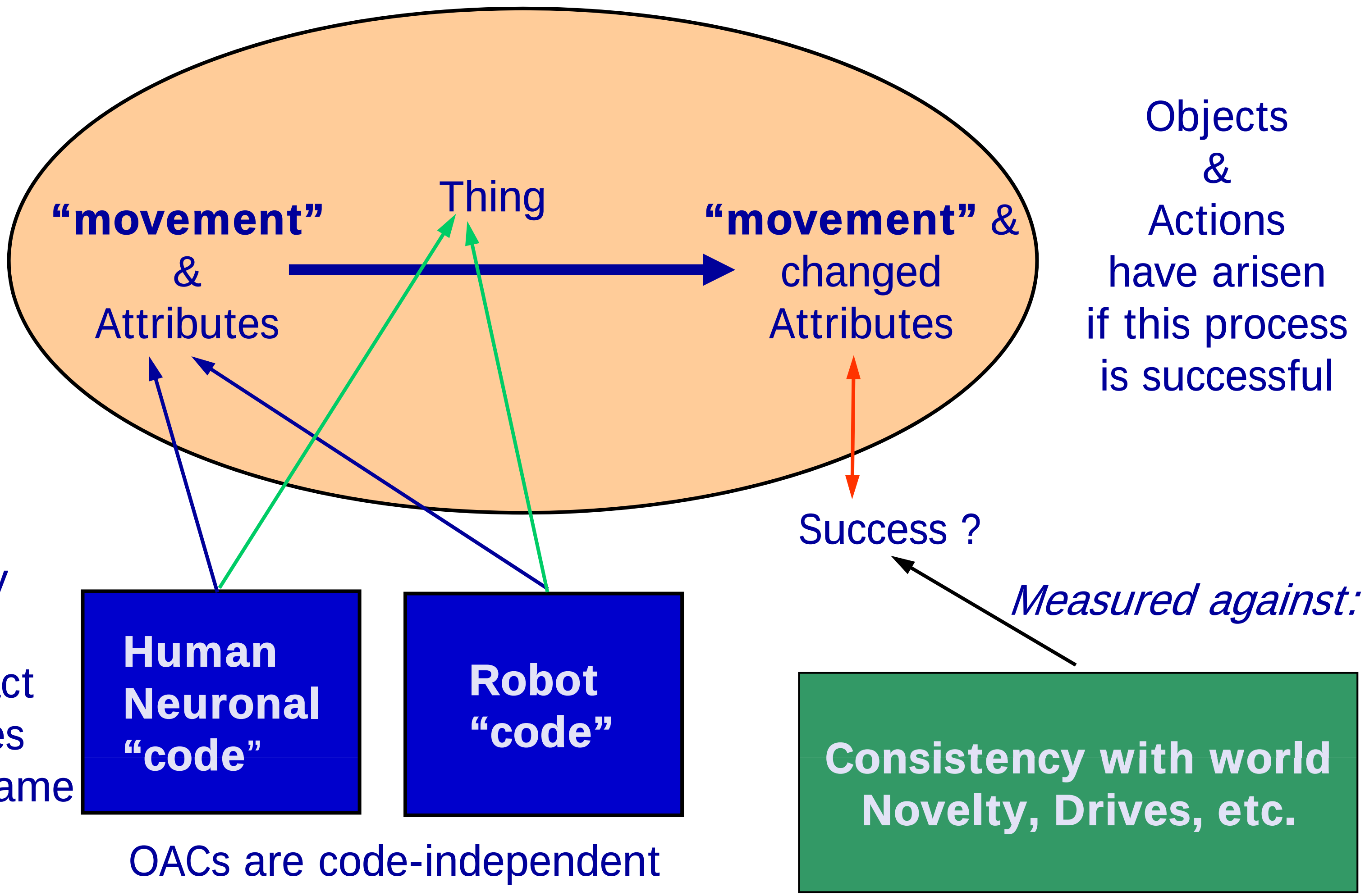
Objects & Actions have arisen if this process is successful

Code-similarity emerges only through the fact that both codes describe the same physical entity

OACs are code-independent

Action Perspective

OAC

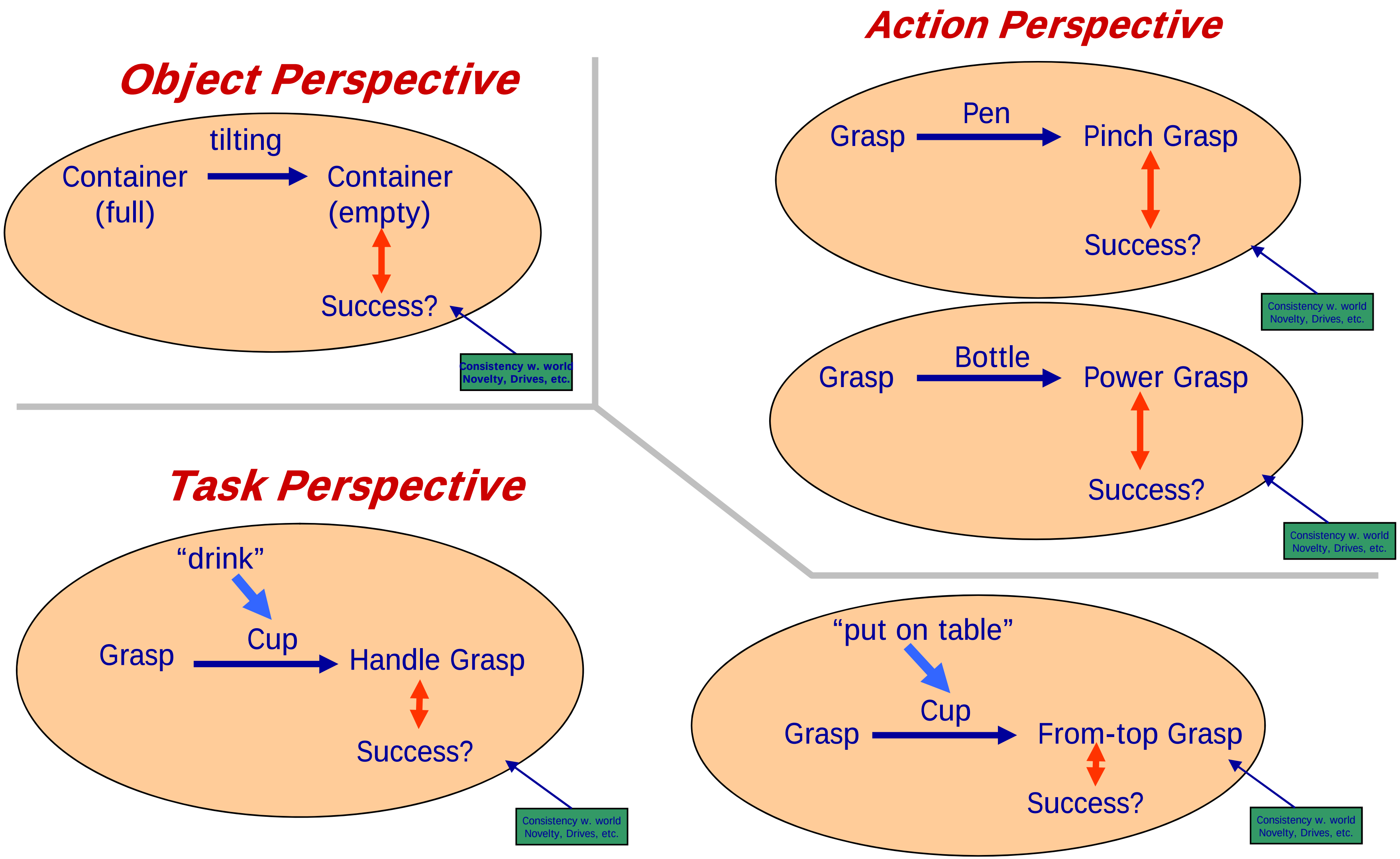


OACs are code-independent

Objects & Actions have arisen if this process is successful

Code-similarity emerges only through the fact that both codes describe the same physical entity

Object, Action and Task Perspective



Formalization of OACs

Krüger et al. 2009. *A Formal Definition of Object-Action Complexes and Examples at Different Levels of the Processing Hierarchy* (*available at www.paco-plus.org*)

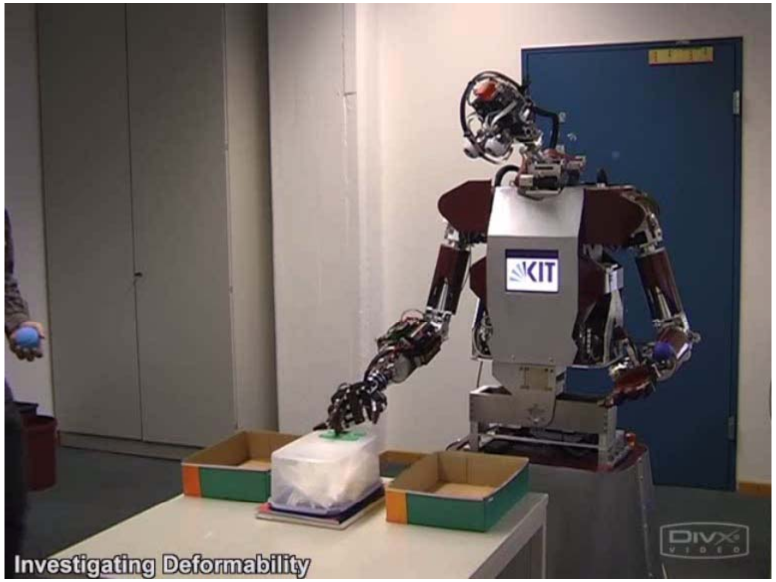
See also www.paco-plus.org

How to relax the limitations in our scenario?

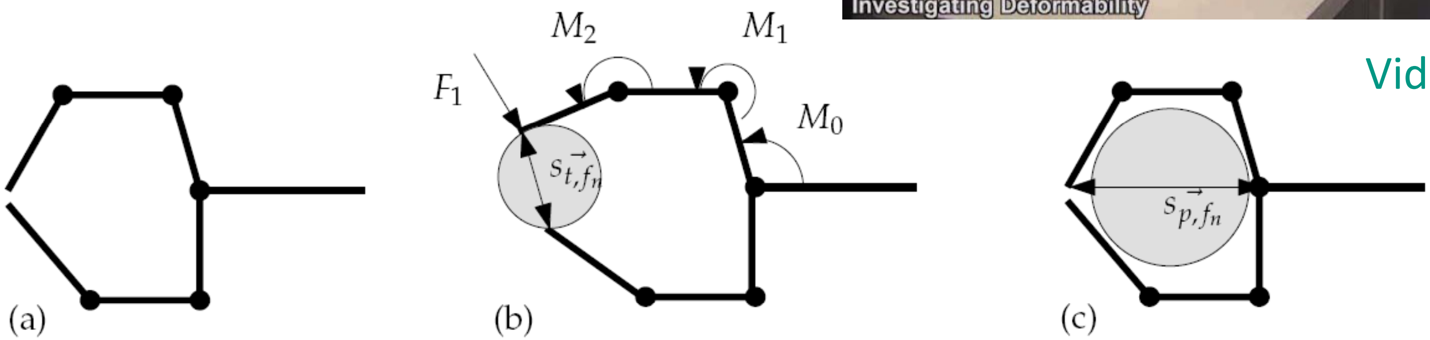
- Autonomous Exploration:
  - Visually-guided haptic exploration
  - Visual object exploration and search
  - Learning actions of objects
- Coaching and Imitation
  - Learning from Observation
  - Goal-directed Imitation

Hand: available skills

- Direct/Inverse Kinematics
- Position/force control
- Detection of contact and "objectness"
- Assessment of deformability and object size



Video



Failed grasp "no object"

Precision grasps: Distance between fingertips

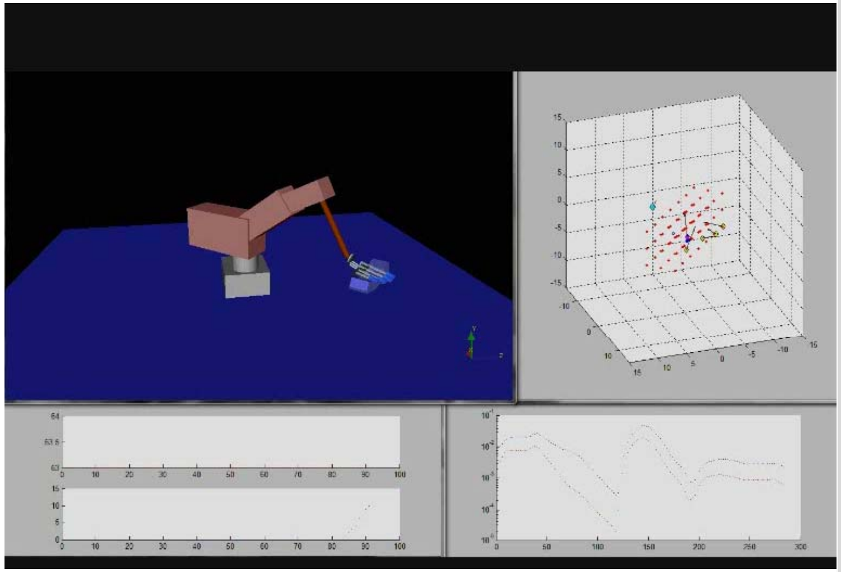
Power grasps: Distance between fingertips and palm

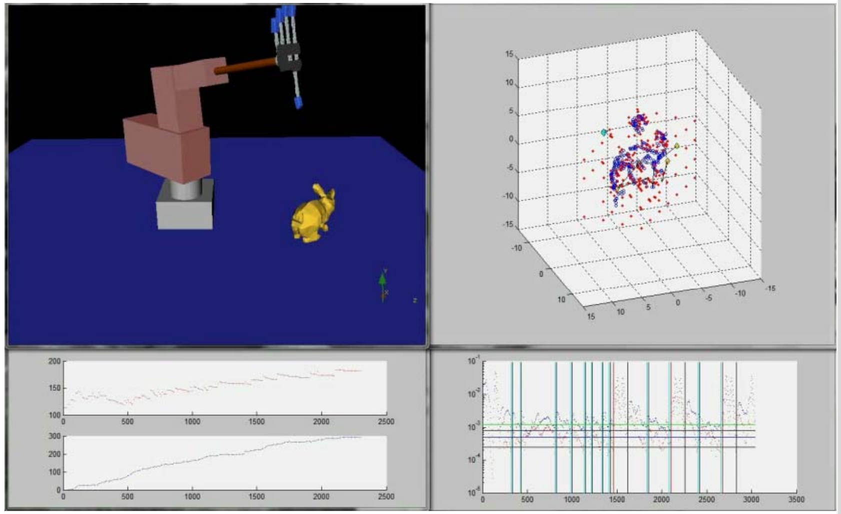
Tactile Object Exploration

Videos

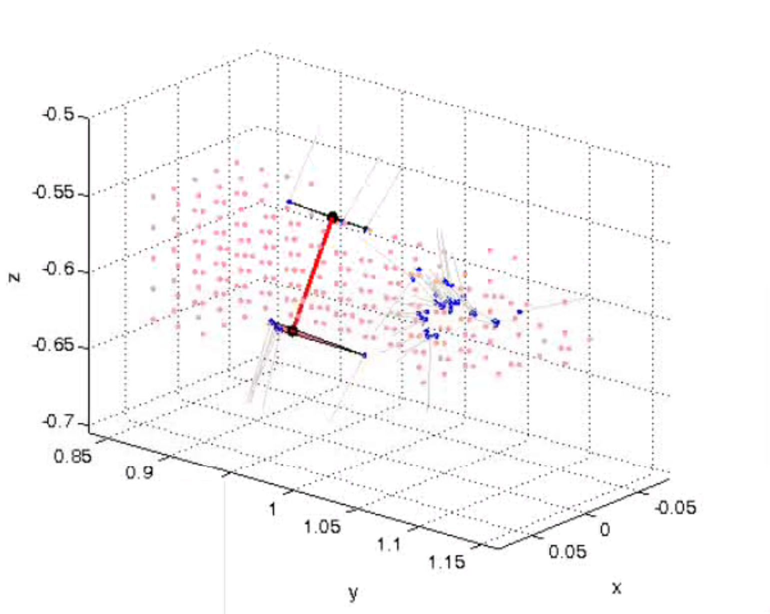
- Potential field approach to guide the robot hand along the object surface
- Oriented 3D point cloud from contact data
- Extract faces from 3D point cloud in a geometric feature filter pipeline
    - Parallelism
    - Minimum face size
    - Face distance
    - Mutual visibility

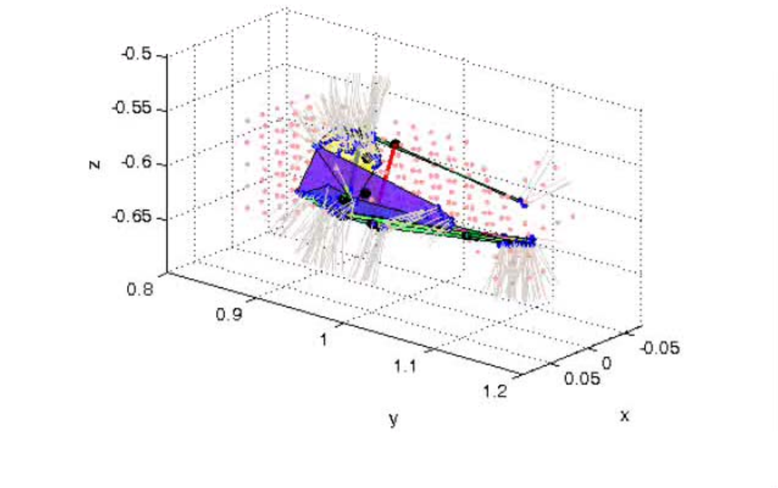
→ Association between objects and actions (grasps) → Symbolic grasps (grasp affordances)



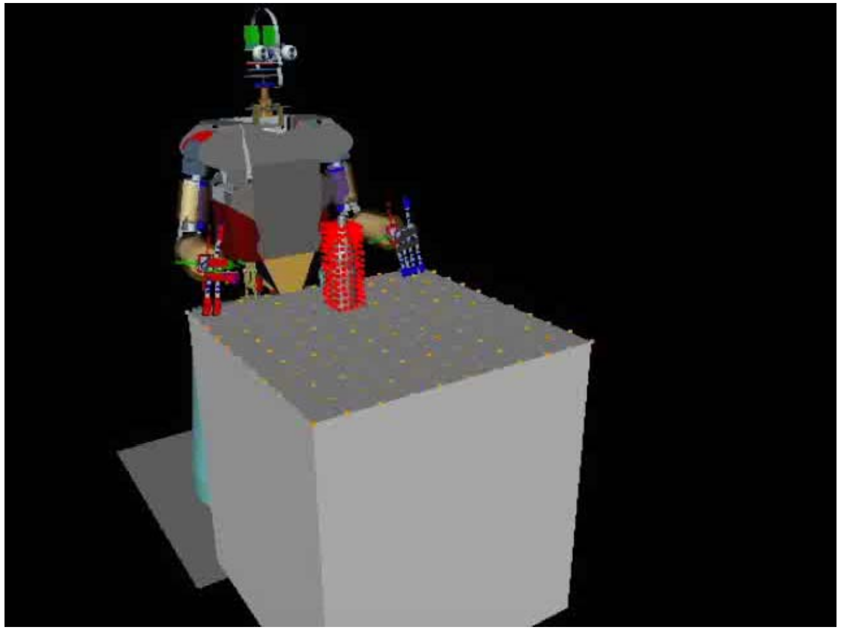


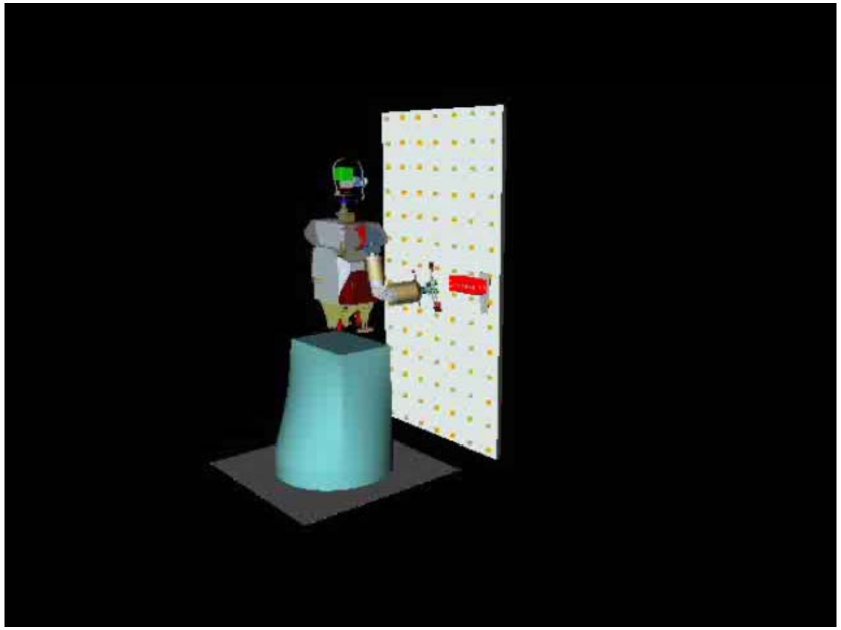
Examples: Bottle





Visually guided haptic exploration on ARMAR





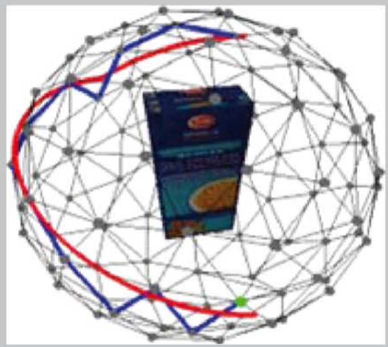
Videos

- In simulation
  - Physics extension for Open Inventor/VRML modeling of complex mechanical systems
  - Modeling of virtual sensors
  - VMC-based inverse kinematics

Active Visual Object Exploration and Search

Exploration

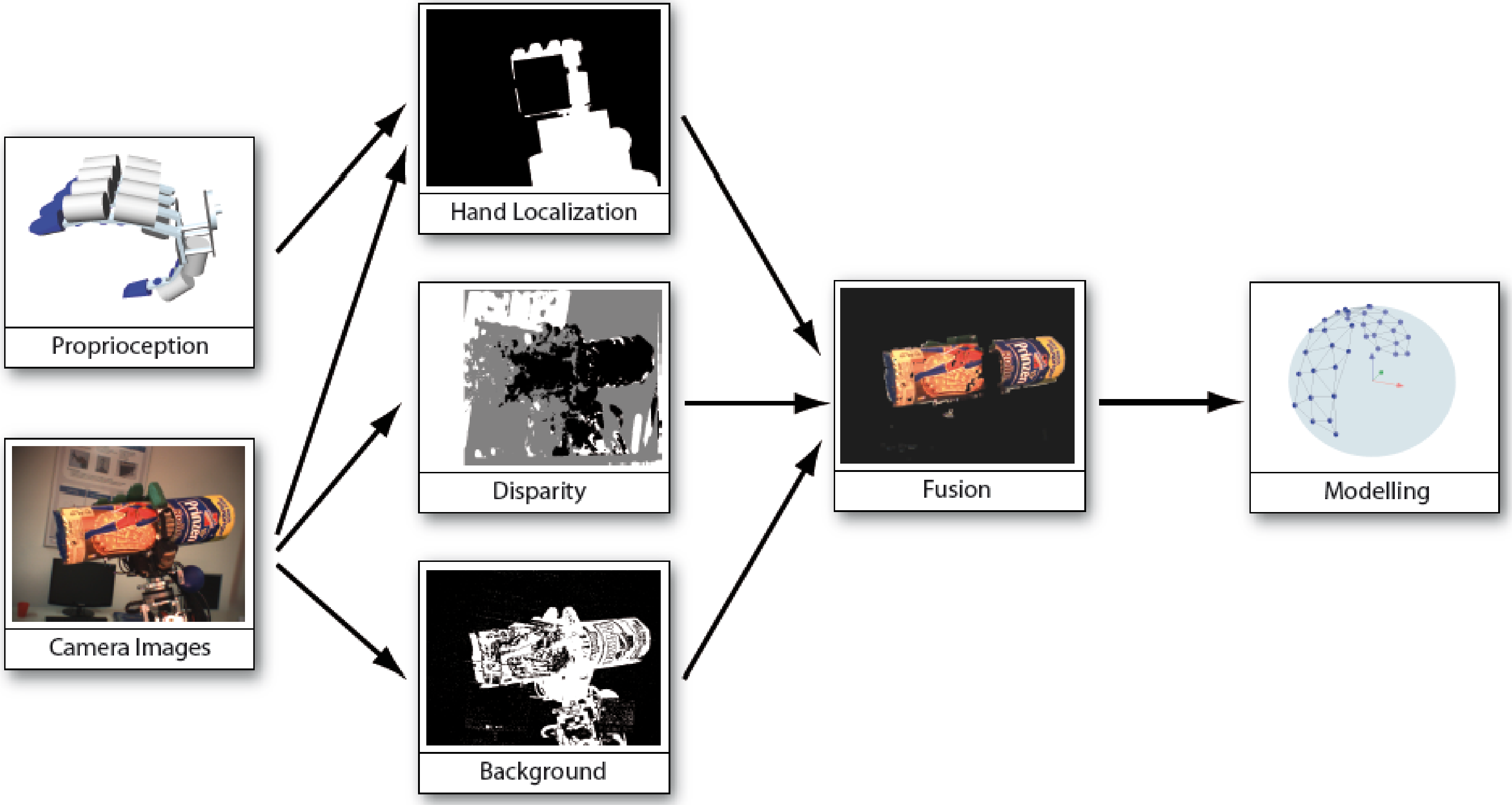
Representation



Visual Search

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

Generation object views through manipualtion



Video

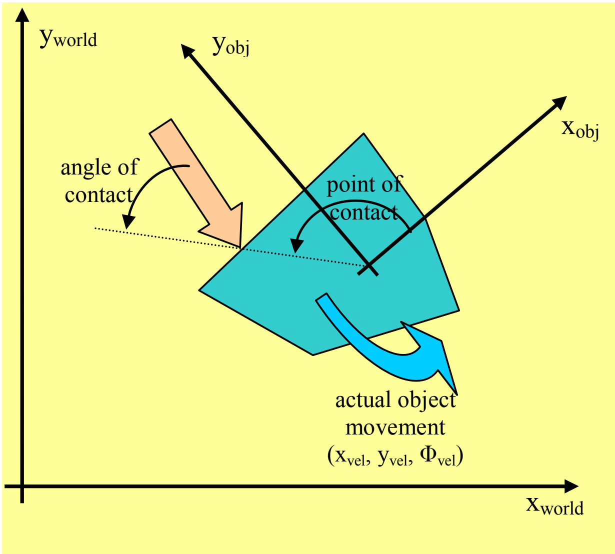
Active visual search

- Active Search
  - Object search using perspective and foveal camera
- Scene memory
  - Integration of object hypotheses in an ego-centric representation

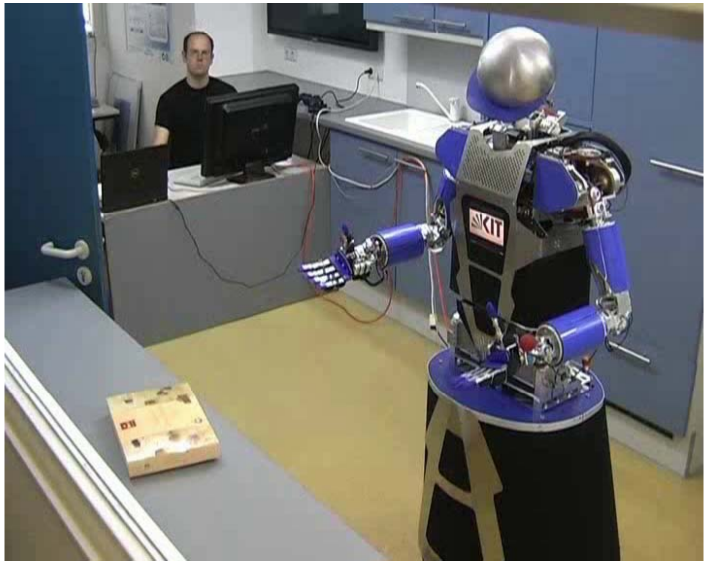
Video

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



Work with Damir Omrcen and Ales Ude

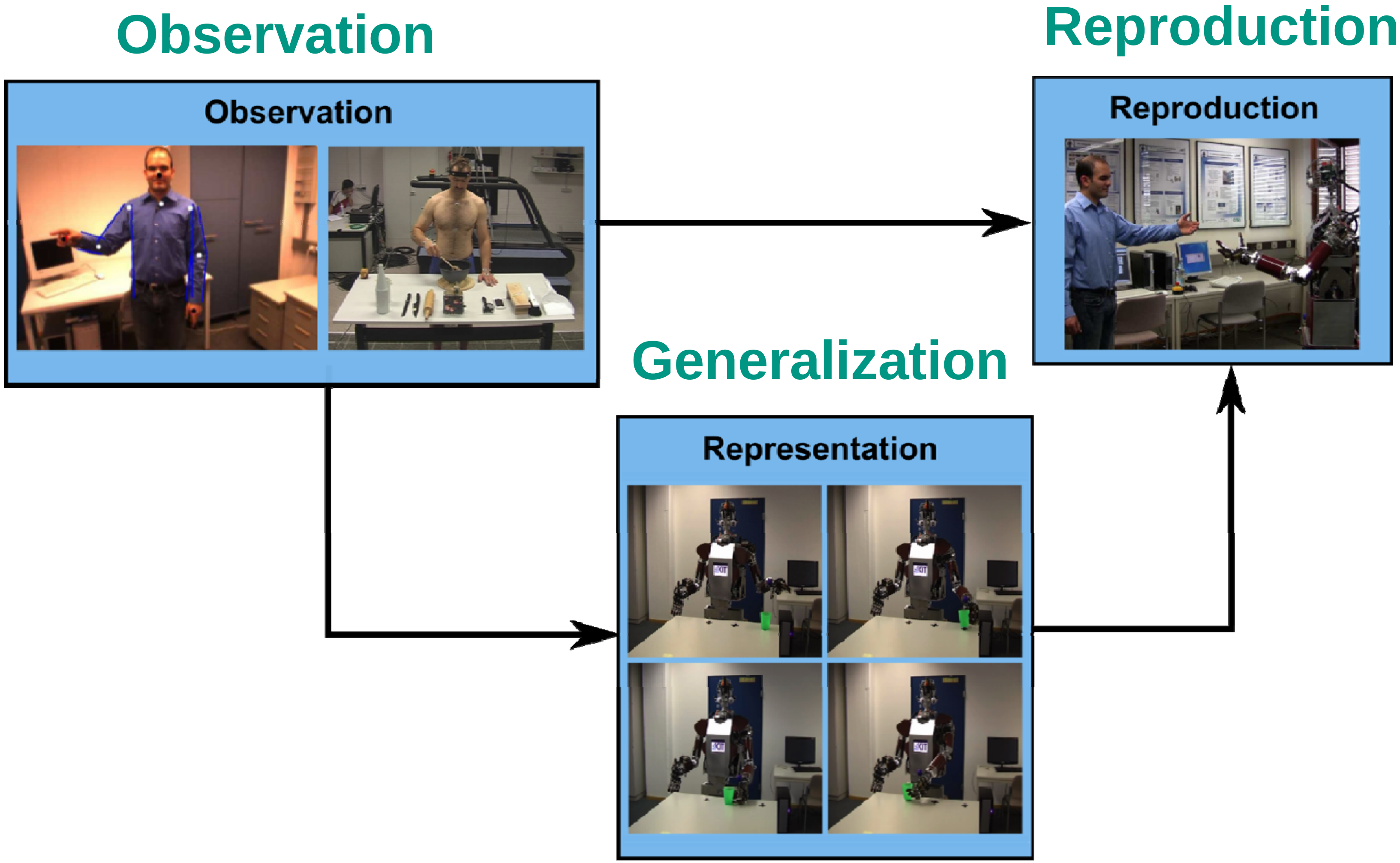


Video

How to relax the limitations in our scenario?

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

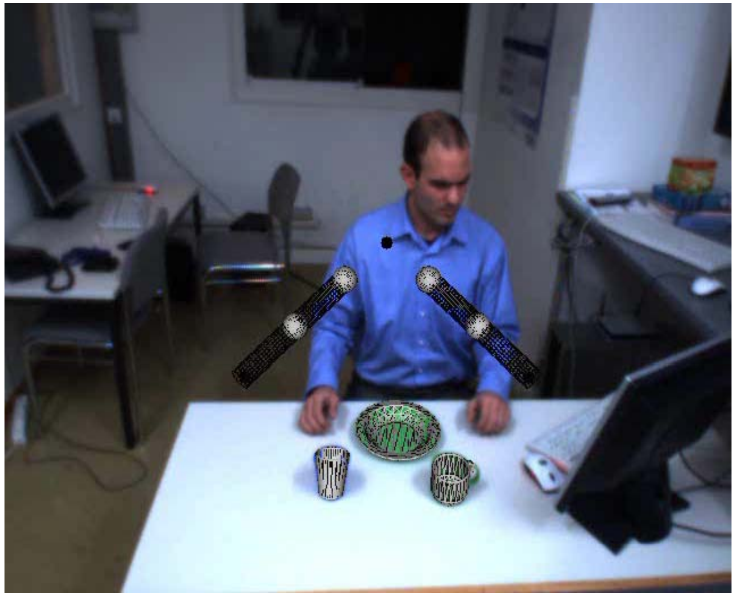
Learning from human observation



Stereo-based 3D Human Motion Capture

- Capture 3D human motion based on the image input from the cameras of the robot‘s head only
- Approach
  - Hierarchical Particle Filter framework
  - Localization of hands and head using color segmentation and stereo triangulation
  - Fusion of 3d positions and edge information
  - Half of the particles are sampled using inverse kinematics
- Features
  - Automatic Initialization
  - 30 fps real-time tracking on a 3 GHz CPU, 640x440 images
  - Smooth tracking of real 3d motion

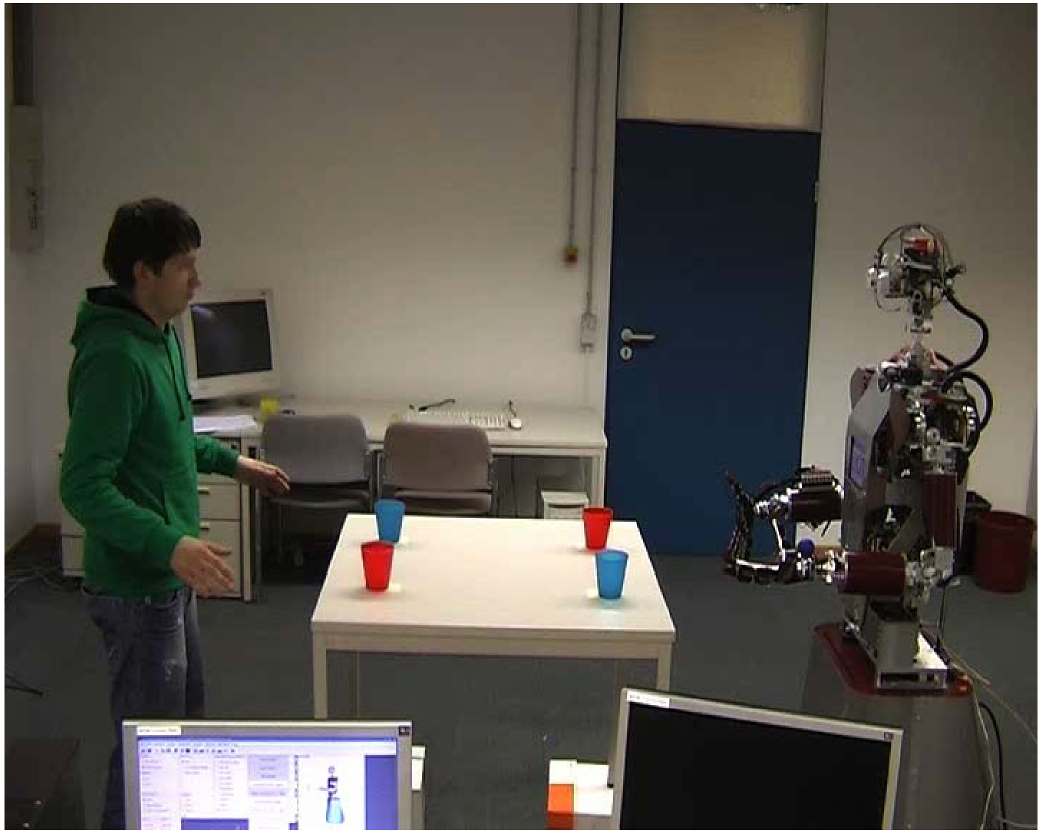
video



Integrating Vision Toolkit: http://ivt.sourceforge.net/

Reproduction

- Tracking of human and object motion
- Visual servoing for grasping



Generalisation?

Video

Action representation

- Hidden Markov Models (HMM) Humanoids 2006, IJHR 2008
  - Extract key points (KP) in the demonstration
  - Determine key points that are common in multiple demonstrations (common key points: CKP)
  - Reproduction through interpolation between CKPs
- Dynamic movement primitives (DMP) ICRA 2009
  - Ijspeert, Nakanishi & Schaal, 2002
  - Trajectory formulation using canonical systems of differential equations
  - Parameters are estimated using locally weighted regression
- Spline-based representations Humanoids 2007
  - fifth order splines that correspond to minimum jerk trajectories to encode the trajectories
  - Time normalize the example trajectories
  - Determine common knot points so that all example trajectories are properly approximated. Similar to via-point, key-points calculation.

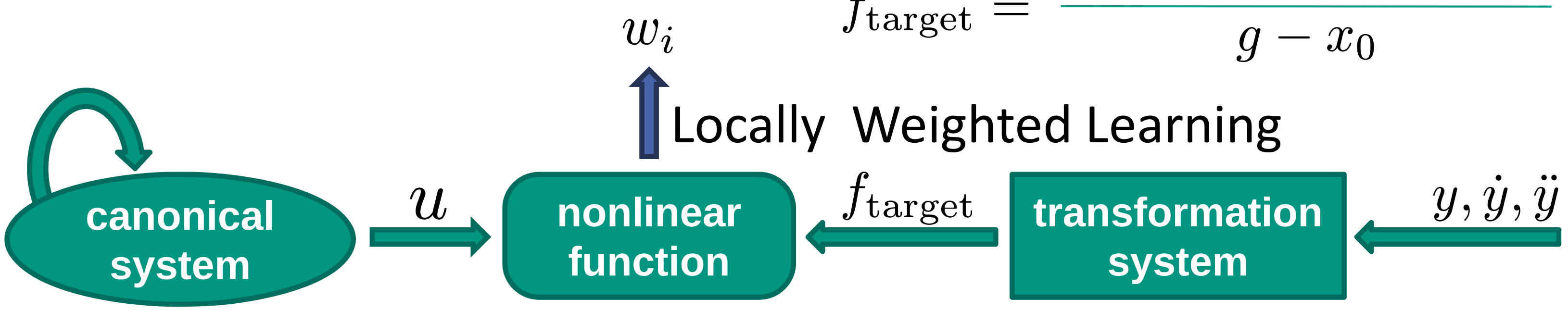
Action representation using DMPs

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

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

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

$$f_{\text{target}} = \frac{-K(g - y) + D\dot{y} + \tau \ddot{y}}{g - x_0}$$



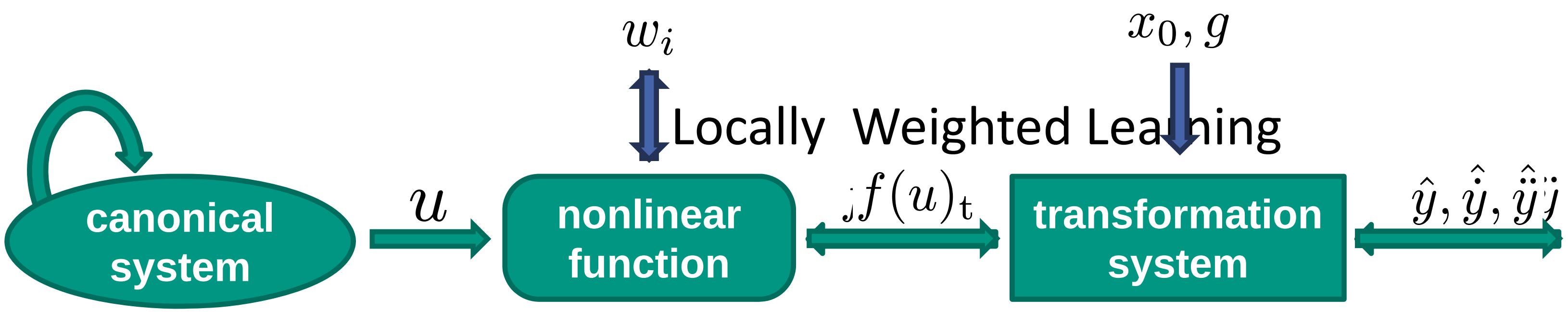
Action representation using DMPs

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

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

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

$\tau \dot{x} = v$



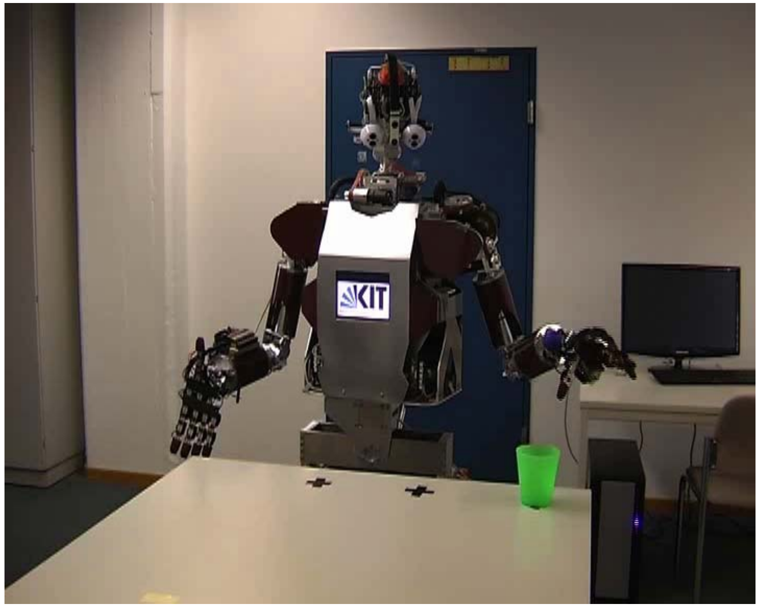
Learning from Observation

- Library of motor primitives
  - Markerless human motion tracking
  - Object tracking

- 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



Video

Learning from Observation

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

Video

Joint work with Andrej Gams and Ales Ude

A. Ude, A. Gams, T. Asfour, J. Morimoto. Task-Specific Generalization of Discrete and Periodic Dynamic Movement Primitives. IEEE Trans. on Robotics, vol. 26, no. 5, pp. 800 – 815, October, 2010

Thanks to the PACO-PLUS Consortium

Karlsruhe Institute of Technology

University of Karlsruhe, Germany
R. Dillmann, T. Asfour

ATR, Kyoto, Japan
M. Kawato & G. Cheng

Kungliga Tekniska
Högskolan, Sweden
J. O. Eklundh, D. Kragic

University of Liege
Belgium
J. Piater

University of
Göttingen
Germany
F. Wörgötter

PACO-PLUS

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

www.paco-plus.org

University of
Southern Denmark
N. Krüger

Aalborg University
Denmark
V. Krüger

University of Edinburgh
United Kingdom
M. Steedman

Jozef Stefan Institute
Slovenia
A. Ude

Leiden University
Netherlands
B. Hommel

Consejo Superior de Investigaciones
Científicas, Spain
C. Torras & J. Andrade-Cetto

Thanks

- Humanoids Group @ KIT
  - Rüdiger Dillmann
  - Stefan Ulbrich
  - David Gonzalez
  - Manfred Kröhnert
  - Niko Vahrenkamp
  - Julian Schill
  - Kai Welke
  - Ömer Terlemez
  - Alex Bierbaum
  - Martin Do
  - Stefan Gärtner
  - Markus Przybylski
  - Tamim Asfour
  - Isabelle Wappler
  - Pedram Azad (not in the picture)
  - Paul Holz (not in the picture)

Thank you ...

... for your attention.

- This work has been conducted within:
  - the German Humanoid Research project SFB588 funded by the German Research Foundation (DFG)
    www.sfb588.uni-karlsruhe.de
  - the EU Cognitive Systems projects funded by the European Commission
    - PACO-PLUS www.paco-plus.org
    - GRASP www.grasp-project.eu