Karlsruher Institut für Technologie

Hochperformante Humanoide Technologien

Robotics II: Humanoid Robotics

Chapter 3 – Grasping

Tamim Asfour

http://www.humanoids.kit.edu

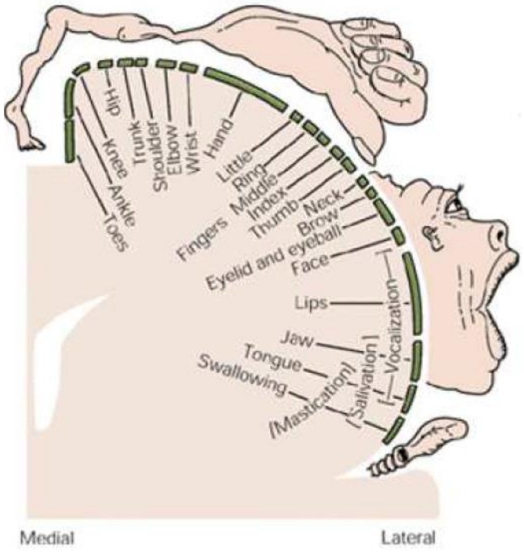
Table of Contents

Fundamentals and Definitions

Cognitive Grasping

- Grasping and manipulation as **a control problem** have been studied since the beginning of robotics. **HOWEVER**, very little has been done in terms of cognitive aspects of grasping, implementation and evaluation of systems
- Large part of the human cortex is dedicated to grasping and manipulation, and it would seem reasonable to assume that all of this cognitive machinery is dedicated to finely controlling individual joints and generating highly flexible hand postures
- Understanding how the human brain controls the hand

Homunculus

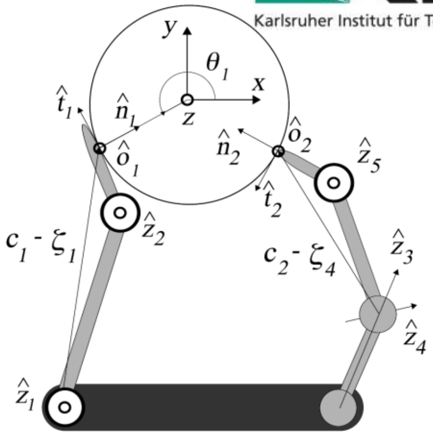


Ghez, C., and Krakauer, J. "The organization of movement." *Principles of neural science* 4 (2000): 653-73.

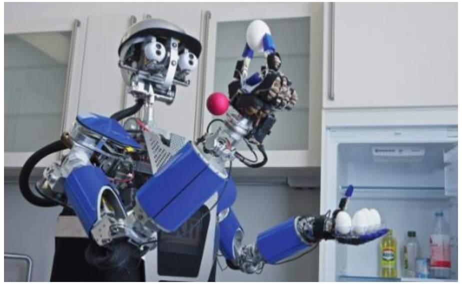
Understanding Hands = Understanding Intelligence

What Is a Grasp?

- A system wherein a desired object is gripped by the fingers of a robot (or human) hand is generally called a **grasp**
- **Precision grasp:** object gripped by fingertips only
- **Grasp = Set of contact points**
- **Force-closure grasp:** is a grasp which is able to
    1. generate any external force that the grasped object may have to exert on an external body and
    2. counteract any external disturbing forces that may try to loosen the grip



Prattichizzo and Trinkle. *Handbook of Robotics*. Chapter 28, Springer, 2016



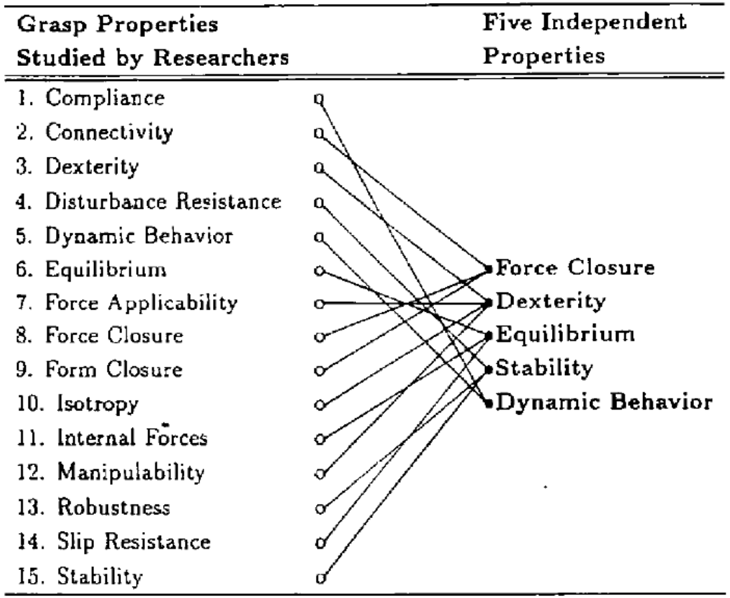
What Properties Are Essential to Grasps (I)

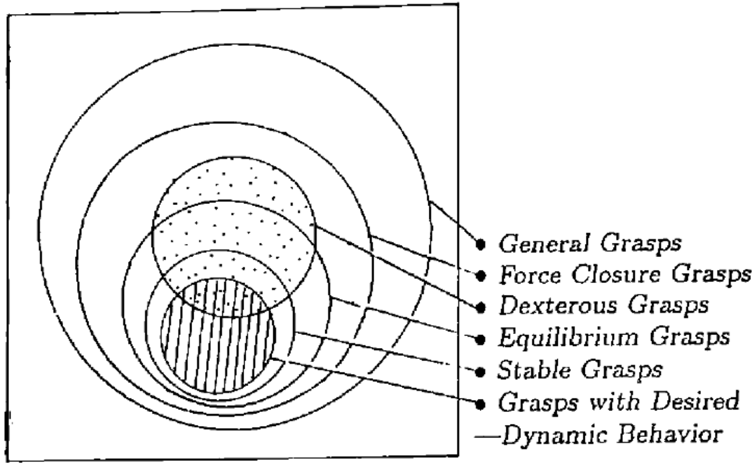
- Researchers have identified a multitude of properties that an articulated force-closure grasp must possess in order for it to be able to perform everyday tasks similar to those performed by human hands

- Four mutually independent **grasp properties**:
  1. **Dexterity:** How should grasping fingers be configured?
  2. **Equilibrium:** How hard to squeeze the grasped object?
  3. **Stability**: How to remain unaffected by external disturbances?
  4. **Dynamic behavior:** How soft a grasp should be for a given task?

Shimoga, K. B. "Robot grasp synthesis algorithms: A survey." *The International Journal of Robotics Research* 15.3 (1996): 230-266.

What Properties Are Essential to Grasps (II)





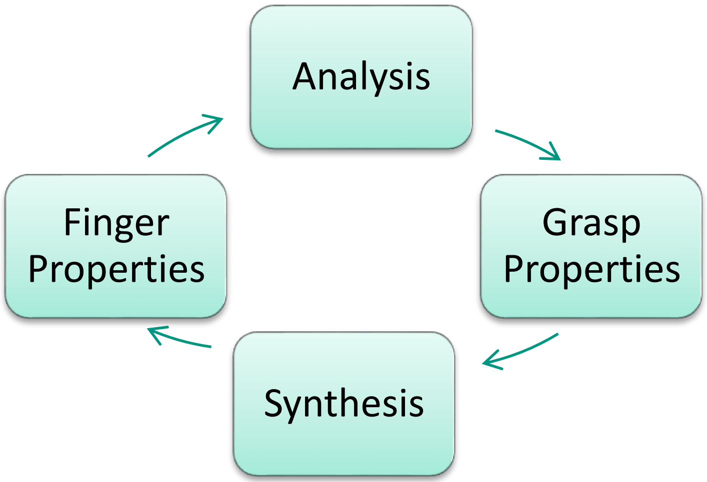
Shimoga, K. B. "Robot grasp synthesis algorithms: A survey." *The International Journal of Robotics Research* 15.3 (1996): 230-266.

Grasp Analysis and Grasp Synthesis

- **Analysis** means the study of grasp properties for a given set of finger properties.

- **Synthesis** means the determination of the required finger properties in order for the grasp to acquire some desired properties.

- **Grasp = Set of contact points**

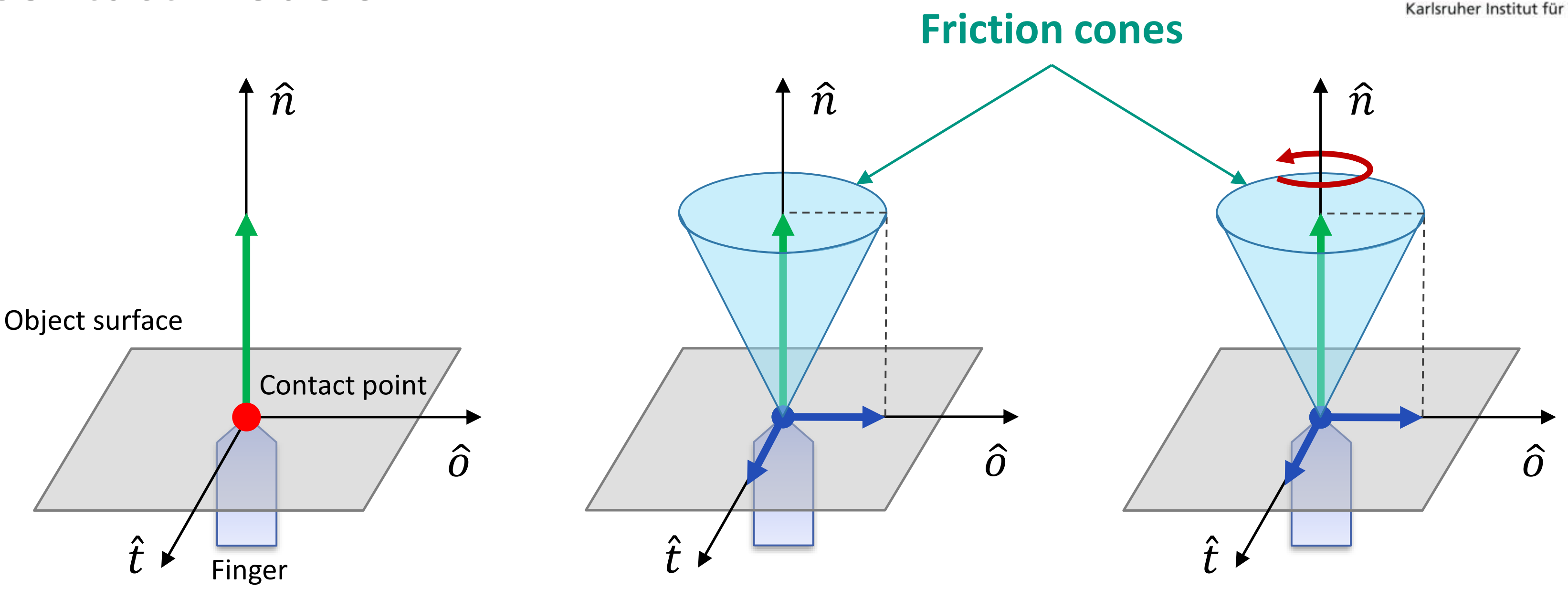


Shimoga, K. B. "Robot grasp synthesis algorithms: A survey." *The International Journal of Robotics Research* 15.3 (1996): 230-266.

Grasp Contacts

- Each point contact can be modelled as either
  - **Frictionless point contact:** Finger can only exert a force along the common normal at the point of contact
  - **Frictional point contact:** A contact that can transmit both a normal and tangential force
  - **Soft contact:** Allows the finger to exert a pure torsional moment about the common normal at the point of contact
- See Lecture Robotics I

Contact models



Rigid contact without friction
(normal force)

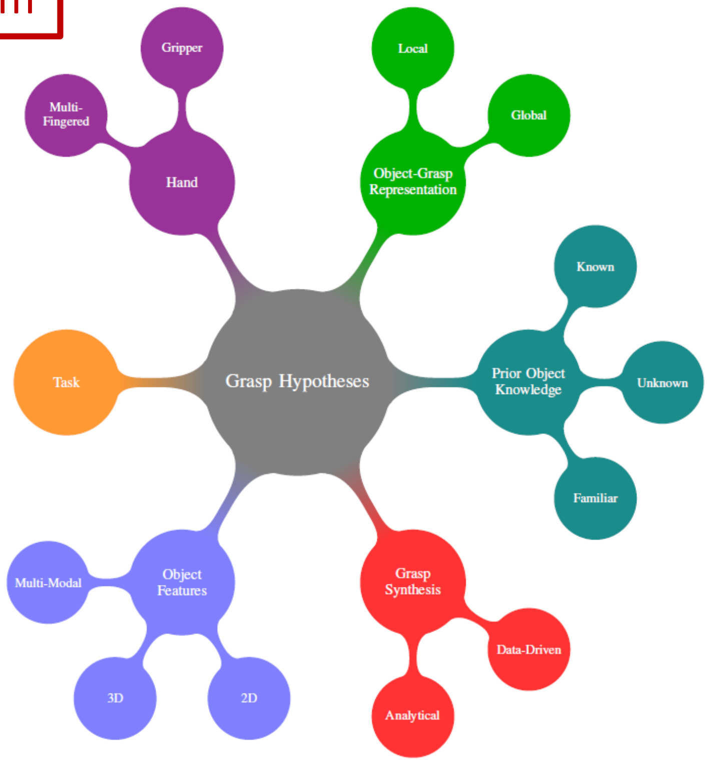
Rigid contact with friction
(normal and tangential forces)

Soft contacts
(normal and tangential forces as well as axial torque at contact point)

What Influences the Generation of Grasp Hypotheses?

Red: relevant for the exam

- Prior object knowledge
- Object-grasp representations
- Features of different modalities such as 2D or 3D vision or tactile sensors
- Grasp synthesis
- Task
- Hand kinematics



Bohg, J., Morales A., Asfour, T. and Kragic, D. "Data-driven grasp synthesis – a survey." IEEE Transactions on Robotics 30.2 (2013): 289-309.

Object Classes for Robot Grasping

- **Known objects** (This is the domain of Grasp Planning!)
  - Known object geometry (i.e. we have a complete geometric object model)
  - Approach: Use various grasp planning methods (only for known objects!)
  - **Hard**
- **“Familiar” objects**
  - Class of object is known (e.g. “bottle”)
  - Approach: Reuse grasp knowledge from known class members for new object
  - **Harder**
- **Unknown objects**
  - No knowledge of the object
  - Challenges: Dealing with (incomplete) sensor data (stereo vision, RGB-D, laser scan, haptic data…), segmentation from the background, building a (partial) object model
  - Ideas: Multi sensor fusion, pushing the object, …
  - **Hardest!**

Object Classes for Robot Grasping

- **Known objects** (This is the domain of Grasp Planning!)
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  - Ideas: Multi sensor fusion, pushing the object, …
  - **Hardest!**

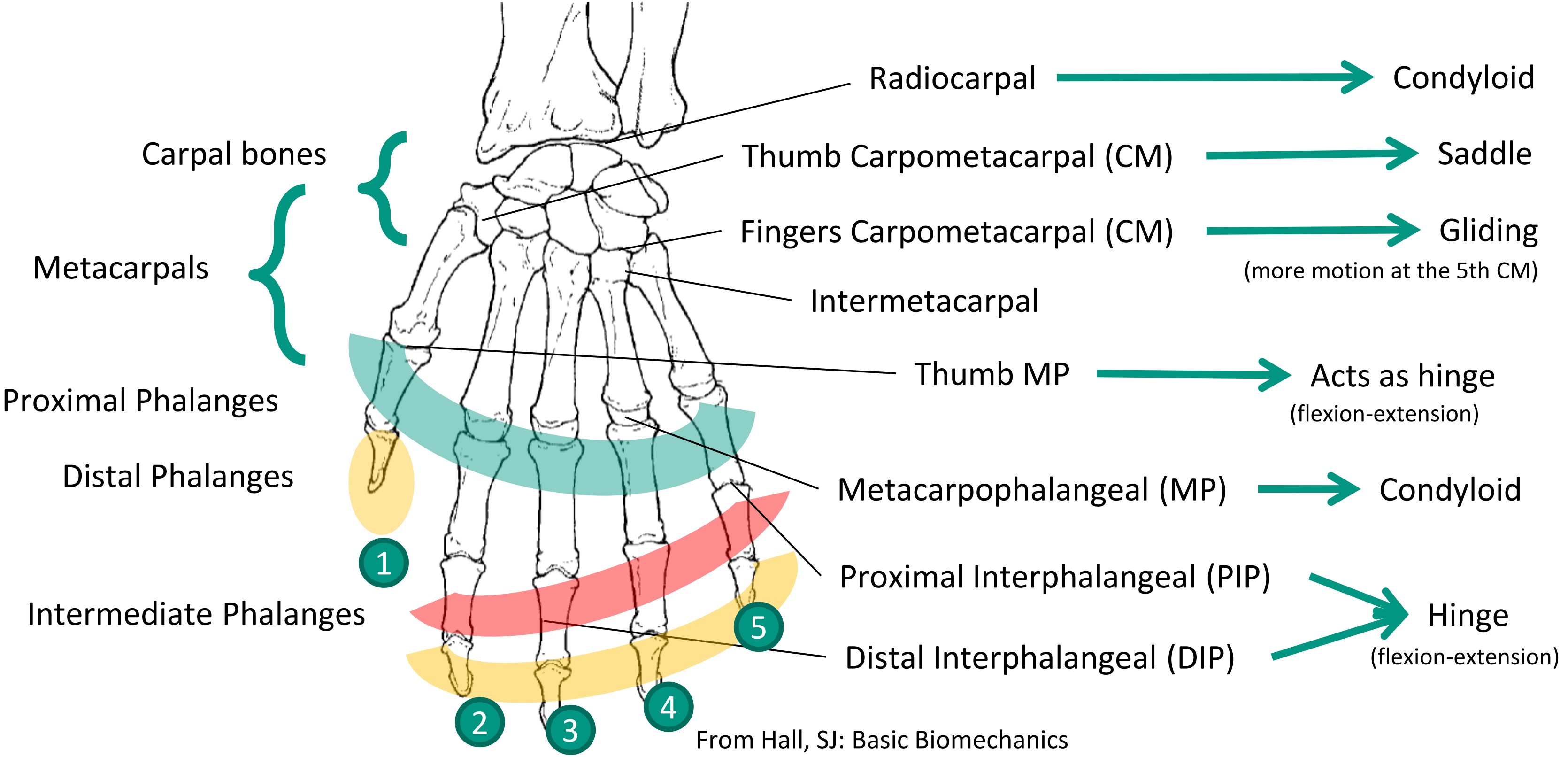
Grasp planning is always about known objects!

Review Papers on Grasping

- Antonio Bicchi, Vijay Kumar, **Robotic grasping and contact: A review.** International Conference on Robotics and Automation, ICRA 2000
- Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic. **Data-Driven Grasp Synthesis - A Survey.** IEEE Transactions on Robotics, pp. 289-309, vol. 30, no. 2, 2014
- Rhys Newbury, Morris Gu, Lachlan Chumbley, Arsalan Mousavian, Clemens Eppner, Jürgen Leitner, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, Dieter Fox, Akansel Cosgun. **Deep Learning Approaches to Grasp Synthesis: A Review.** https://doi.org/10.48550/arXiv.2207.02556
(accepted to IEEE Transactions on Robotics in April 2023)

Grasping in Humans – Human Hand Models

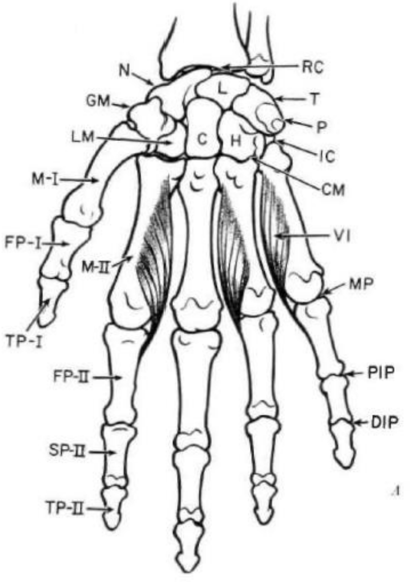
The Human Hand: Bones and Joints



From Hall, SJ: Basic Biomechanics

The Human Hand: Anatomy

- 27 bones
- 27 DoF (total)
  - 3 DoF flexion/extension type per finger
  - 1 DoF abduction/adduction type per finger
  - 5 DoF thumb:
    - 3 DoF flexion/extension type
    - 2 DoF abduction/adduction type
  - 6 DoF at the carpus (palm)



Schmidt, U. and Lanz, H.-M. Chirurgische Anatomie der Hand. Stuttgart, New York, 2003. Georg Thieme Verlag

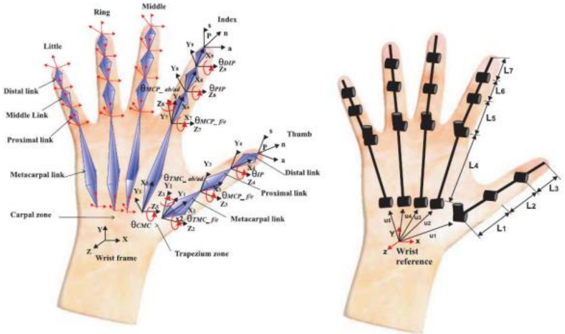
Human Hand Models in the Literature

- Large variety of human hand models
  - Different kinematic models
  - Varying numbers of DoF
  - Depending on the purpose
  - Not only in robotics but also in computer vision, Human-Computer Interaction, biomedical engineering, …
- Different applications
  - Grasp planning and analysis: More complex thumb kinematics useful
  - Prosthetics hands
  - Understanding human grasping
  - Tracking (usually no intrinsic DoFs in the palm necessary)
- Always trade-off between requirements for intended use and complexity

Human Hand Models (I)

Cobos et al., 2008

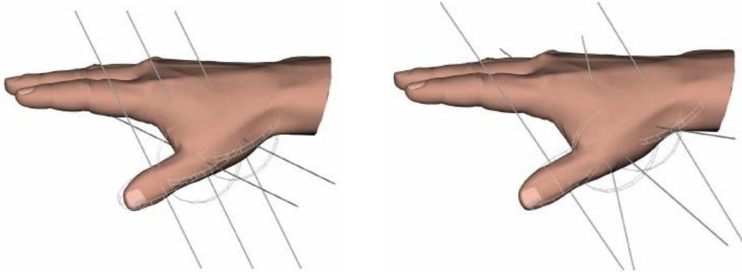
- 24 DoF (total)
- 1 DoF carpometacarpal (CMC) joint per finger
- 4 DoF thumb



Cobos, Salvador, et al. "Efficient human hand kinematics for manipulation tasks." *IEEE/RSJ International Conference on Intelligent Robots and Systems* (2008)

Miller et al., 2005

- 21 DoF (total)
- 5 DoF thumb, 2 versions:
  - perpendicular joint axes
  - non-perpendicular joint axes

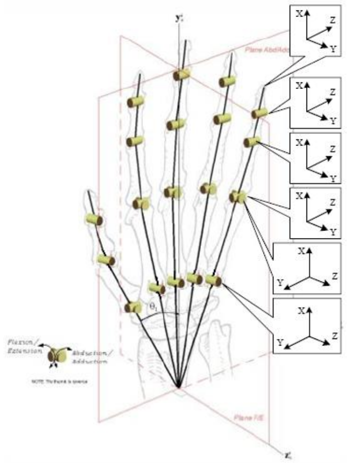


Miller, Andrew, et al. "From robotic hands to human hands: a visualization and simulation engine for grasping research." *Industrial Robot: An International Journal* (2005).

Human Hand Models (II)

Du and Charbon 2007

- 24 DoF (total)
- 1 DoF TM joint (twist type) per finger
- 4 DoF thumb



Du, H., and Charbon, E. "3D hand model fitting for virtual keyboard system." *IEEE Workshop on Applications of Computer Vision* (2007)

Kuch and Huang 1994

- 23 DoF (total)
- 2 DoF at the palm: at the base of ring and pinky metacarpals
- 5 DoF thumb

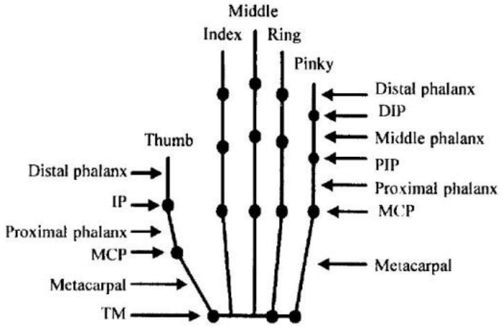


Figure 1. Notational diagram for the human hand.

Kuch, J. J., and Huang, T.S. "Human computer interaction via the human hand: a hand model." *Asilomar Conference on Signals, Systems and Computers* (1994)

Human Hand Models (III)

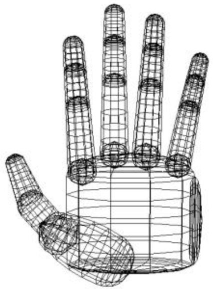
Pollard and Zordan 2005

- 19 ball joints for a total of 57 DoF
- for motion capturing use

Pollard, N. S., and Zordan, V. B. "Physically based grasping control from example." *Proceedings of the ACM SIGGRAPH/Eurographics symposium on Computer animation* (2005): 311-318.

Stenger et al. 2001

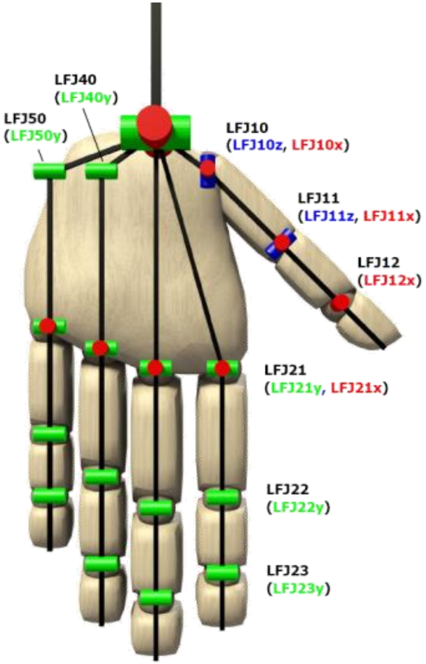
- 20 intrinsic DoF (total)
- 4 DoF per finger
- 4 DoF thumb
- no DoF at the palm
- Used for hand tracking
- Hand joints represent segments in the model

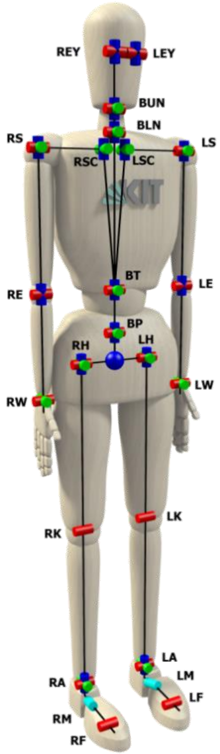


Stenger, B., Mendonça, P. and Cipolla, R. "Model-based 3D tracking of an articulated hand." *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (2001): 310-315*

Karlsruhe Human Hand Model (MMM Model)

- Kinematics
  - 23 DoF
- Anthropometric data
  - Anatomically correct finger segment lengths depend on total hand length
  - Based on data from (Buchholz et al. 1992)
- Part of the MMM at H^{2}T
  https://git.h2t.iar.kit.edu/sw/mmm





Grasping in Humans – Neuroscience of Grasping

The Neuroscience of Grasping (I)

Red: relevant for the exam

Karlsruher Institut für Technologie

- Umberto Castiello. ***The neuroscience of grasping,*** Nature Rev. Neurosci. 6, 726–736 (2005)

THE NEUROSCIENCE OF GRASPING

Umberto Castiello

Abstract | People have always been fascinated by the exquisite precision and flexibility of the human hand. When hand meets object, we confront the overlapping worlds of sensorimotor and cognitive functions. We reach for objects, grasp and lift them, manipulate them and use them to act on other objects. This review examines one of these actions — grasping. Recent research in behavioural neuroscience, neuroimaging and electrophysiology has the potential to reveal where in the brain the process of grasping is organized, but has yet to address several questions about the sensorimotor transformations that relate to the control of the hands.

The Neuroscience of Grasping (II)

The study of grasping was advanced by Napier's landmark work on PRECISION and POWER GRIPS.

- **Precision grasp:** characterized by opposition of the thumb to one or more of the other fingers.
- **Power grasp:** the fingers are flexed to form a clamp against the palm.

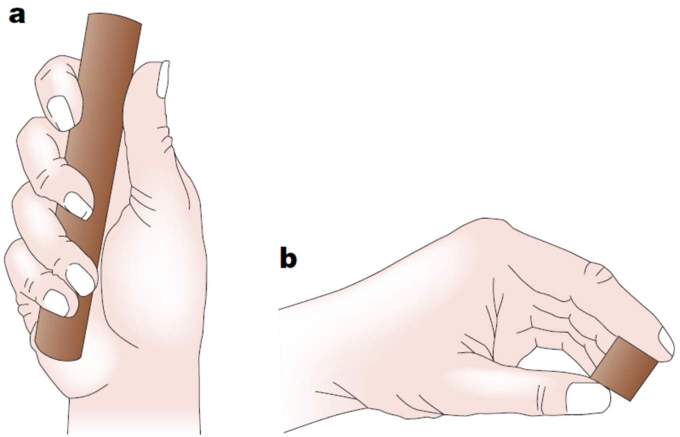
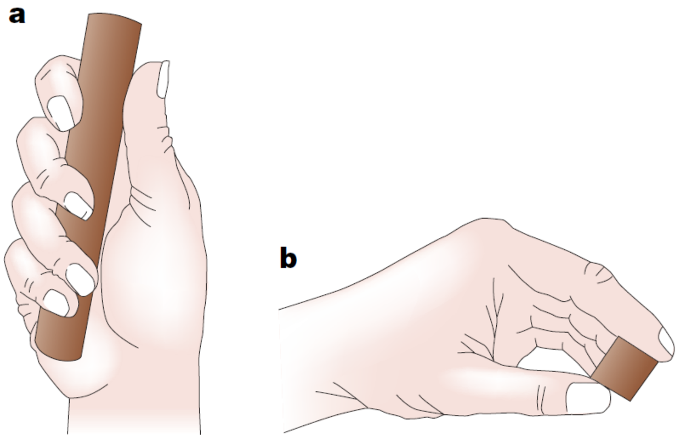


Figure 1 | **Examples of different grasps. a** | Power grip between thumb and all fingers. **b** | Precision grip between index finger and thumb. Modified, with permission, from REF. 10 © (1994) Elsevier Science.

Napier, J. R. Hands (George Allen & Unwin Ltd, London, 1980).
Napier, J. R. "Studies of the hands of living primates" *Proc. Zool. Soc. 134* (1960): 647–657
Napier, J. R. "Prehensility and opposability in the hands of primates" *Symp. Zool. Soc. 5* (1961): 115–132

The Neuroscience of Grasping (III)

- Napier showed that despite the enormous variability in aspects of movement such as force, posture, duration and speed, the underlying control principles were amazingly elegant.
- These principles were based on the supposition that the **intended activity determines what type of grasp is used for any given action**
  - **Example**: grasping a pen to write involves a different grip from grasping it to put it in a box.



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Napier, J. R. “Prehensility and opposability in the hands of primates” *Symp. Zool. Soc. 5* (1961): 115–132

The Neuroscience of Grasping (IV)

- Since these early studies, grasping has been widely investigated in humans and monkeys using various tasks and techniques.
- **Goal:** Integrate information from various domains to ascertain which neural circuits underlie grasping
- Paper's contributions:
  - **Kinematics** of grasping in humans and macaque monkeys.
  - **Evidence** that **grasping requires several neural mechanisms**, some of which are concerned with individual **finger force and movement**, and others that involve a specialized **visuomotor system** that encodes object features and generates the corresponding hand configurations.
  - **Evidence** from lesion and neuroimaging studies in humans is compared with neurophysiological studies in monkeys.
  - Although much of the work on grasping comes from monkeys, and this work has contributed to our understanding, **caution is necessary when drawing homologies across species.**
  - **Factors that should be taken into account by neuroscientists** in the quest to understand the neural bases of grasping.

The Kinematics of Grasping (I)

- **Kinematics** consider movement in terms of position and displacement (angular and linear) of body segments, center of gravity, and acceleration and velocities of the whole body or segments of the body.

- The mechanics of grasping in humans and macaque monkeys **vary depending on object attributes**.

- Although the substantial **differences in hand morphology** between these two species are the focus of current debate, it is important to compare grasping in humans and monkeys because of the common practice of looking for homologies between the two species’ brains.

The Kinematics of Grasping (II)

- Jeannerod coded grasping in terms of **changes in grip aperture**
  - Grip aperture is the separation between the thumb and the index finger
  - During a reach-to-grasp movement, there is first a progressive **opening** of the grip with **straightening** of the fingers, followed by a gradual **closure** of the grip until it matches the object's size
  - The point in time at which the thumb-finger opening is the largest (**maximum grip aperture**) is a clearly **identifiable landmark** that
    - occurs within 60–70% of the duration of the reach and
    - is highly correlated with the size of the object

Jeannerod, Marc, ed. *Attention and performance XIII: motor representation and control*. Psychology Press (2018)
This paper was the first to characterize kinematically the reach-to-grasp movement in humans. This seminal work laid the foundation of much of our current understanding of grasping.

Jeannerod, M. "The timing of natural prehension movements." *Journal of motor behavior* 16.3 (1984): 235-254.

The Kinematics of Grasping (III)

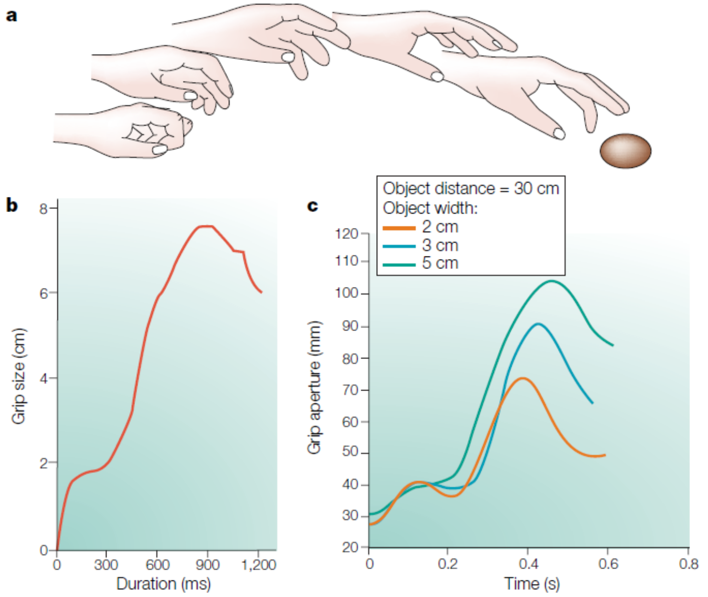


Figure 2 | **Kinematics of grasping. a** | The hand preshapes during its journey to the target object. **b** | Maximal grip aperture (distance between the tip of thumb and the tip of index finger) typically occurs within 70% of movement completion. **c** | Representation of traces demonstrating the scaling of maximum grip aperture with respect to object size. Panels **a** and **b** modified, with permission, from REF. 12 © (1984) Heldref Publications. Panel **c** modified, with permission, from REF. 13 © (1991) Springer.

Castiello, Umberto. "The neuroscience of grasping." *Nature Reviews Neuroscience* 6.9 (2005): 726-736

Kinematics of Grasping in Monkeys and Humans

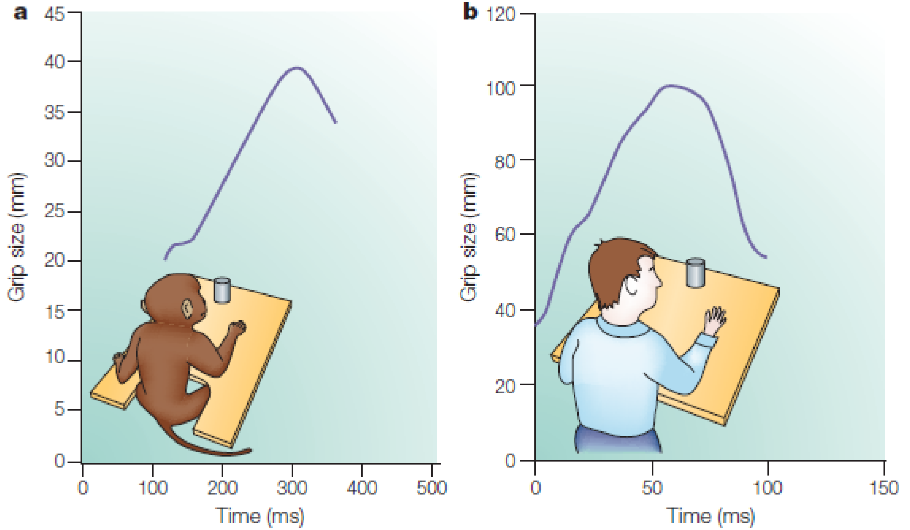
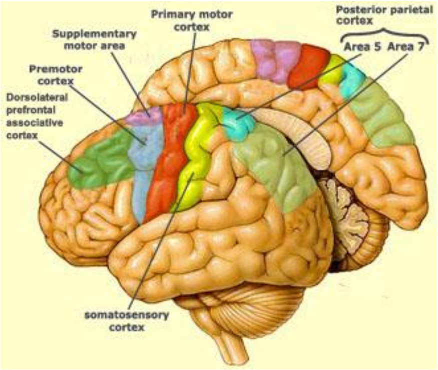


Figure 3 | **Comparison of the kinematics of grasping in monkeys and humans: effect of size.** Grip size in (**a**) a macaque monkey and (**b**) a human subject. In both species, the grasping component is characterized by a grip size that increases up to a maximum and then decreases towards the end of the movement. The macaque data are presented in absolute time, whereas those for the human participants are presented in normalized time, as a percentage of movement duration. The object diameter was 15 mm. Modified, with permission, from REF. 44 © (2000) Elsevier Science.

Castiello, Umberto. "The neuroscience of grasping." *Nature Reviews Neuroscience* 6.9 (2005): 726-736

The Neurophysiology of Grasping (I)

- Study of single cells in the monkey brain.
- **Three specific areas relating to grasping** have been identified in the monkey cortex
  - the primary motor cortex (**F1**),
  - the premotor cortex (**PML/F5**)
  - and the anterior intraparietal sulcus (**AIP**).
- In terms of neural mechanisms, performing a successful grasping action depends primarily on the **integrity of the primary motor cortex (F1)**
  - In monkeys, lesions of this area produce a profound deficit in the control of individual fingers and consequently disrupt normal grasping



thebrain.mcgill.ca/flash/a/a_06/a_06_cr/a_06_cr_mou/a_06_cr_mou.html

www.wikiwand.com/en/Primary_motor_cortex

Neural Circuits for Grasping in Monkeys and Humans

Karlsruher Institut für Technologie

- Given the wealth of **evidence for a grasping circuit involving several areas in the monkey brain**, the natural question is whether a similar circuit exists in humans.

- For **ethical reasons**, invasive physiological recording of **brain activity is rarely possible in humans**. Nonetheless, considerable progress has been made towards understanding the neural substrates of grasping in humans, mainly from studies of **patients with brain damage and neuroimaging experiments**.

The Neuropsychology of Grasping (II)

Jeannerod found that in reaching out to grasp an object, the **finger grip aperture of patients with optic ataxia was abnormally large, and the usual correlation between maximum grip aperture and object size was missing**.

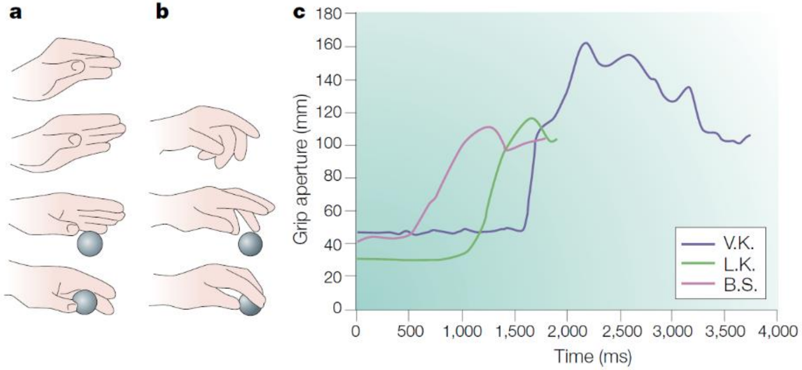


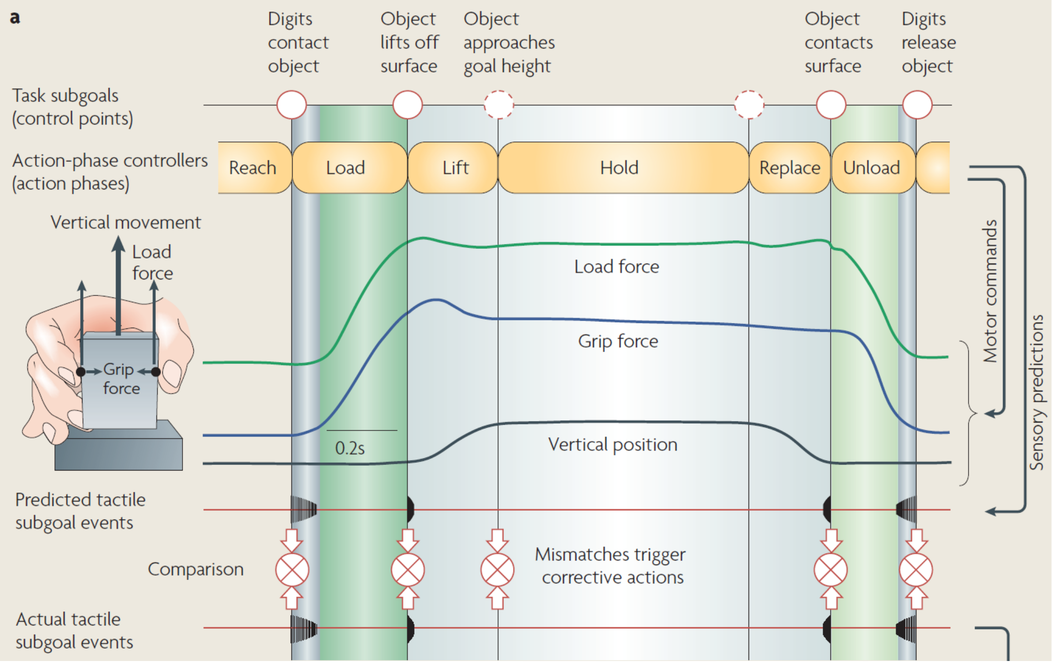
Figure 6 | **Grip aperture profiles of patients with brain damage.** Comparison of the pattern of finger grip in a patient, 'Biz', with optic ataxia during reaching with the affected hand (**a**) and the normal hand (**b**). **c** | Comparison of the abnormal pattern of finger grip in a patient, V.K., with the pattern of finger grip of two neurologically healthy participants (L.K. and B.S.). Panels **a** and **b** modified, with permission, from REF. 79 © (1986) Elsevier Science. Panel **c** modified, with permission, from REF. 80 © (1991) Elsevier Science.

Castiello, Umberto. "The neuroscience of grasping." *Nature Reviews Neuroscience* 6.9 (2005): 726-736

Optic ataxia is classically considered to be a specific disorder of the visuomotor transformation caused by posterior parietal lesions, in particular, lesions of the superior parietal lobe (SPL). Subjects with optic ataxia are unable to perform goal-directed vision-based hand motions

Grasp Phases in Humans

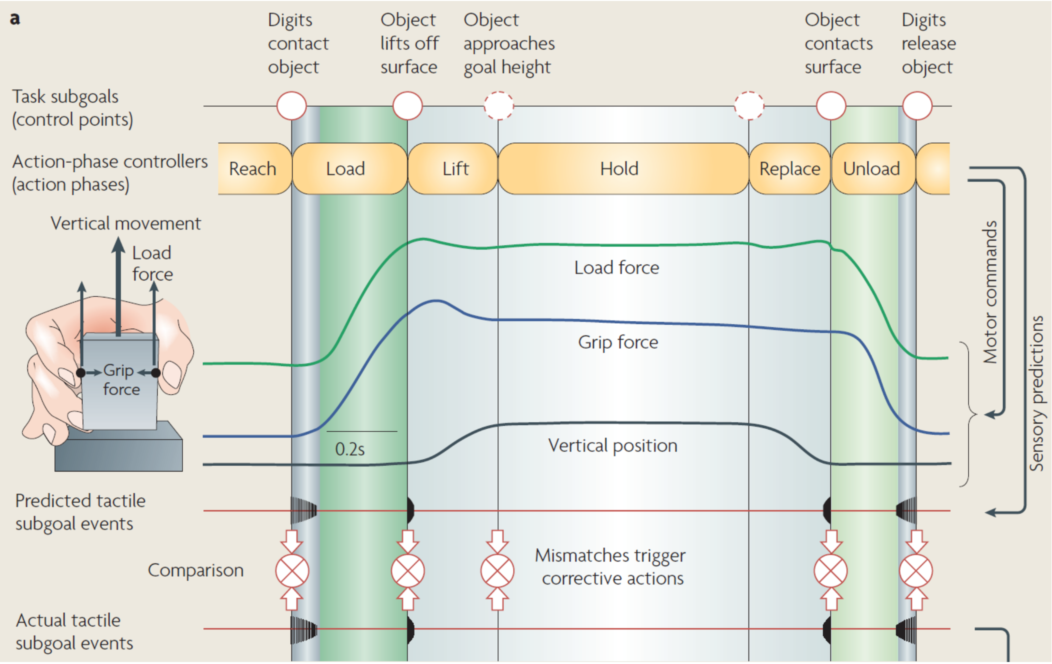
- Humans divide the grasping process into distinct action phases: reach, load, lift, hold, replace and unload
- Dexterous manipulation tasks are subdivided into different action phases.
- For each action phase, the brain selects and execute an appropriate controller.
- Comparison between predicted and current sensory signal (tactile information) used to monitor the progression and detect errors.



Johansson, R., Flanagan, J. Coding and use of tactile signals from the fingertips in object manipulation tasks. *Nat Rev Neurosci* **10,** 345–359 (2009)

Grasp Phases in Humans

- Humans divide the grasping process into distinct action phases: **reach, load, lift, hold, replace and unload**
- Our work:
  - Detection of phases with a soft humanoid hand
  - Implementation of controllers for each individual phase



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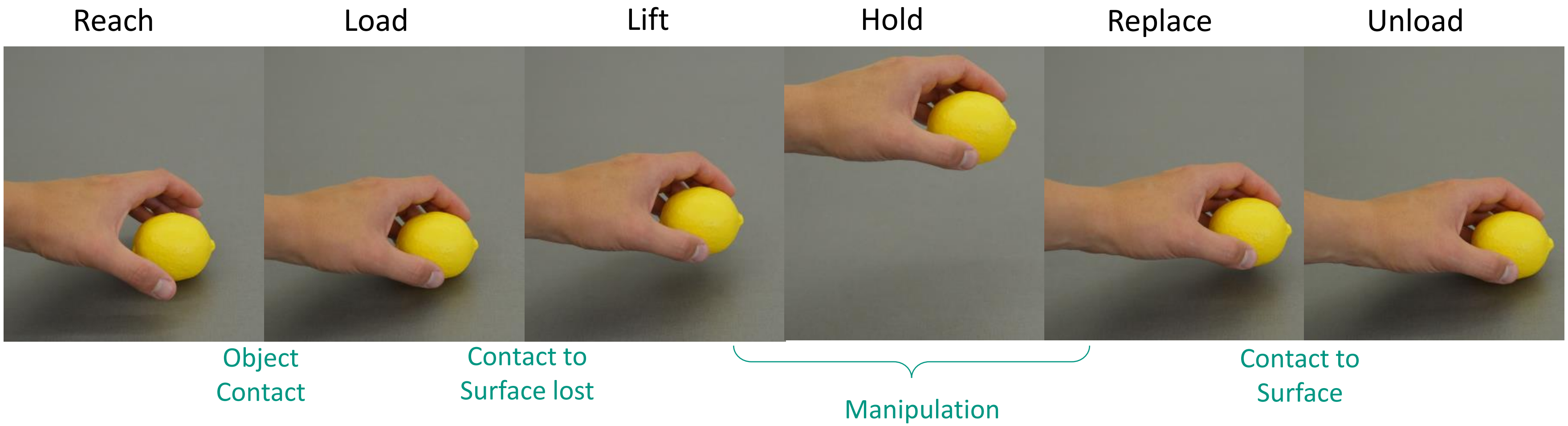
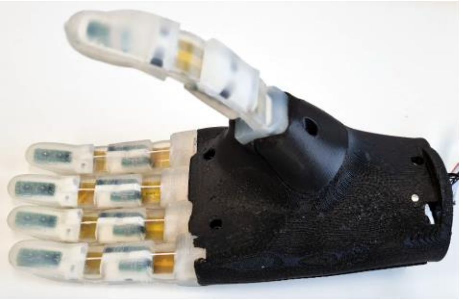
Grasp Phases in Humans

- Humans divide the grasping process into distinct action phases (Johansson, R., Flanagan 2009)
  - Each phase is triggered by sensory events dependent on the phase
  - Each phase is associated with specific control goals

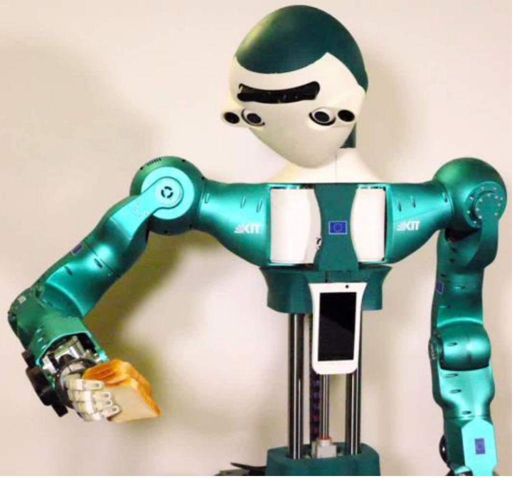


How to Transfer this to Robotics



Soft, sensorized hand

Grasp-Phases Controller

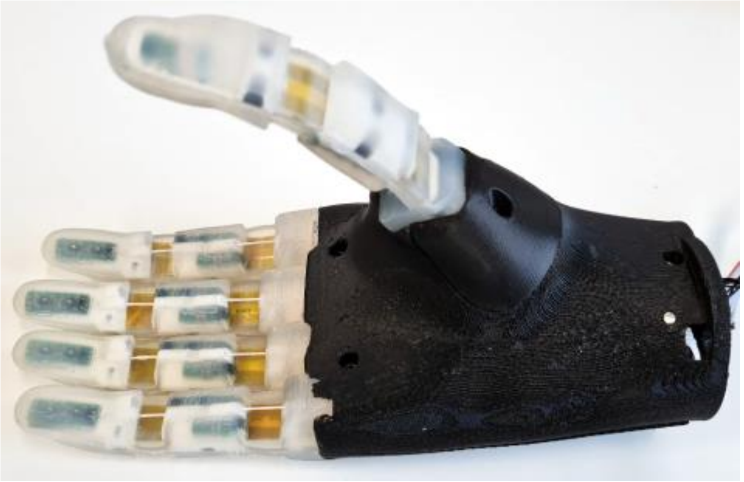


Grasping and placing of unknown objects

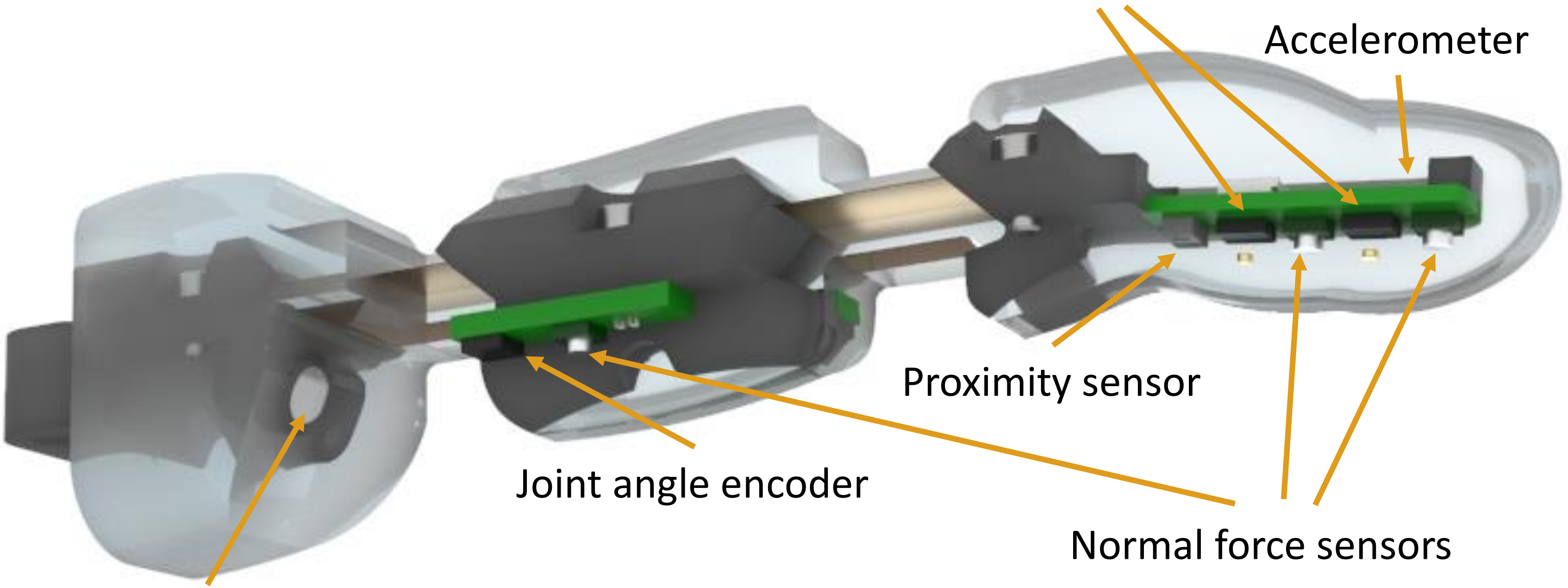
Weiner, P., Hundhausen, F., Grimm, R. and Asfour, T., *Detecting Grasp Phases and Adaption of Object-Hand Interaction Forces of a Soft Humanoid Hand Based on Tactile Feedback*, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 3956-3963, September, 2021

KIT Soft Humanoid Hand

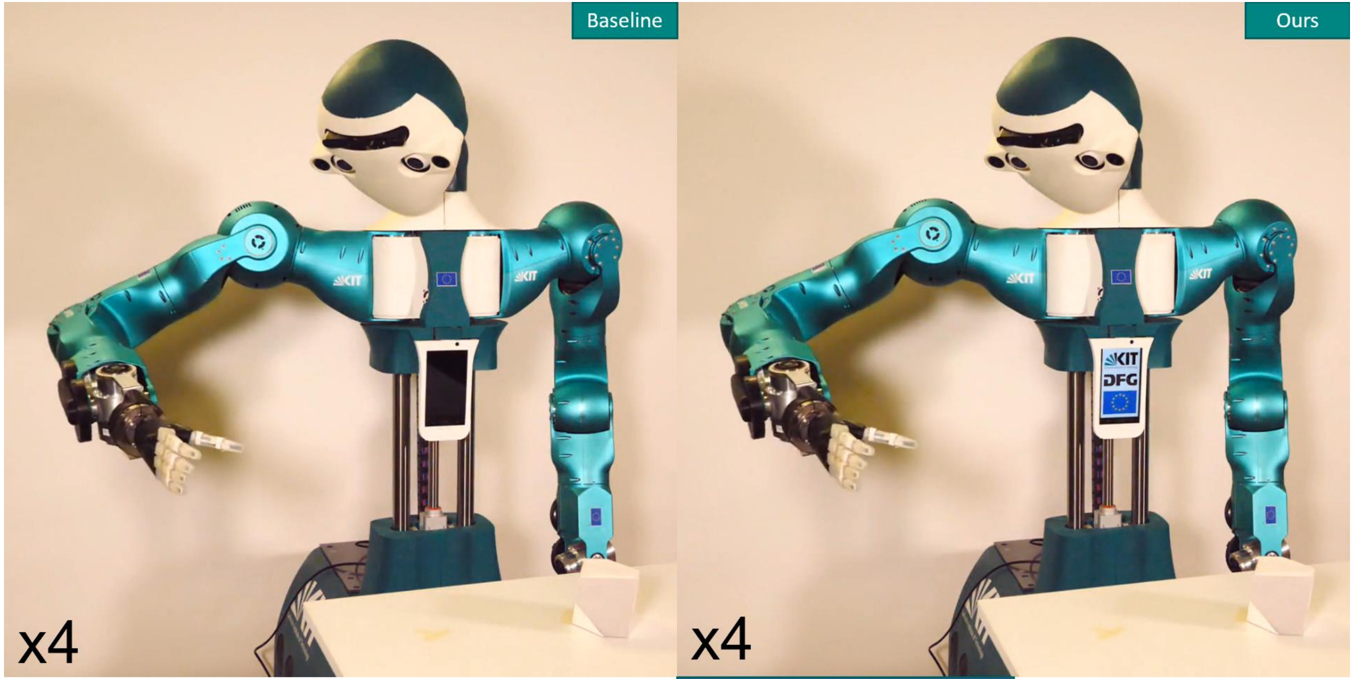
- Tendons driven by three motors:
  - Thumb
  - Index finger
  - Middle, ring and little finger
- Adaptive underactuation for the third motor
  - If one of the three fingers is blocked, the others can still close
- Sensors
  - Joint Angle encoders
  - Distance Sensors
  - Accelerometers
  - **Tactile sensors**
    - Normal force sensors (MEMS barometers)
    - Shear forces sensors (Hall-effect sensors)



Soft Sensorized Fingers – Sensors



Grasp Phases in Humanoid Robotics



Grasp Phase of the proposed Controller: Reach & Close

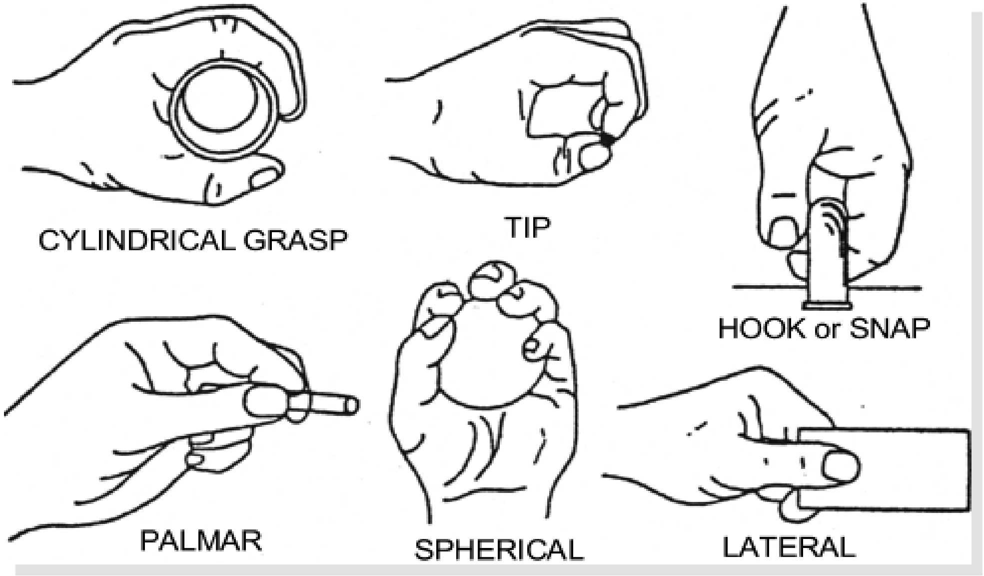
Weiner et al. (2021)

Grasping Taxonomies

Grasping Taxonomies

- Cutkosky Grasp Taxonomy
- Kamakura Taxonomy
- Feix GRASP Taxonomy
- Bullock & Dollar Taxonomy
- Taxonomy of Everyday Grasps in Action
- Taxonomy of Bimanual Manipulation
- KIT Taxonomy for Whole-Body Grasps

Typical Grasp Motions of Daily Life



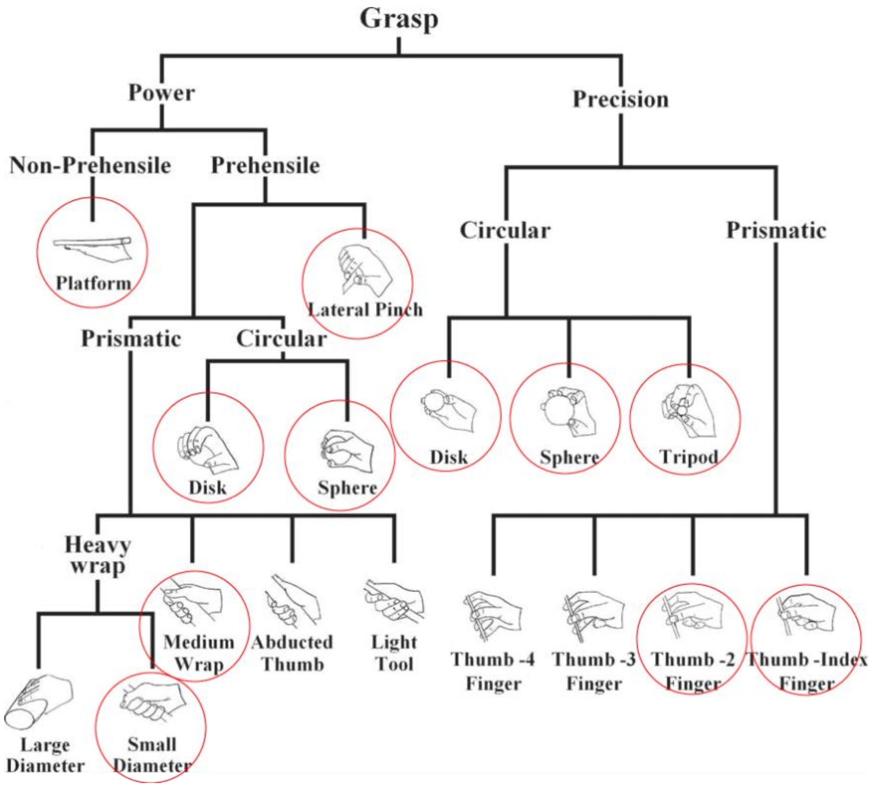
Keller, A. D., Taylor, C. L. and Zahm, V. “Studies to determine the functional requirements for hand & arm prostheses”, Dept. of Engr., UCLA., CA (1947)

Why a Taxonomy?

- Deal with the hand complexity
- Simplify grasp synthesis
- Inspire hand design
- Benchmark to test hand abilities (robotics and prosthetics)
- Optimization of synergies: Formulation of dexterity/functionality as number of achievable grasps for maximization
- Guide autonomous grasp selection

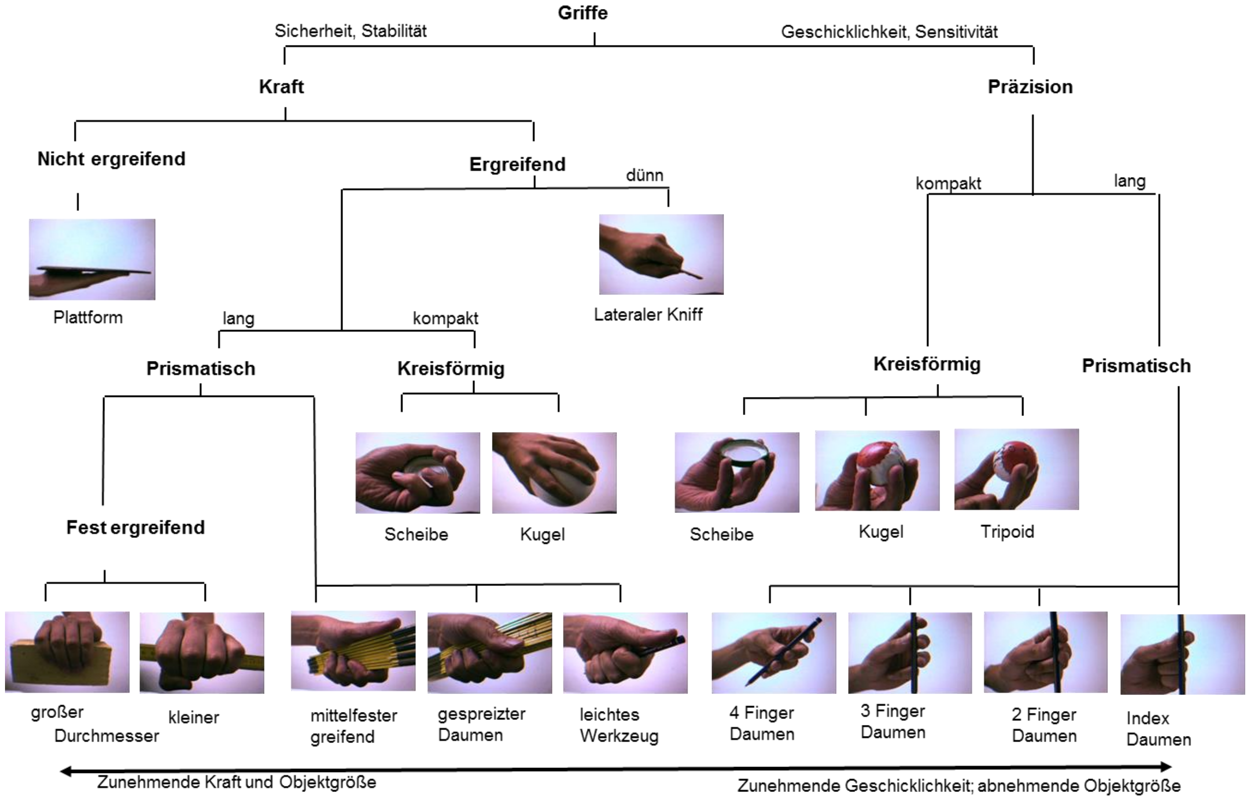
Cutkosky's Grasp Taxonomy (I)

- **16 grasp types** organized in a hierarchical tree structure
- **Power** and **Precision** grasps
- Obtained by observing machinists during their work
- Focus on using tools in a workshop



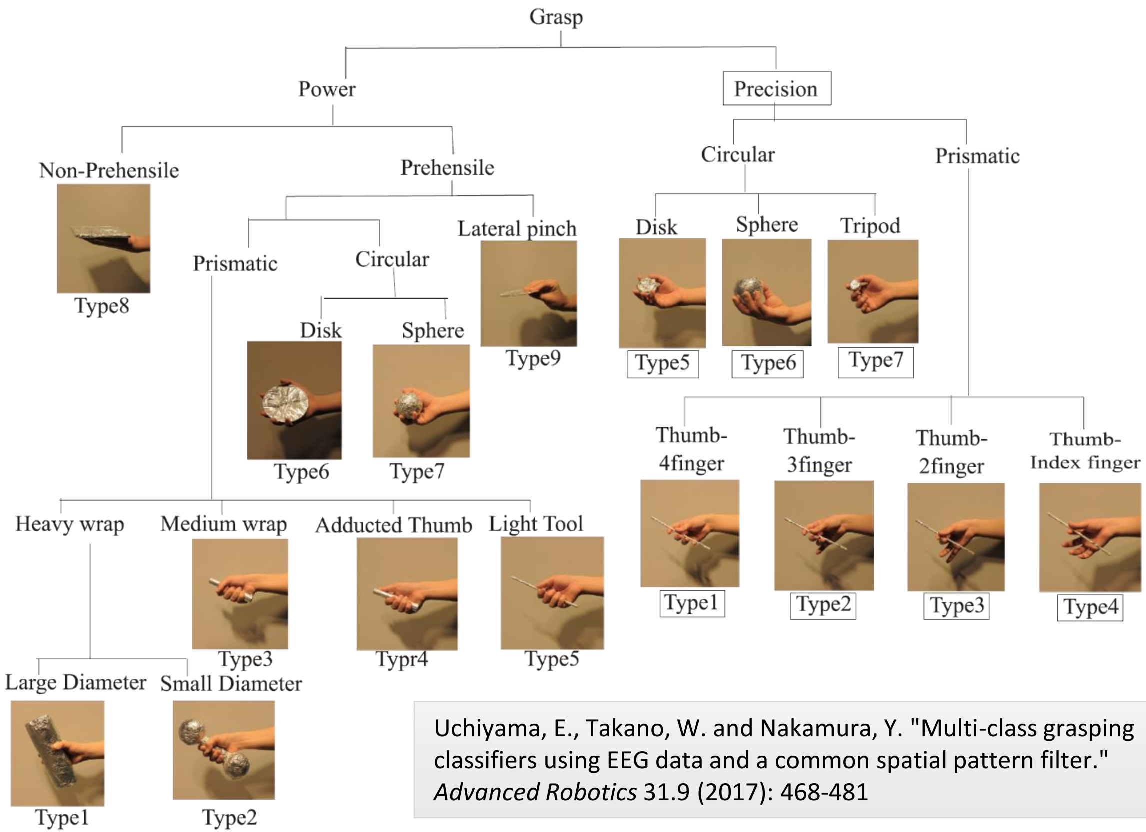
Cutkosky, M. R. "On grasp choice, grasp models, and the design of hands for manufacturing tasks." *IEEE Transactions on robotics and automation* 5.3 (1989): 269-279

Cutkosky's Grasp Taxonomy (II)



Cutkosky's Grasp Taxonomy (III)

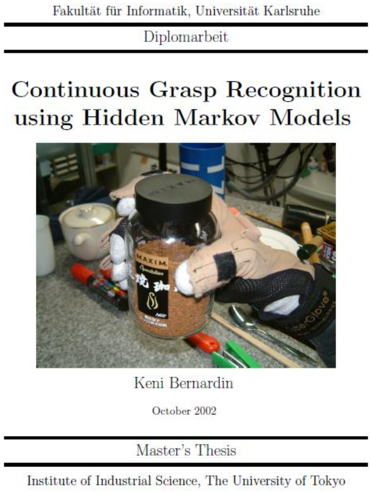
- In Uchiyama et al. 2027, the taxonomy is used for the classification of human grasping actions based on brain activity (EEG)
- Taxonomy provides a guideline for collecting data in the conducted user study (show and ask participant to perform a certain grasp)



Uchiyama, E., Takano, W. and Nakamura, Y. "Multi-class grasping classifiers using EEG data and a common spatial pattern filter." *Advanced Robotics* 31.9 (2017): 468-481

Kamakura Taxonomy (I)

- Kamakura, N., et al. "Patterns of static prehension in normal hands." *American Journal of Occupational Therapy* 34.7 (1980): 437-445
- N. Kamakura. Te no ugoki, Te no katachi (Japanese). Ishiyaku Publishers, Inc., Tokyo, Japan (1989)
- Keni Bernardin, Master Thesis, 2002, University of Karlsruhe


Fakultät für Informatik, Universität Karlsruhe

Diplomarbeit

Continuous Grasp Recognition using Hidden Markov Models

Keni Bernardin

October 2002

Master's Thesis

Institute of Industrial Science, The University of Tokyo

Kamakura Taxonomy (II)

- Classification of grasps based on
  - **Finger positions**
  - **Contact area** with the object
- **14 grasp patterns** in **4 categories**:
  - power
  - mid-power-precision
  - precision
  - thumbless
- Considers **static** (not dynamic) phases of **prehensile** grasps
- Humans use the grasping patterns based on **object shape** and **object functionality**
- **7 subject** and **98 objects**
- General enough to describe most manipulation tasks

Table 4.1: Grasp Taxonomy by Kamakura

Category	Class	Notation
Power Grips	Power Grip-Standard Type	PoS
	Power Grip-Hook Type	PoH
	Power Grip-Index Extension Type	PoI
	Power Grip-Extension Type	PoE
	Power Grip-Distal Type	PoD
Mid-Power-Precision Grips	Lateral Grip	Lat
	Tripod Grip-Standard Type	Tpd
	Tripod Grip-Variation I	TVI
	Tripod Grip-Variation II	TVII
Precision Grips	Parallel Mild Flexion Grip	PMF
	Circular Mild Flexion Grip	CMF
	Tip Grip	Tip
	Parallel Extension Grip	PE
Thumbless Grips	Adduction Grip	Add

Kamakura Taxonomy (III)

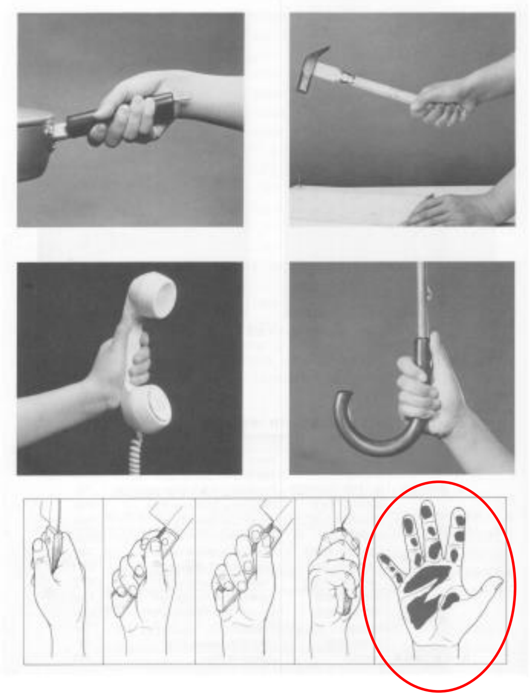


Figure 4.2: The Power Grip Standard Type (PoS)

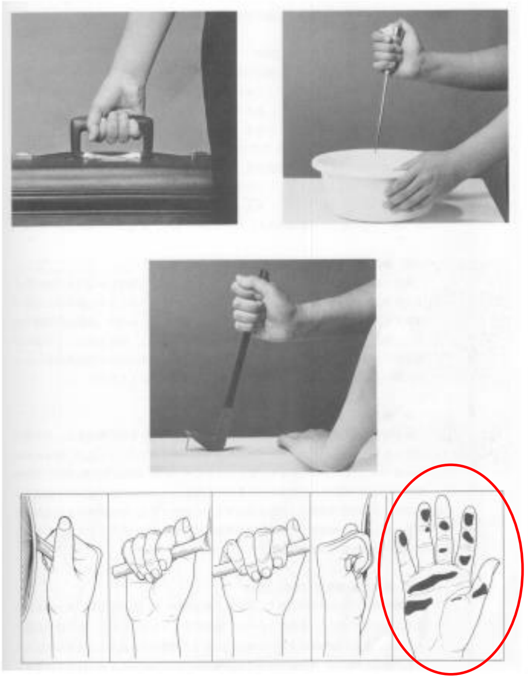


Figure 4.3: The Power Grip Hook Type (PoH)

Figure 4.4: The Power Grip Index Extension Type (PoI)

Kamakura Taxonomy (IV)

Figure 4.5: The Power Grip Extension Type (PoE)

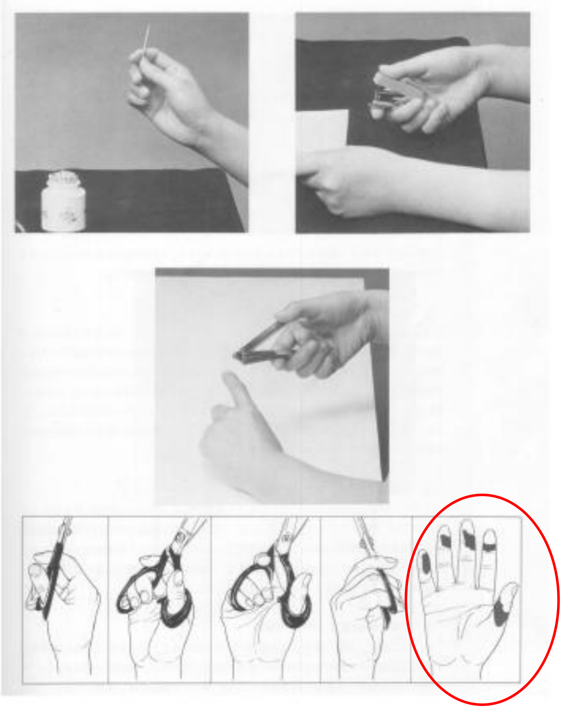


Figure 4.6: The Power Grip Distal Type (PoD)

Figure 4.7: The Lateral Grip (Lat)

Kamakura Taxonomy (V)

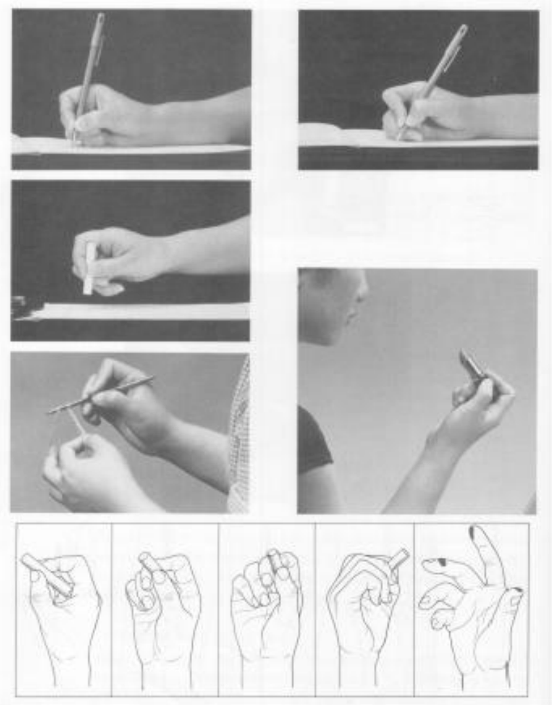


Figure 4.8: The Tripod Grip (Tpd)

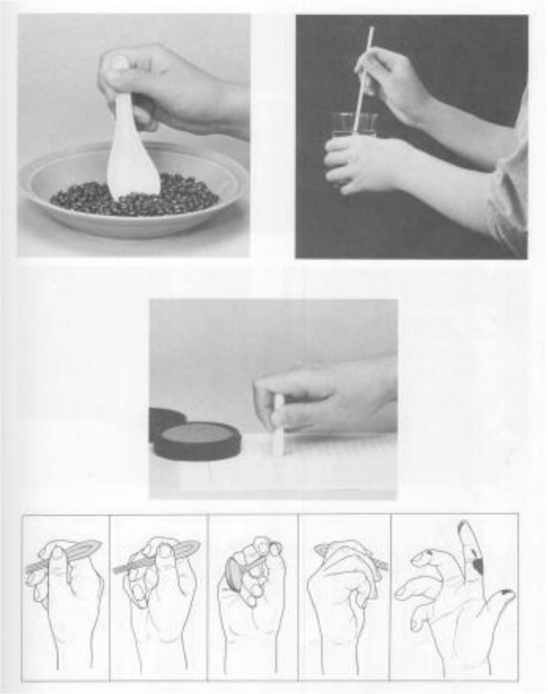


Figure 4.9: The Tripod Grip Variation I (TVI)

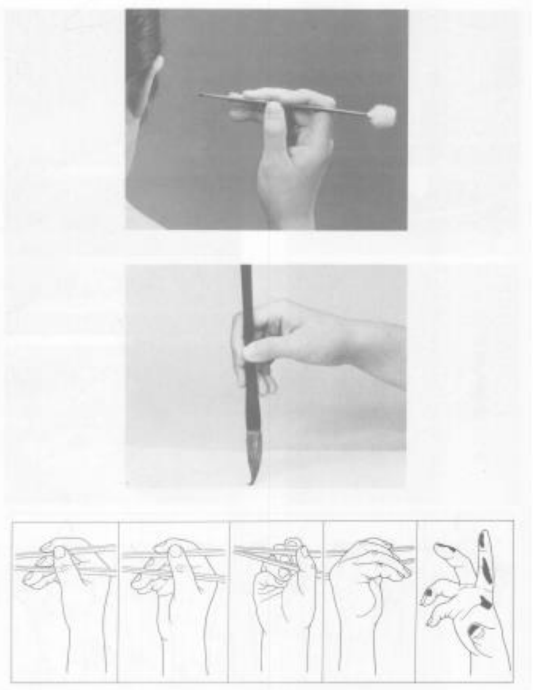


Figure 4.10: The Tripod Grip Variation II (TVII)

Kamakura Taxonomy (VI)

Figure 4.11: The Parallel Mild Flexion Grip (PMF)

Figure 4.12: The Circular Mild Flexion Grip (CMF)

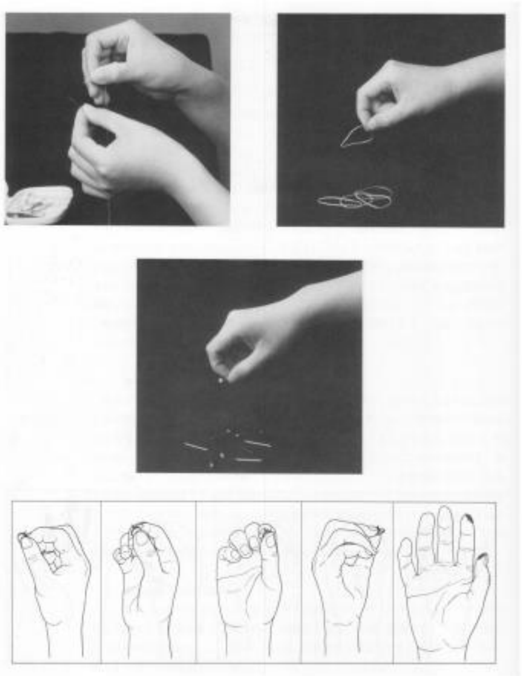


Figure 4.13: The Tip Grip (Tip)

Kamakura Taxonomy (VII)

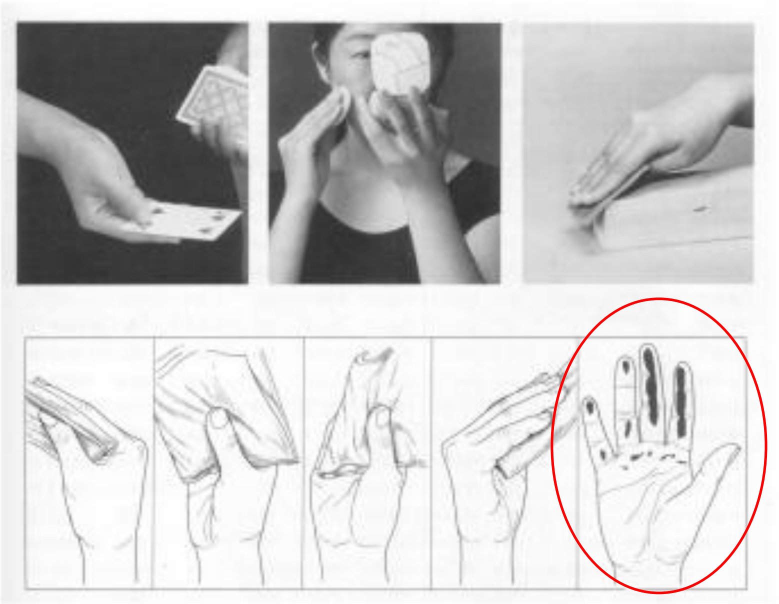


Figure 4.14: The Parallel Extension Grip (PE)

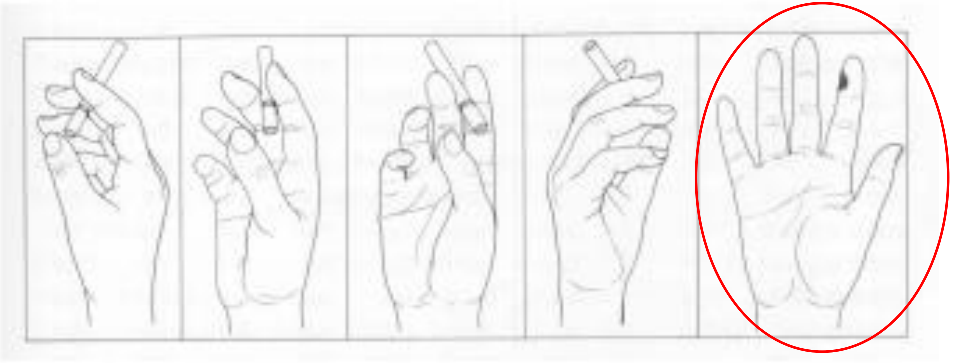


Figure 4.15: The Adduction Grip (Add)

The GRASP Taxonomy of Human Grasp Types

- **Goal:** Compare existing taxonomies and synthesize them into a single taxonomy
- Only single-handed **static** and stable grasps considered
- **33 different grasps types** arranged according to
  - Type (power, precision, intermediate)
  - Opposition type
  - Virtual finger assignments
  - Position of thumb
- 33 grasp types can be reduced to a set of **17 more general grasps** if only the hand configuration is considered **without** the object shape/size.
- New classes arranged according to the number of fingers in contact with the object and the position of the thumb

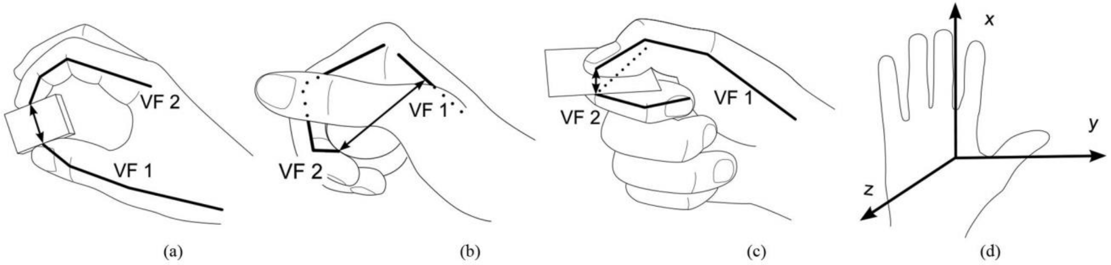
Feix, T., Romero, J., Schmiedmayer, H. B., Dollar, A. M., Kragic, D. "The GRASP Taxonomy of Human Grasp Types“, *IEEE Transactions on Human-Machine Systems*, 2016

The GRASP Taxonomy of Human Grasp Types

Karlsruher Institut für Technologie

Landsmeer, J. M., "Power grip and precision handling", *Annals of the Rheumatic Diseases*, 1962

- **Grip type**
  - **Powergrip:** Rigid relation between object and hand
  - **Precision handling:** the hand is able to perform intrinsic movements on the object without having to move the arm
  - **Intermediate:** Elements of power and precision grasps are presented in roughly the same proportion
- **Opposition types:** differ in the **force direction** applied between hand and object
  a) Pad opposition
  b) Palm opposition
  c) Side Opposition
  d) Hand coordinate System



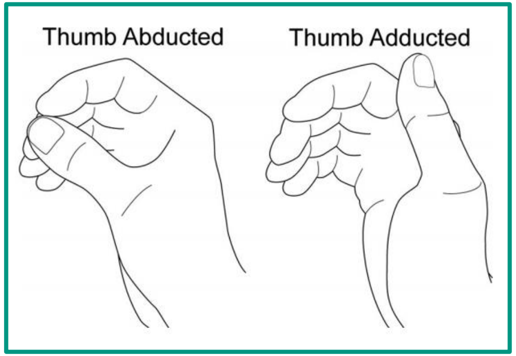
Needle or small ball | Hammer or screwdriver | Key or card

The GRASP Taxonomy of Human Grasp Types

- **Virtual fingers (VF)**
  - In many tasks, several fingers act together as a functional unit, the virtual finger
  - Fingers belong to the same VF if they apply **forces in a similar direction** and act in union

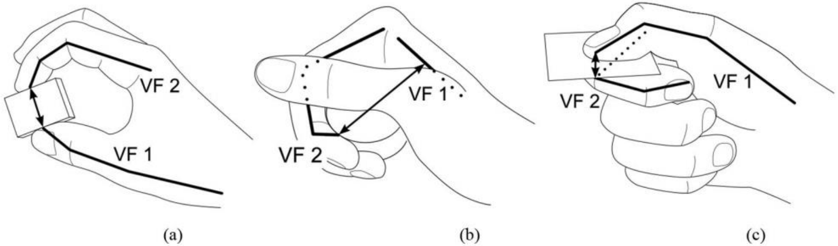
T. Iberall, “Grasp planning from human prehension,” in *Proc. 10th Int. Joint Conf. Artif. Intell.*, 1987, vol. 2, pp. 1153–1156.

- **Position of the Thumb**

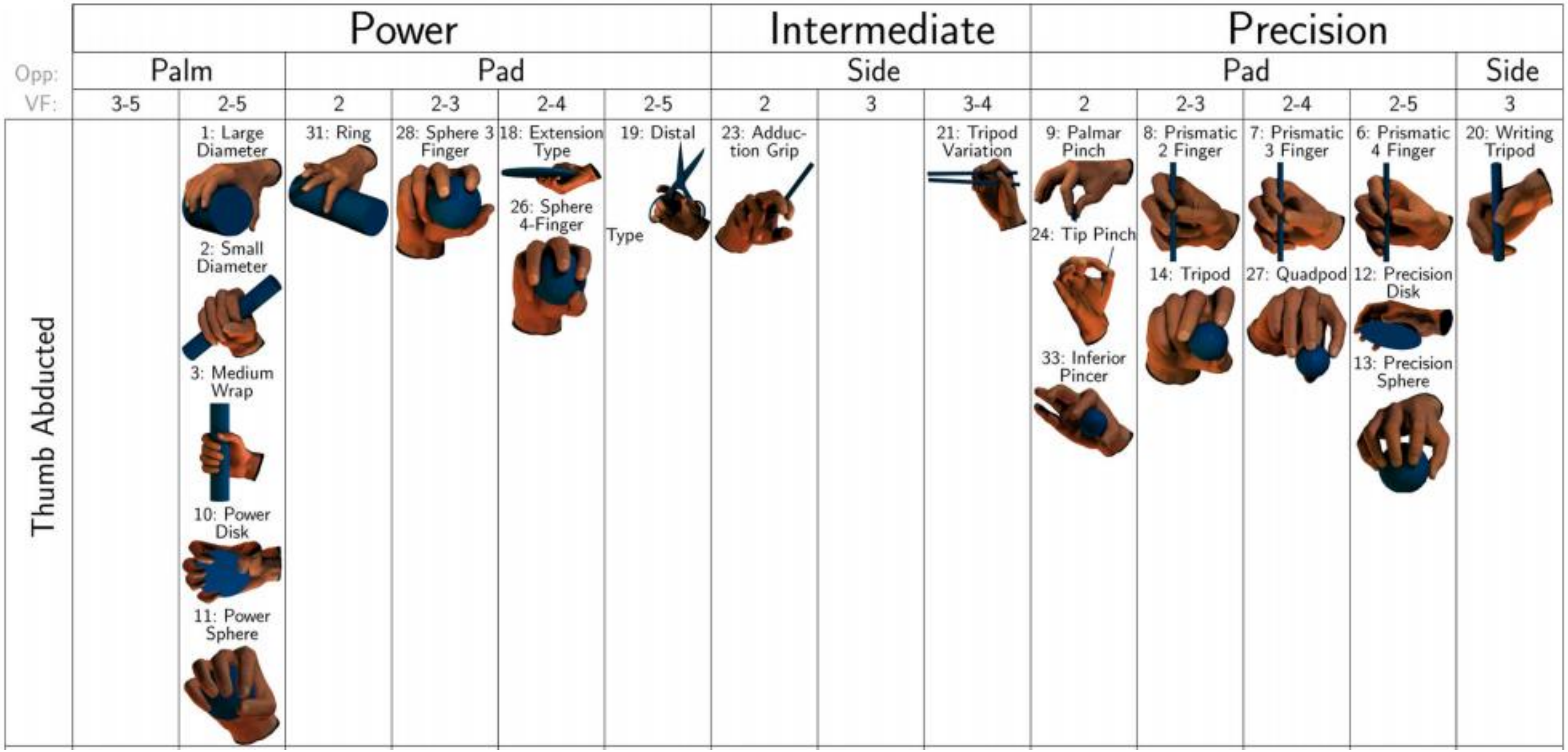


Examples:

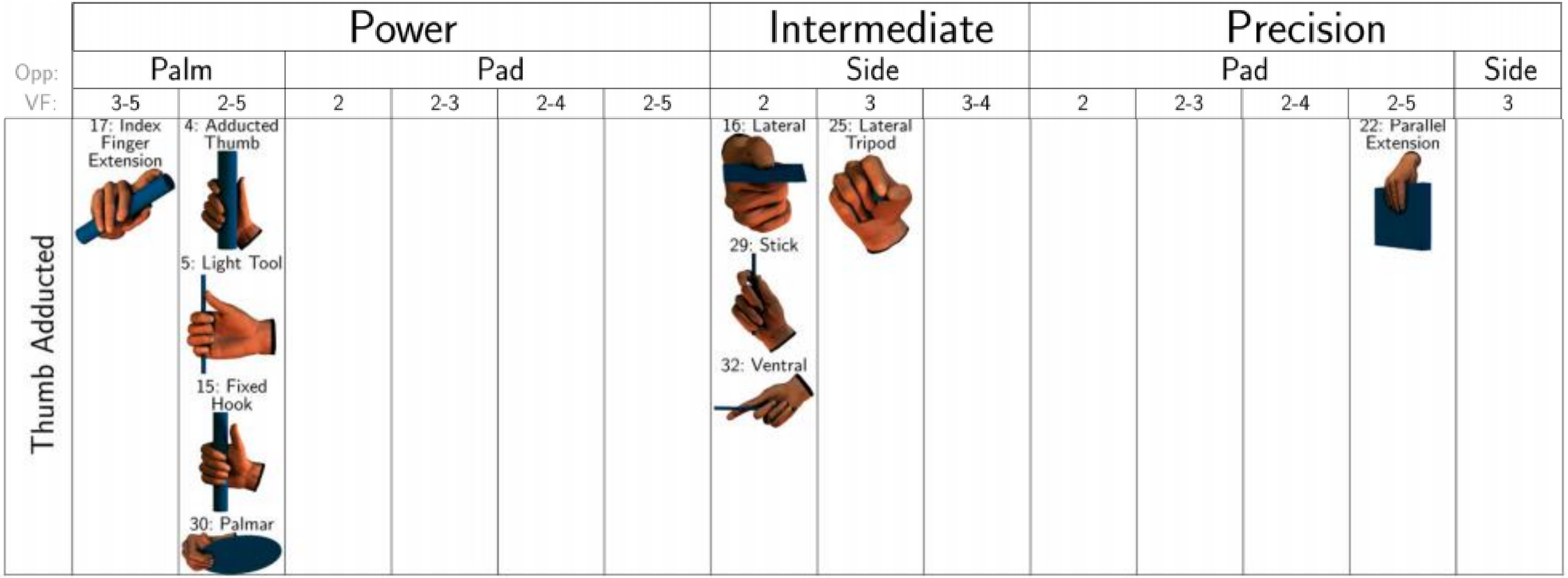
Thumb opposition | Palm opposition | Thumb opposition



The GRASP Taxonomy of Human Grasp Types



The GRASP Taxonomy of Human Grasp Types



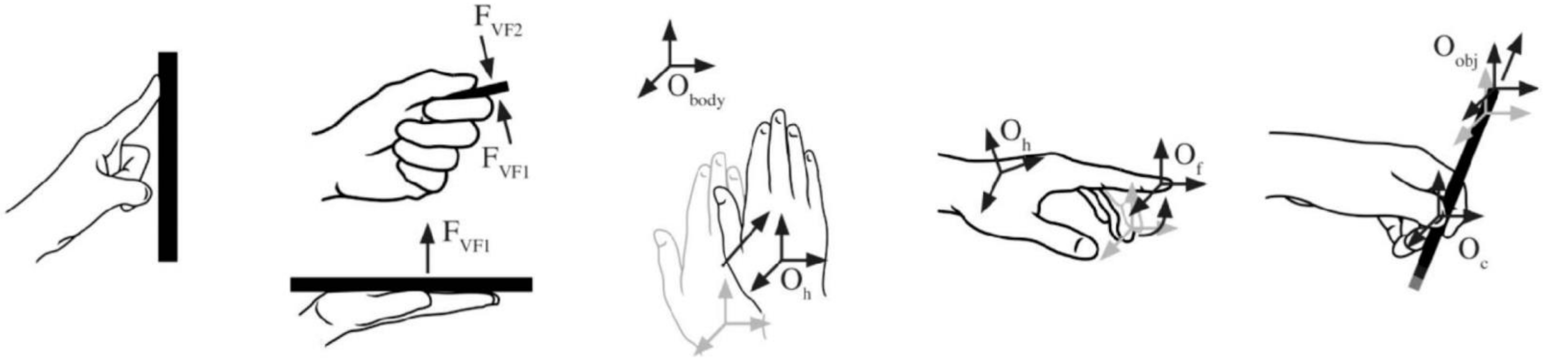
Bullock & Dollar Taxonomy

Red: relevant for the exam

- Hand-centric and motion-centric manipulation classification
- Descriptive framework that can be used to effectively **describe hand movements during manipulation (in-hand manipulation)** in a variety of contexts
- Combined with existing object centric or other taxonomies to provide a complete description of a specific manipulation task.

Bullock, I. M., Raymond, R. M. and Dollar, A.M. "A hand-centric classification of human and robot dexterous manipulation." IEEE transactions on Haptics 6.2 (2012): 129-144

Bullock & Dollar Taxonomy: Terminology



Contact
Hand is touching an external object or the environment.

Prehensile
Action of hand on object must be described with more than one virtual finger.

Motion
Any part of the hand moves relative to body fixed frame.

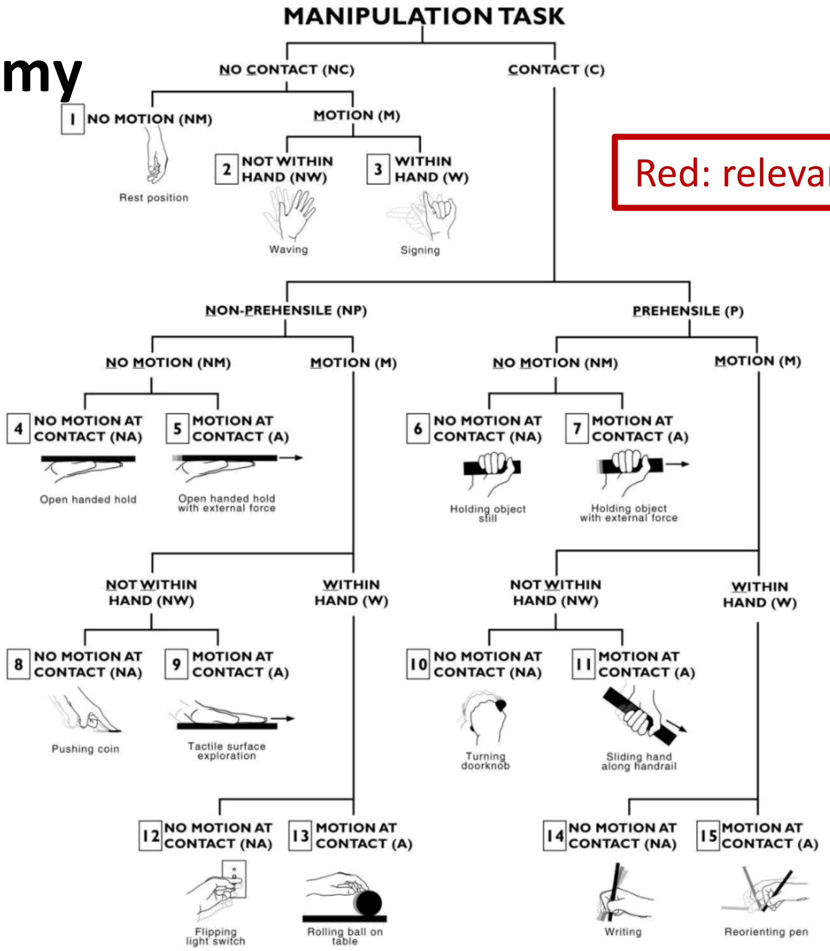
Within Hand
Points on the hand are moving relative to the hand base frame.

Motion at contact
Object reference frame moves relative to contact point frame(s).

Bullock, I. M., Raymond, R. **M**. and Dollar, A.M. "A hand-centric classification of human and robot dexterous manipulation." IEEE transactions on Haptics 6.2 (2012): 129-144

Bullock & Dollar Taxonomy

- Hand-centric and motion-centric manipulation classification



Red: relevant for the exam

Bullock, I. M., Raymond, R. M. and Dollar, A.M. "A hand-centric classification of human and robot dexterous manipulation." IEEE transactions on Haptics 6.2 (2012): 129-144

Taxonomy of Everyday Grasps in Action

Red: relevant for the exam

- May daily grasps can be classified into existing taxonomies
- **but** grasp types in the taxonomies do not describe important grasp features such as **indented motion, force, stiffness**

Similar grasps ???

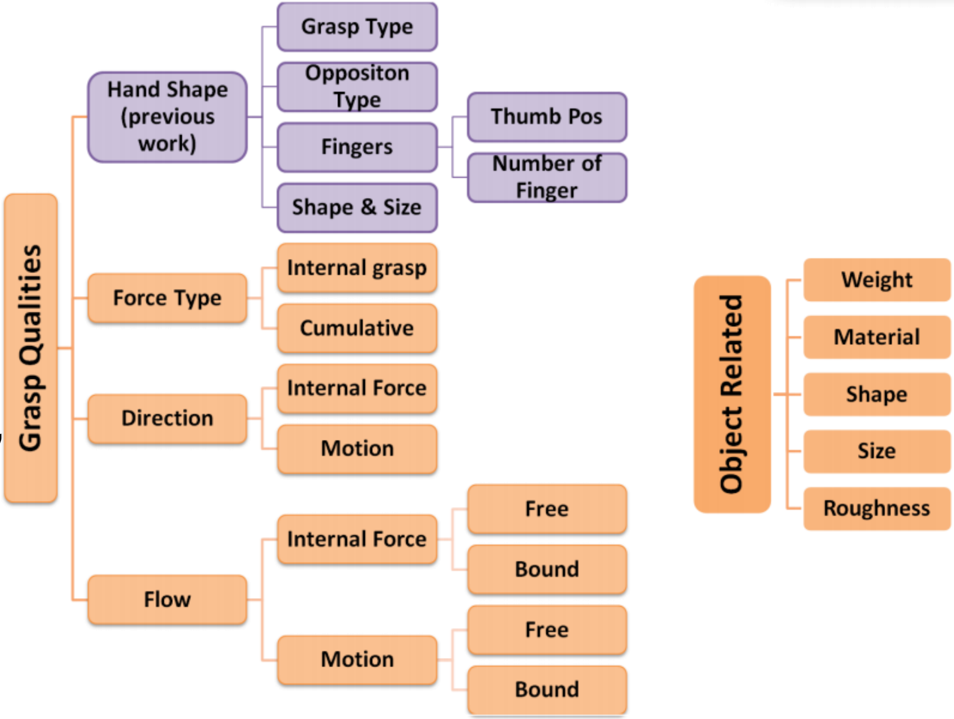
- **Goal:** Augment grasp taxonomies with more action related features

Liu, J., Feng, F. Nakamura, Y. C., Pollard, N. S., "A Taxonomy of Everyday Grasps in Action" *IEEE-RAS International Conference on Humanoid Robotics,* 2014

A Taxonomy of Everyday Grasps in Action

Grasp classification based on

- **Hand shape:** similar to Feix and Napier
- **Force type:** described by verbs (hold, lift, press, lever, roll, pull, push, squeeze, twist, …), 20 verbs in total
- **Direction** (of force or motion) along a linear axis, rotation around an axis, movement within a plane, or inwards/outwards, towards or away from the center of an object
- **Flow:** effort factor (Laban Effort), i.e. "attitude toward bodily tension and control" and can be free (free motion in moving direction), bound (stiff, tightly coupled) and half-bound (bound along one or more axis, free along the rest.



A Taxonomy of Everyday Grasps in Action

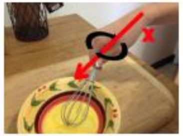
- 20 different force types

Example		
Force Type	Squeeze	Hold
Annotation	Squeeze toothpaste	Hold a pan

Example		
Force Type	Throw	Grab&Press
Annotation	Shoot a basket ball	Press down a door handle

Example		
Force Type	Grab	Hold
Annotation	Grab the ladder	Hold a laundry detergent

- Direction

Example			
Motion Axes	along x/-x (object)	around x axis (hand)	along xz plane (hand)
Force Axes	inward, hold zipper	inward, hold egg beater	against the surface
Annotation	Zip a zipper	Beat with egg beater	Move a mouse

Example			
Coordinate Frame	Hand	Global	Object
Motion Axes	along x/-x	along z/-z	along x/-x
Annotation	Rub hands	Dribble basketball	Measure with a tape measure

A Taxonomy of Everyday Grasps in Action

- Flow

Example		
Flow	Bound Motion/ Bound Force	Free Motion/ Half Bound Force
Annotation	Stick key into key hole	Hold keys

- Object related information

Example		
Object weight	Light	Heavy
Annotation	Grab an empty box	Hold a heavy box

Example			
Size	Thin	Thick	Thick
Roughness	Slippery	Rough	Slippery
Annotation	Grab a wire	Grab a rope	Grab exercise bar

Taxonomy of Bimanual Manipulation

Bimanual Manipulation

- In Activities of Daily Living (ADL) humans commonly employ both hands

KIT Bimanual Manipulation Dataset

- Robot programming by demonstration (PbD) for bimanual skills
  → goal: motion library

- Multi-modal human motion recordings provide information on symbolic and sub-symbolic level

- Intra-action variations should be included to allow the generation of generalizable action representations

Krebs*, F., Meixner*, A., Patzer, I. and Asfour,T. “The KIT Bimanual Manipulation Dataset“, *IEEE/RAS International Conference on Humanoid Robots*, 2021

Taxonomies for Bimanual Manipulation

- Previously presented taxonomies only deal with unimanual manipulations
  → however, humans execute most daily activities using both hands
- Bimanual taxonomies focus on the coordination between the hands

Neuroscience/rehabilitation:

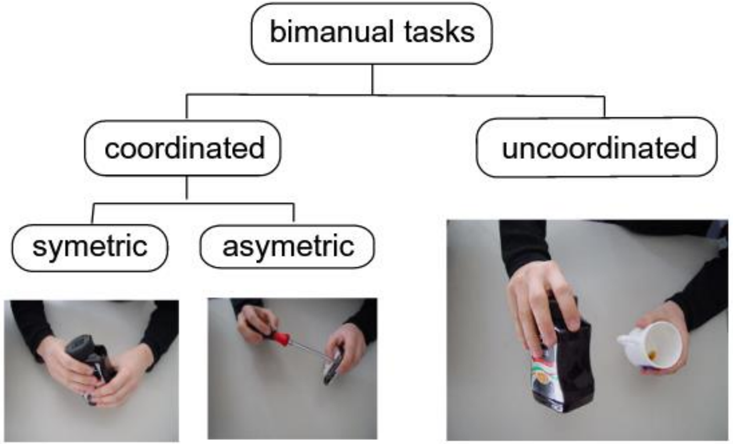
- Kelso, 1984
- Guiard, 1987
- **Kantak et al., 2017**

Robotics:

- **Zöllner et al., 2004**
- Surdilovic et al., 2010
- Park et al., 2016
- Volkmar et. al., 2019
- Rakita et al., 2019

Bimanual Taxonomy in Robotics

- Context: Programming by Demonstration (PbD)

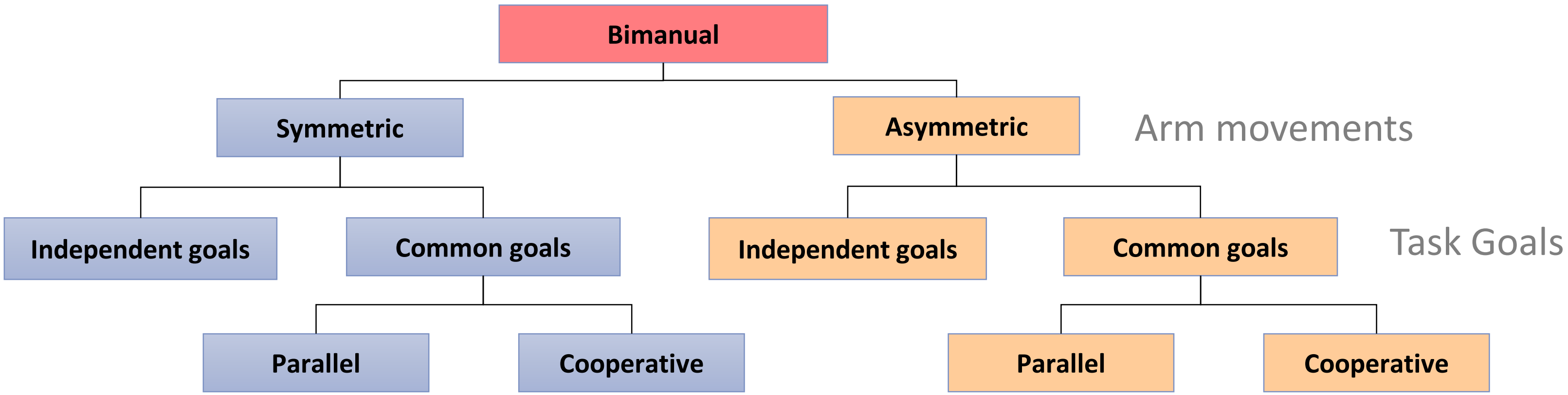


- **Symmetric coordinated:** both hands are manipulating the same object, forming a closed kinematic chain
- **Asymmetric coordinated:** hands are manipulating different objects like in a tool handling task
- **Uncoordinated:** no coordination needed, could also be executed by a single arm sequentially

Zöllner, R., Asfour, T. and Dillmann, R. "Programming by demonstration: Dual-arm manipulation tasks for humanoid robots." IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2004.

Bimanual Taxonomy in Rehabilitation (Kantak et al.)

- **Context:** Identify bimanual coordination deficits for rehabilitation
- Based on 1) Symmetry and 2) task goal



Kantak, S., Jax, S. and Wittenberg, G. "Bimanual coordination: A missing piece of arm rehabilitation after stroke." Restorative neurology and neuroscience, 2017

Bimanual Taxonomies: Problems and Challenges

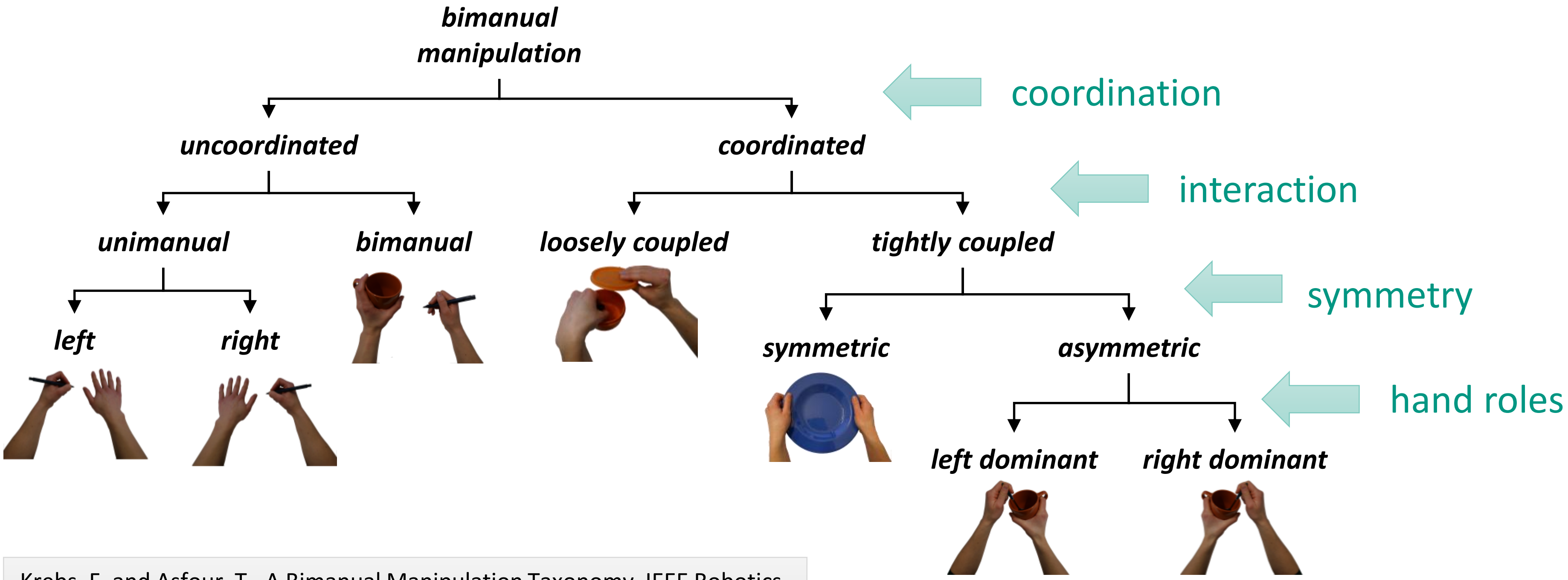
Problems:

- Inconsistent terminology e.g. symmetric for the same motion direction vs. grasping the same object
- Structure vastly depends on the desired application

Challenges in robotics:

- Include all features relevant for successful and robust motion reproduction e.g. interaction forces, temporal and spatial constraints
- A representation extendable to multi-agents (more than two) would be desirable, e.g. multi-robot interaction, human-robot interaction

KIT Bimanual Manipulation Taxonomy



Krebs, F. and Asfour, T., A Bimanual Manipulation Taxonomy, IEEE Robotics and Automation Letters (RA-L), vol. 7, no. 4, pp. 11031-11038, 2022

Extracting Bimanual Categories

hand poses

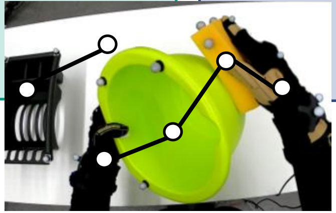
hand configurations

object poses

3D models

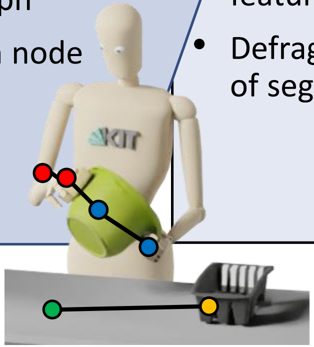
Contact Graph

- Nodes are the hands and all objects
- Edges are contact relations detected using the 3D models



Motion Feature Extraction

- Extract poses and velocities of each node of the contact graph
- Assign each node to a group



Rule-Based Classification

- Classification based on contact graph and motion features
- Defragmentation of segmentation

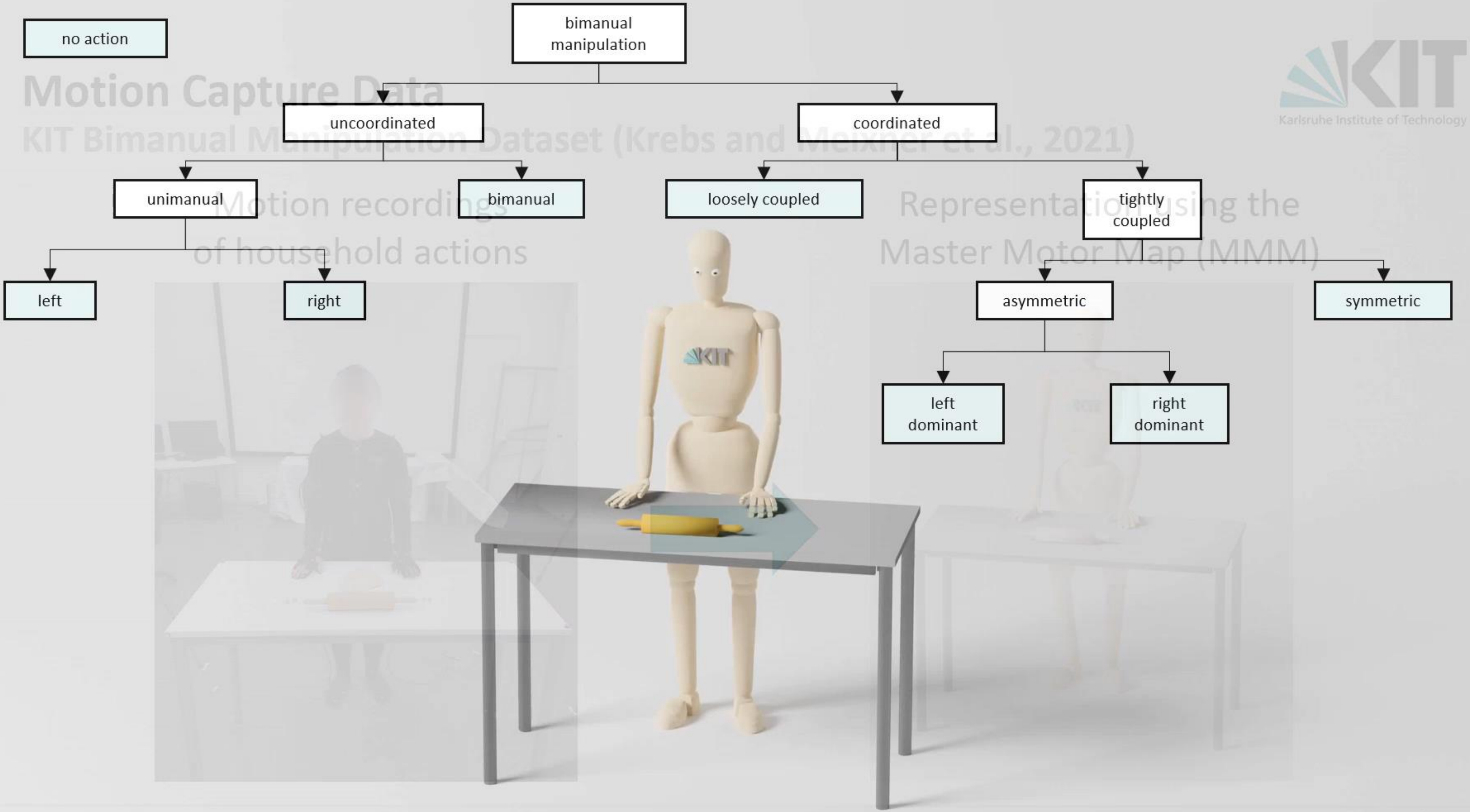
tightly_asym_right

Motion Capture Data

KIT Bimanual Manipulation Dataset (Krebs and Meixner et al., 2021)

Motion recordings of household actions

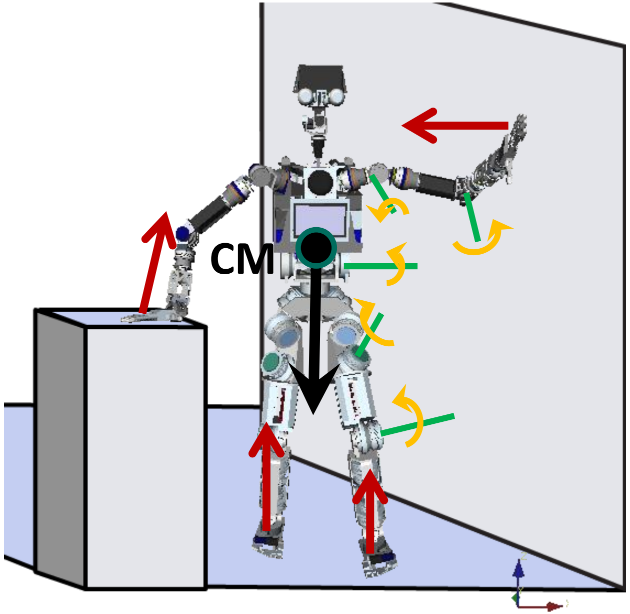
Representation using the Master Motor Map (MMM)

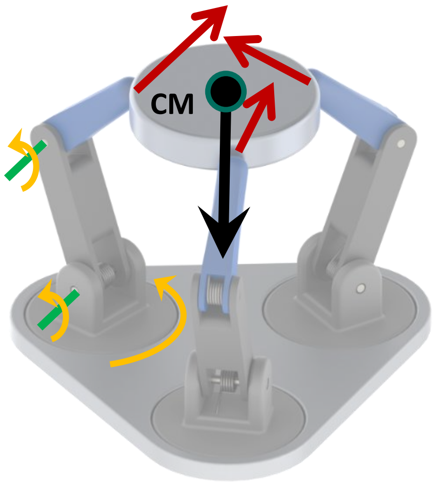


KIT Taxonomy of Whole-Body Poses (Grasps)

Duality of grasping and balancing

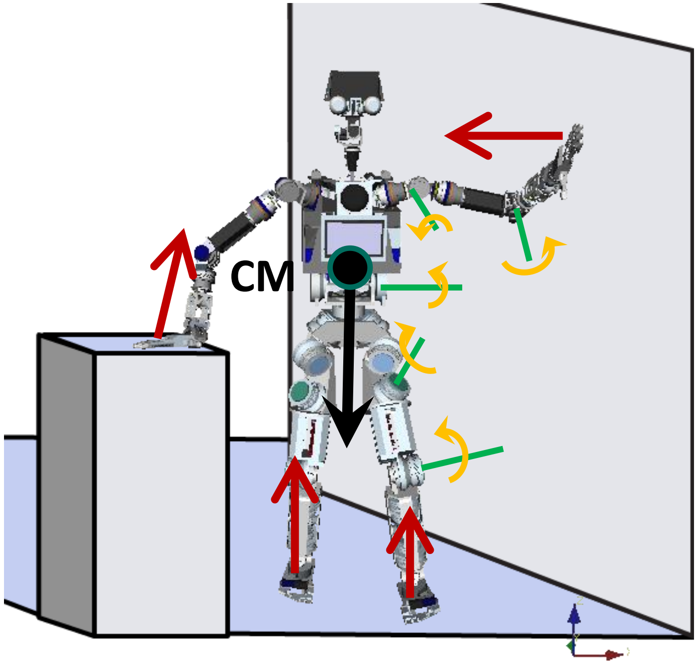
Equilibrium is reached by balancing similar sets of forces





Ground reaction forces	⟷	Fingertip forces
Weight of the body (CM)	⟷	Weight of the object (CM)
Torques on the joints	⟷	Torques on the joints

Duality of Grasping and Balancing (II)



Concepts of grasping can be applied to loco-manipulation

$$\mathbf{G}^T\mathbf{T} = \mathbf{J}_H\dot{\Theta}$$
$$\mathbf{J}_H^T\lambda_f = \tau$$
$$-\mathbf{G}\lambda_f = \mathbf{W}$$
$$\lambda_f \in \mathscr{F}$$

Balance $\longleftrightarrow$ Stable grasp

Step planning $\longleftrightarrow$ Grasp synthesis

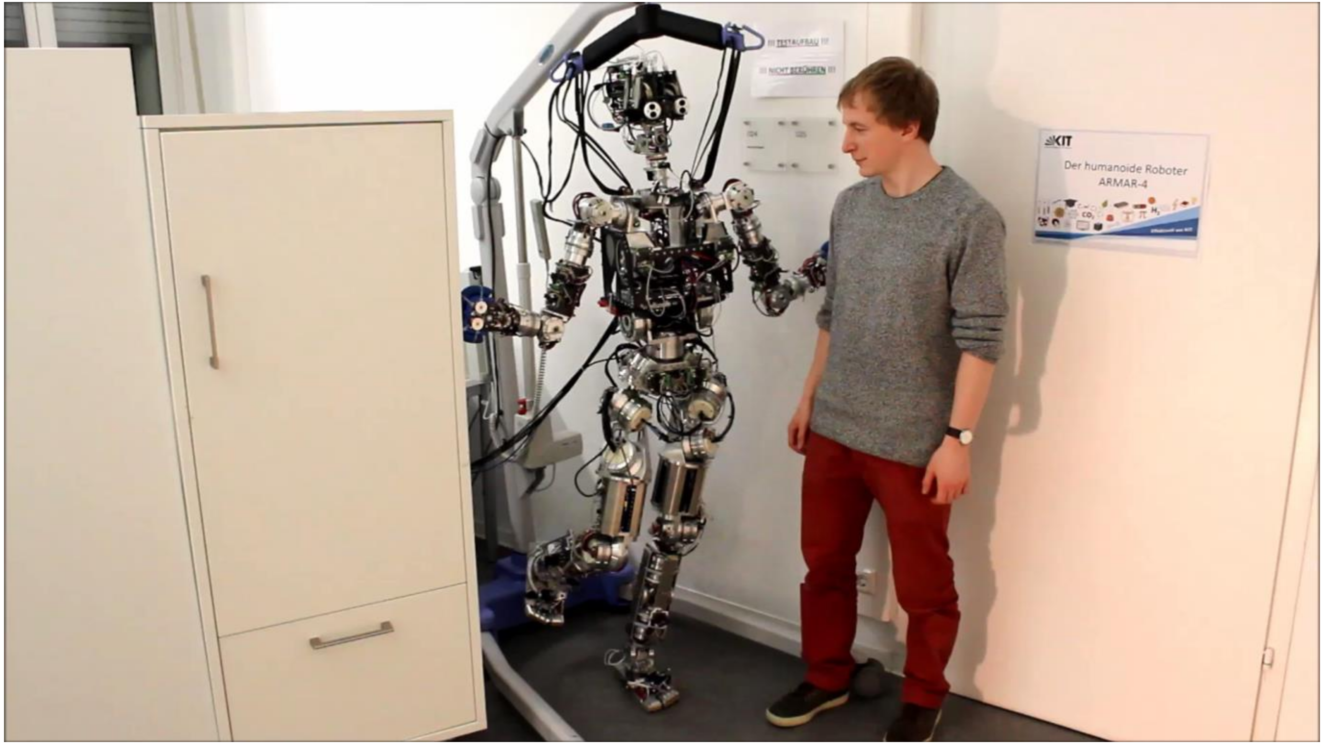
Duality of Grasping and Balancing (III)

Red: relevant for the exam

Selection of support pose	⟷	Grasp selection
Selection of contact points	⟷	Grasp synthesis
Classification of support pose possibilities	⟷	Grasping taxonomies

- Asfour, T., Borràs, J., Mandery, C., Kaiser, P., Aksoy, E. E. and Grotz, M. „On the dualities between grasping and whole-body loco-manipulation tasks“ *Robotics Research, Springer Proceedings in Advanced Robotics, Springer* (2018)
- Borras, J., and Asfour, T. "A whole-body pose taxonomy for loco-manipulation tasks." 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE (2015)
- Borràs, J., Mandery, C. and Asfour, T., A Whole-Body Support Pose Taxonomy for Multi-Contact Humanoid Robot Motions, **Science Robotics**, vol. 2, no. 13, 2017 (http://robotics.sciencemag.org/content/2/13/eaaq0560)

Whole-Body Grasps



Whole-Body Poses in Loco-Manipulation Tasks (I)

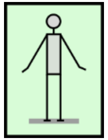
Given: humanoid, task and scene and its affordances:

- How many poses can be realized?
- Which pose should be selected ?
- How to realize it? planning, control

The whole-body can adopt many poses for balancing

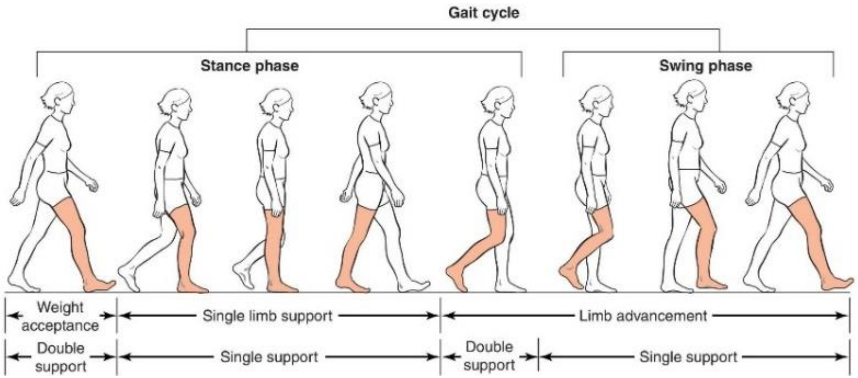
Classic postures:

Single foot support



Double foot support

Postures and their transitions are very well studied



http://www.innovatefpga.com/cgi-bin/innovate/teams.pl?Id=EM040

Whole-Body Poses in Loco-Manipulation Tasks (II)

Given: humanoid, task and scene and its affordances:

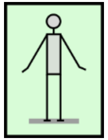
- How many poses can be realized?
- Which pose should be selected ?
- How to realize it? planning, control

→ Taxonomy

The whole-body can adopt many poses for balancing

Classic postures:

Single
foot support

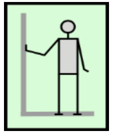


Double
foot support

Postures and their transitions are very well studied

Other possible combinations:

1 Hand
1 Foot



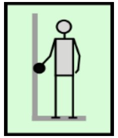
1 Hand
2 Feet

Double
knee support

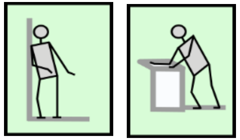
1 Hand
2 Knees

1 Foot
1 Knee

Considering other types of contacts:



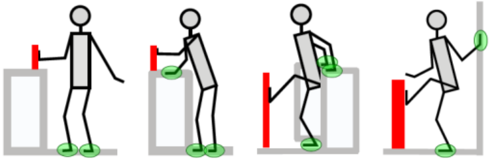
Double foot support
with hold (hand grasping
a handle)



Arm contacts

Towards a Taxonomy of Whole-Body Support Poses

- **Support pose:** defined by contacts that provide balance support



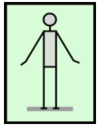
We ignore contacts with manipulation objects

- Criteria for classification:
  - **Number of contacts**: Relevant for balance conditions/control
  - **Type of contacts**: Determine the mobility (DoFs) and the transmission of contact forces
  - **Possible transitions**: We only allow one contact change at a time.

- Possible poses beyond walking

Classic postures

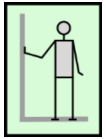
Single foot support



Double foot support

How many combinations are possible?

1 Hand 1 Foot



1 Hand 2 Feet

Double knee support

1 Hand 2 Knees

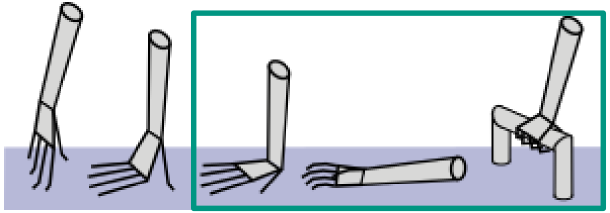
1 Foot 1 Knee

It depends on types of contacts considered!

Type of Contacts

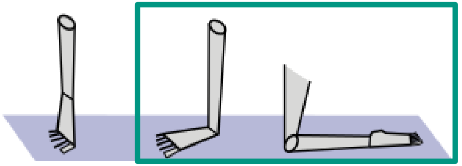
- Possible contacts with extremities

Type of contacts with arms



Tips Fingers Palm Arm + Hold

Type of contacts with legs



Tip-toes Feet Knees

- Combinatory between **number** of contacts and **type** of contacts considered

$$f(CL, CA) = \sum_{NL=1}^{2} \binom{CL + NL - 1}{NL} \cdot \sum_{NA=0}^{2} \binom{CA + NA - 1}{NA}$$

CA = # type of arm contacts

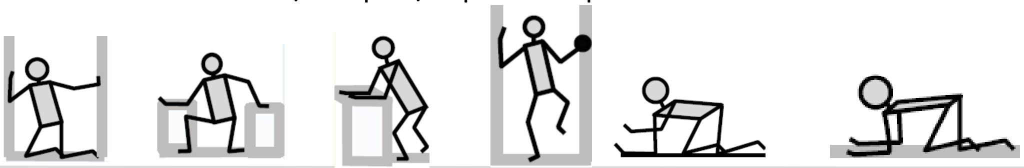
CL = # type of leg contacts

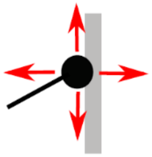
$f(3,5) = 189$

$\boxed{f(2,3) = 50}$

A total of 36 poses are selected. Difficult/complex/improbable poses are discarded.

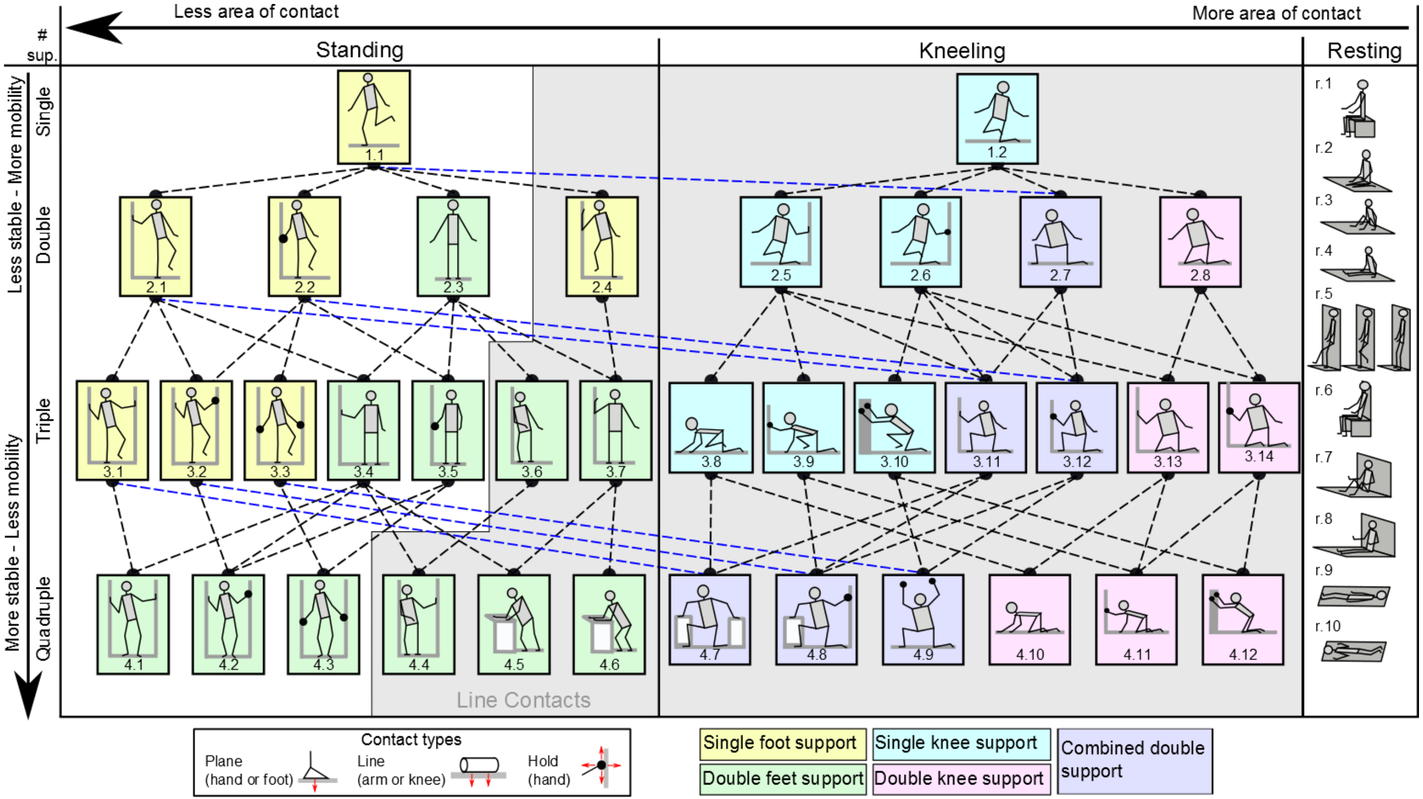
Examples of **discarded** poses





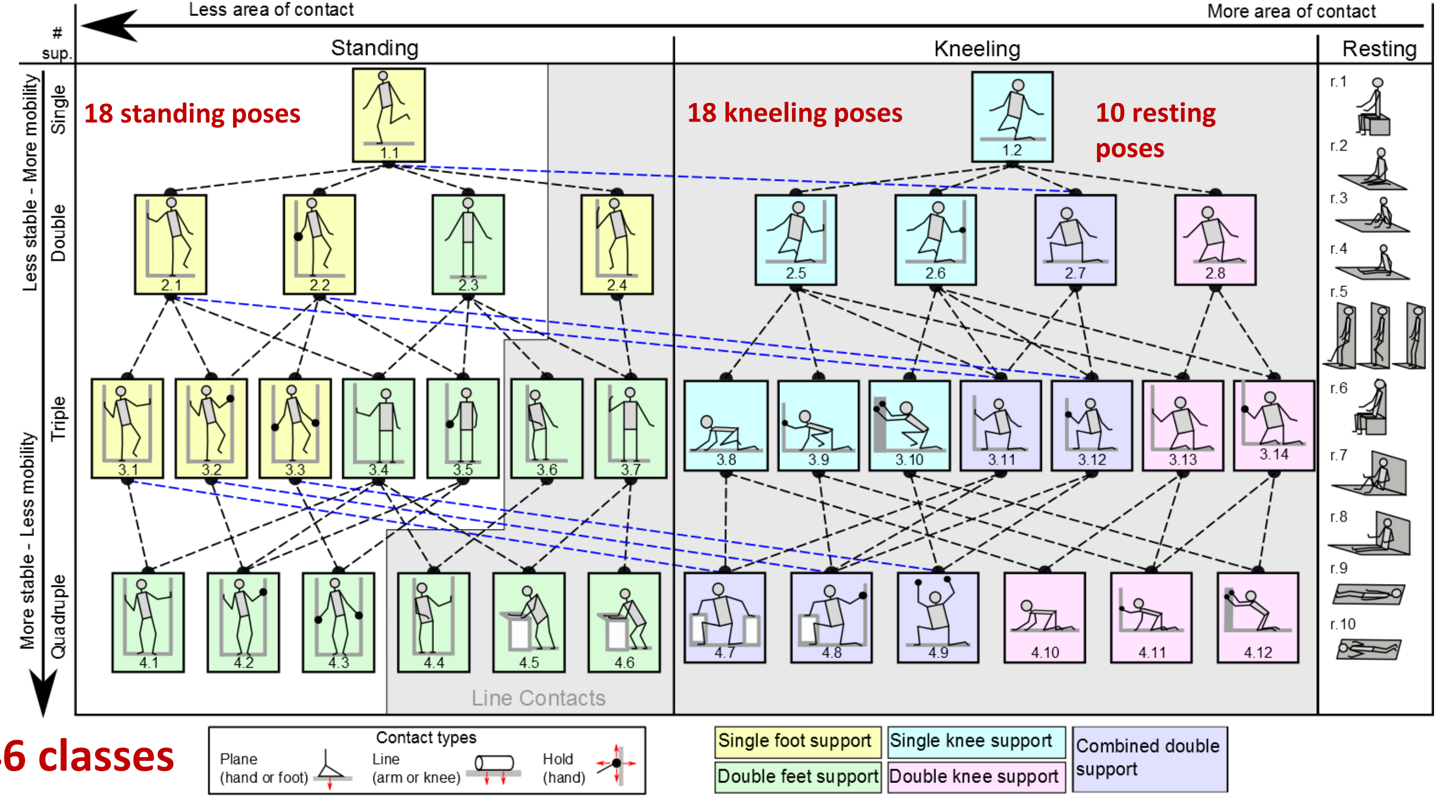
Hold is represented

Taxonomy of Whole-Body Poses (I)



Borras, J., and Asfour, T. "A whole-body pose taxonomy for loco-manipulation tasks." 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE (2015)

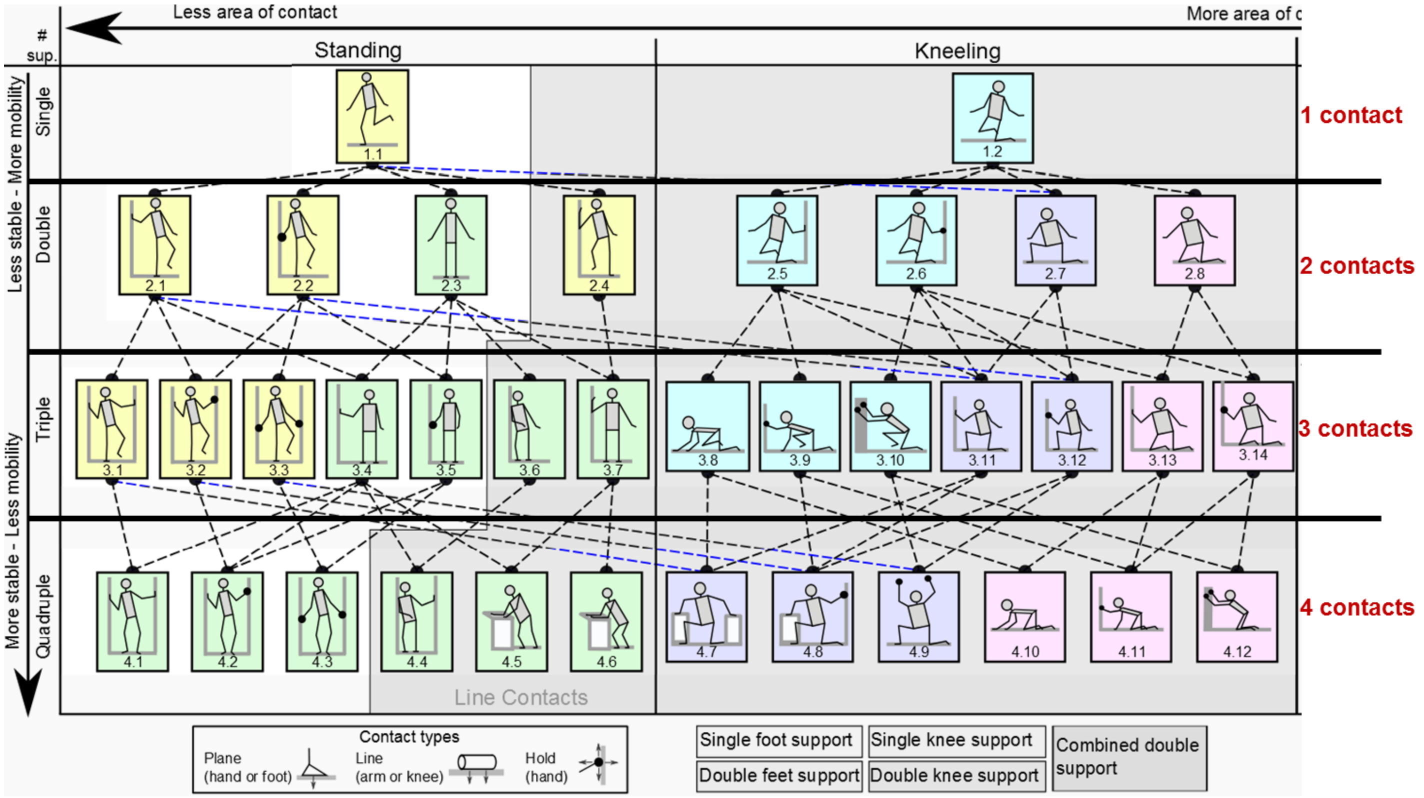
Taxonomy of Whole-Body Poses (II)



Total: 46 classes

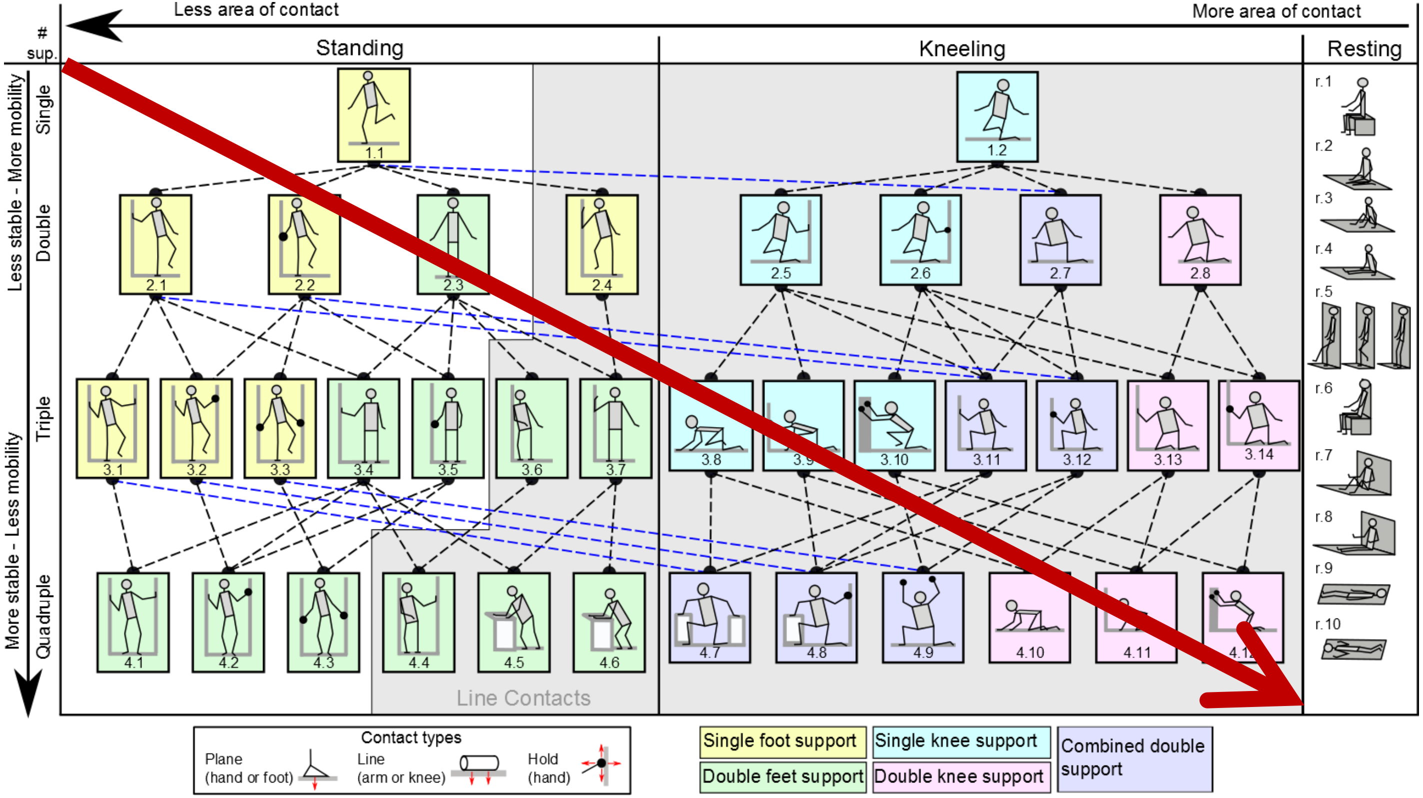
Borras, J., and Asfour, T. "A whole-body pose taxonomy for loco-manipulation tasks." 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE (2015)

Taxonomy of Whole-Body Poses (III)



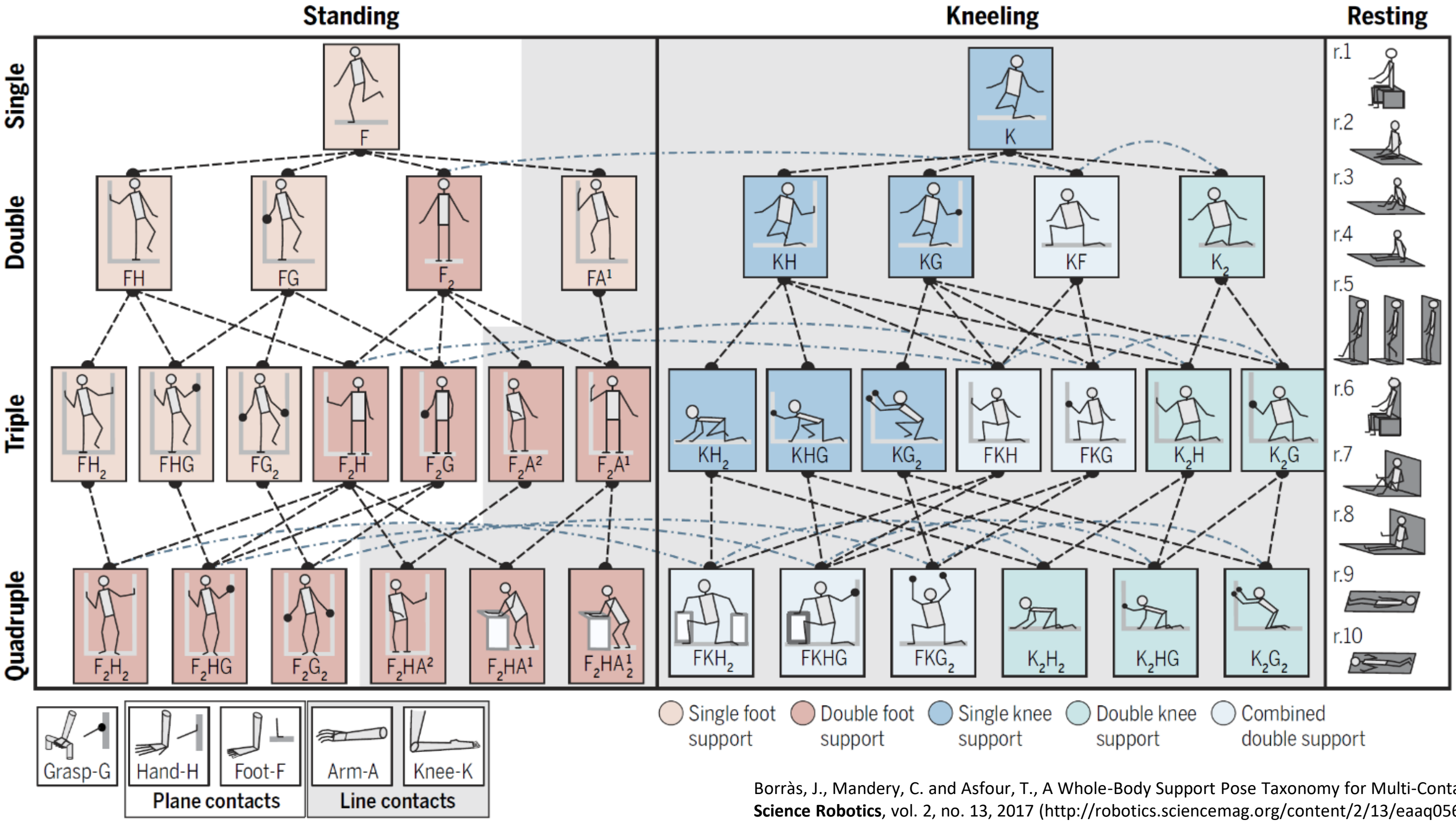
Borras, J., and Asfour, T. "A whole-body pose taxonomy for loco-manipulation tasks." 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE (2015)

Taxonomy of Whole-Body Poses (IV)



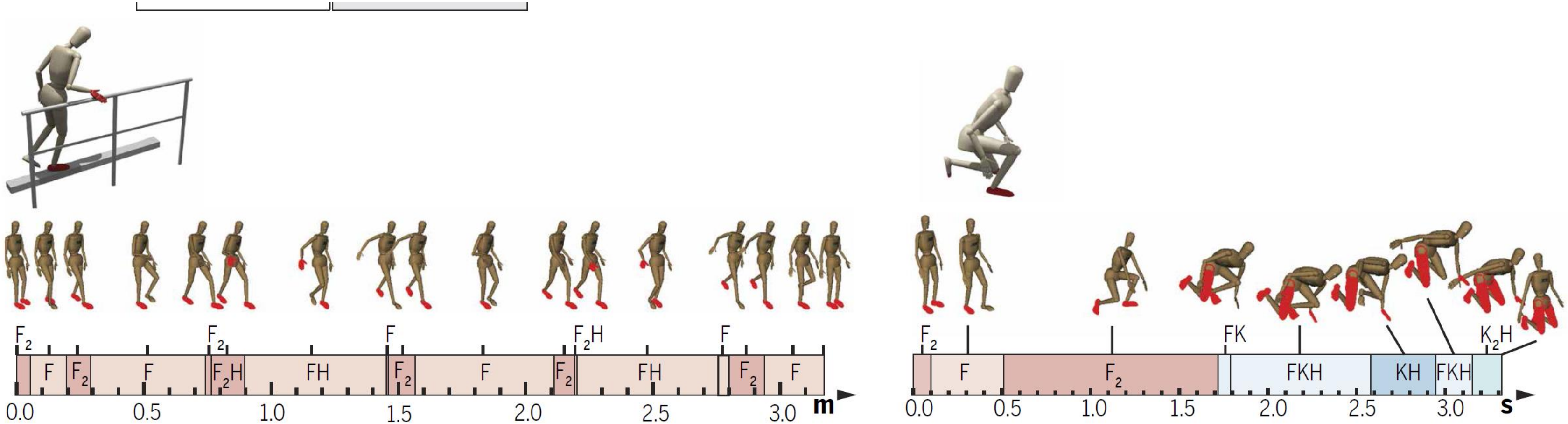
Borras, J., and Asfour, T. "A whole-body pose taxonomy for loco-manipulation tasks." 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE (2015)

Taxonomy of Whole-Body Poses (V)



Borràs, J., Mandery, C. and Asfour, T., A Whole-Body Support Pose Taxonomy for Multi-Contact Humanoid Robot Motions, **Science Robotics**, vol. 2, no. 13, 2017 (http://robotics.sciencemag.org/content/2/13/eaaq0560)

Taxonomy of Whole-Body Poses (VI)



Borràs, J., Mandery, C. and Asfour, T., A Whole-Body Support Pose Taxonomy for Multi-Contact Humanoid Robot Motions, **Science Robotics**, vol. 2, no. 13, 2017 (http://robotics.sciencemag.org/content/2/13/eaaq0560)

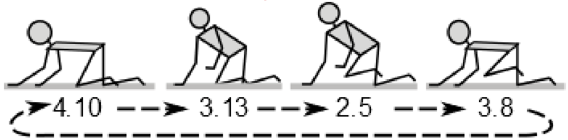
Classification of Whole-Body Actions

- Type I: Actions to change the environment
  - One support pose is selected to perform the **manipulation**
  - Only rows 1 to 3 of taxonomy allow manipulation actions

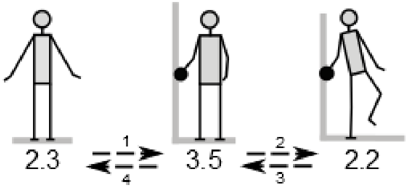
Ex. of pose selection
for action
“Hit an object”

- Type II: Actions to change the body
  - Succession of support poses to allow **locomotion** or **balancing**
  - All rows of taxonomy can be used

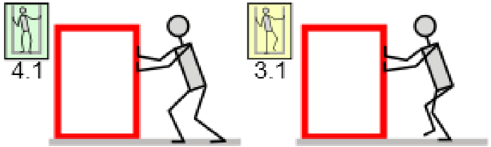
Crawling



Walk on stairs with handle

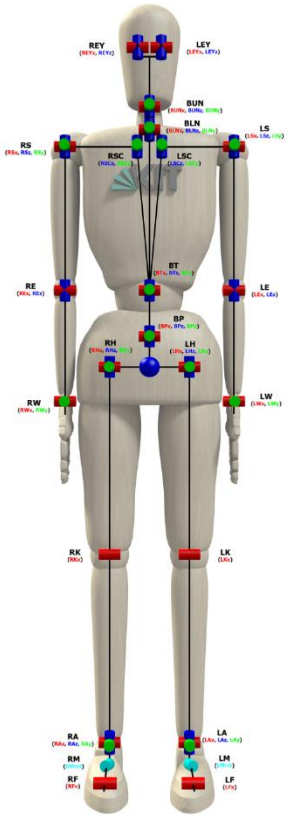


- Type III: Combination of I and II
  - Contacts are used to balance and to change the environment
  - Only rows 2 to 4 of taxonomy



Validation of the Taxonomy (I)

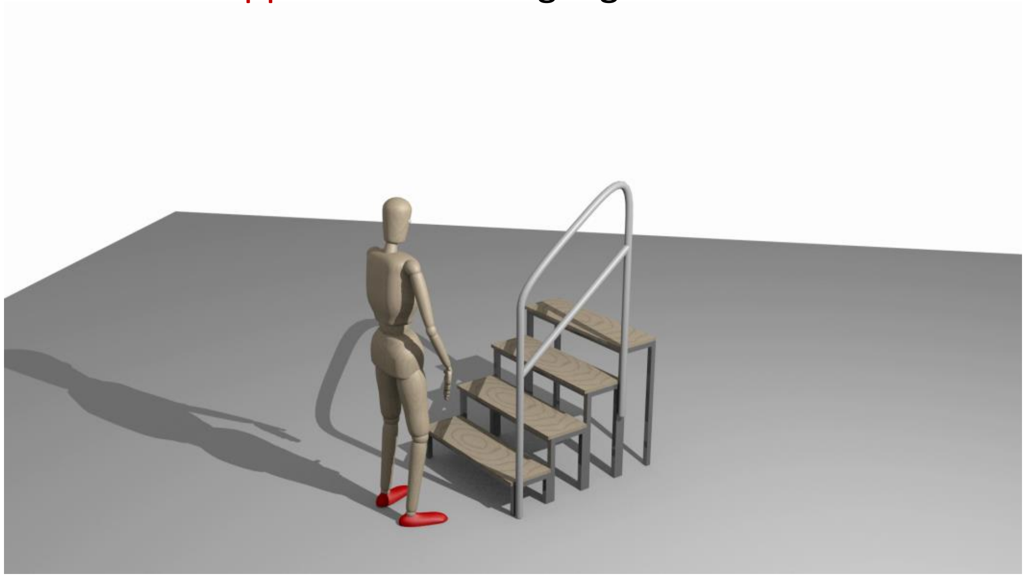
- Analyses of different human loco-manipulation tasks with supports
- Reference model of the human body (Master Motor Map: MMM) with 104 DoF
- Motion capture data mapped to reference model of the human body (MMM)
- Automatic segmentation to detect support poses and transitions
- Automatic generation of a taxonomy of the poses and their transitions in the motion database



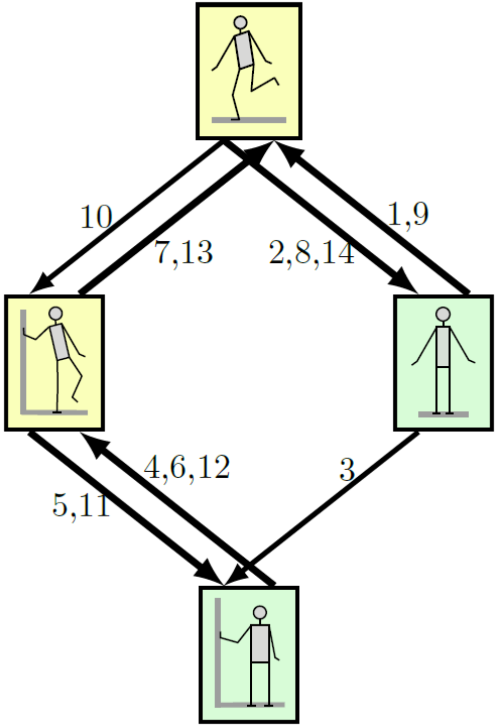
Analysis of Pose Transitions (I)

Going upstairs with a handle

Detection of support contacts highlighted in red



Generated graph of transitions:

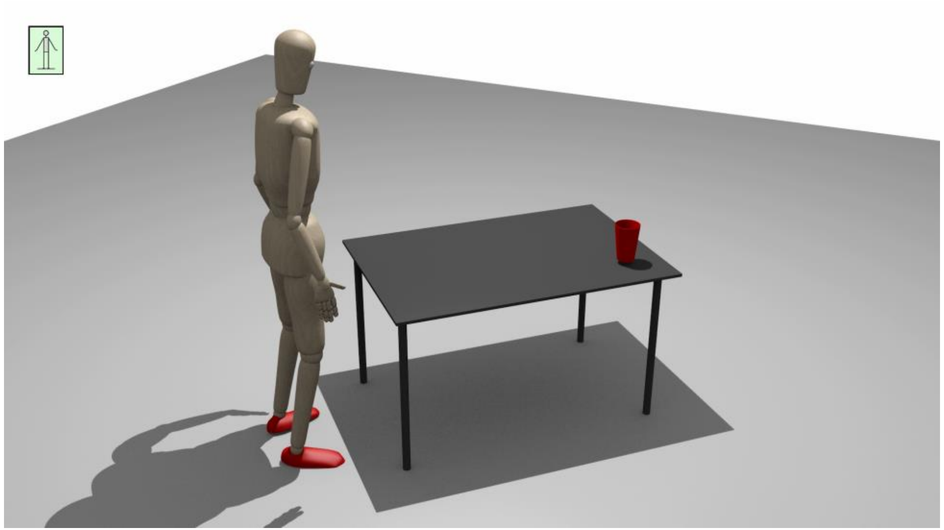


Subject swings left foot with a *right foot – right hand* support pose

Analysis of Pose Transitions (II)

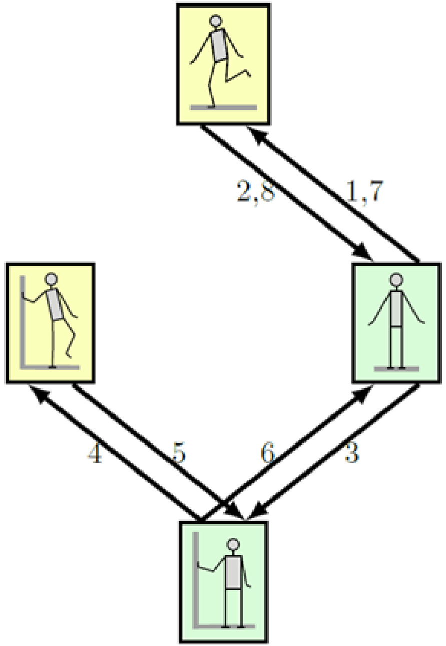
Lean on table to pick up a cup

Detection of support contacts highlighted in red



The manipulation takes place on a *one Hand – one Foot* support pose

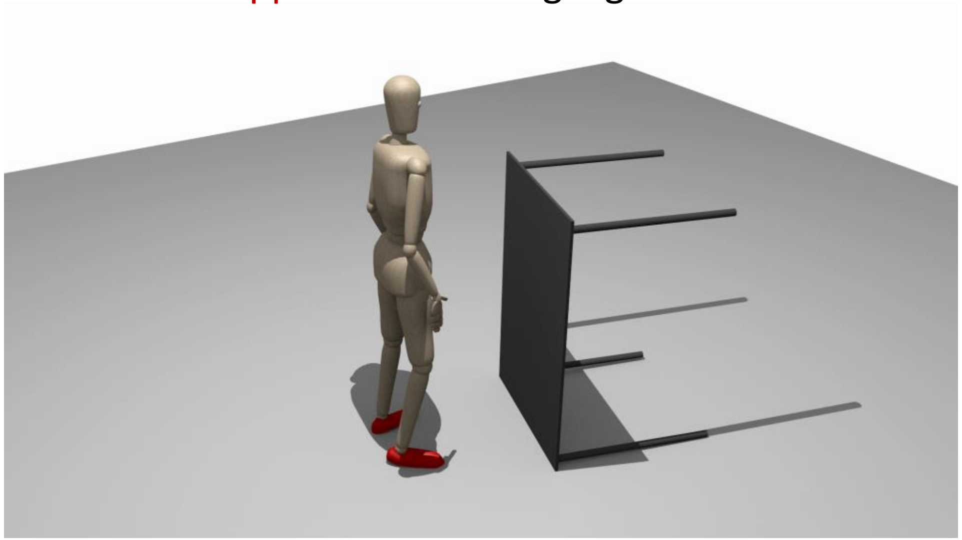
Generated graph of transitions:



Analysis of Pose Transitions (III)

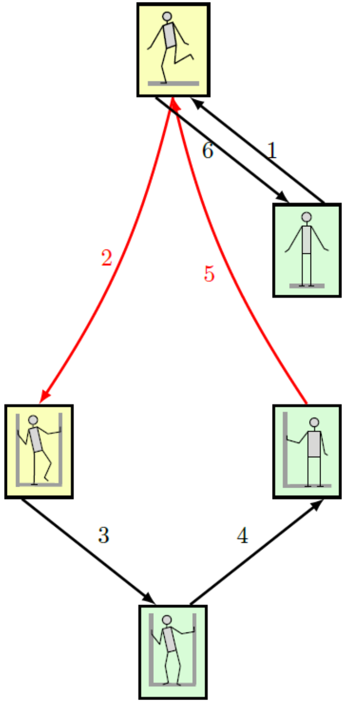
Push recovery from a push from behind

Detection of support contacts highlighted in red

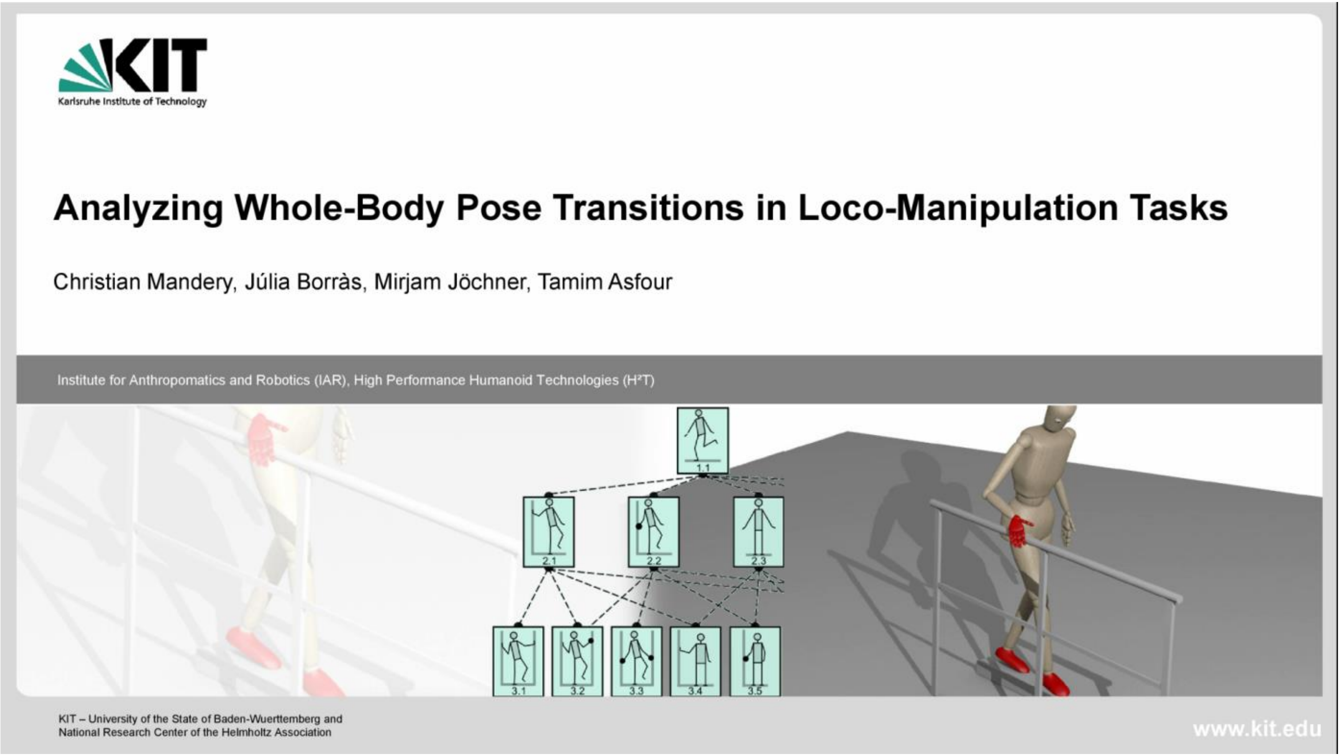


Transitions with 2 changes of contacts.

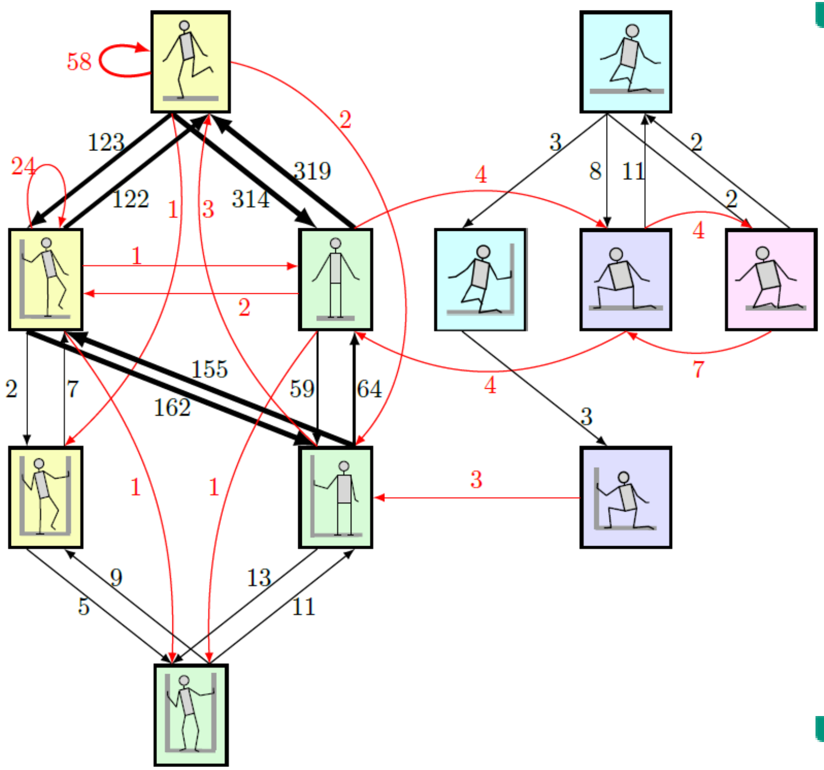
Generated graph of transitions:



Analysis of Pose Transitions (IV)

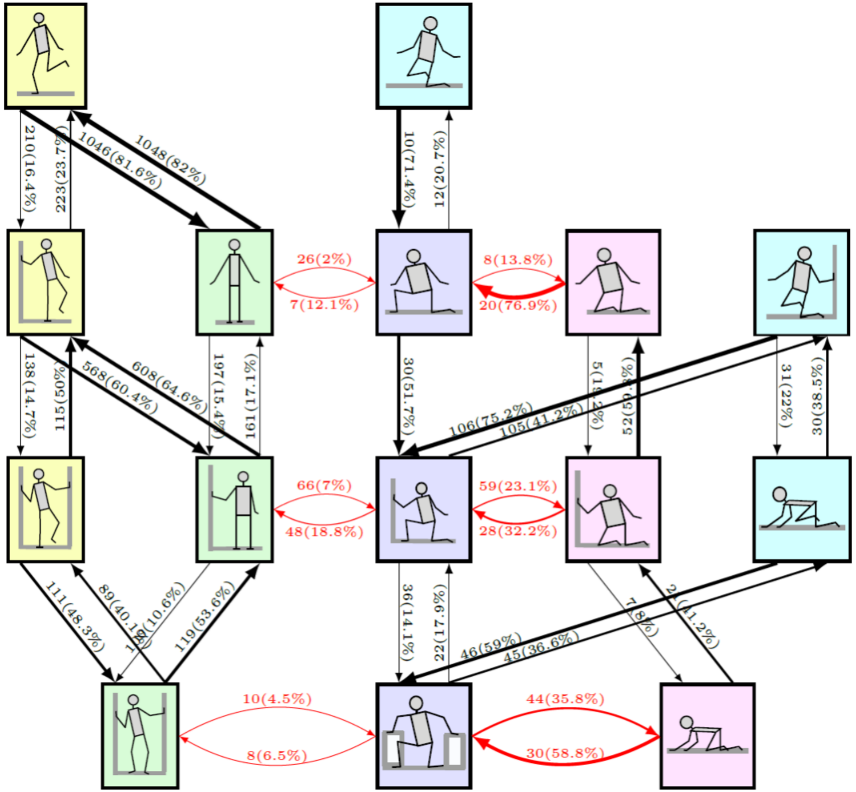


Validation of the Taxonomy (II)



- Total of **121** motions processed
  - **Locomotion**
    - Upstairs/downstairs with handle
    - Walk with handle
    - Walk avoiding obstacles using hand supports
  - **Loco-manipulation**
    - Lean to reach/place/wipe
    - Bimanual pick and place of big objects
  - **Balancing**
    - push recovery
    - recovery due to lost balance
  - Kneeling motions
- **4,5%** of poses missed
  - all double foot supports (the looping edges)

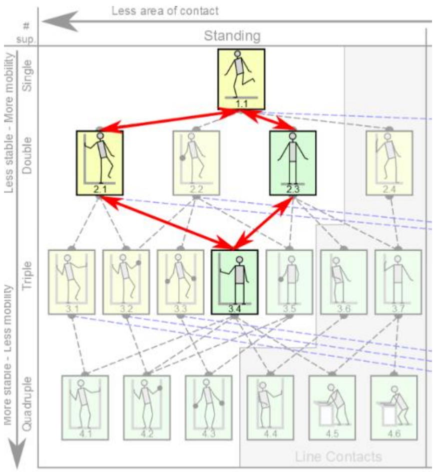
Validation of the Taxonomy (III)

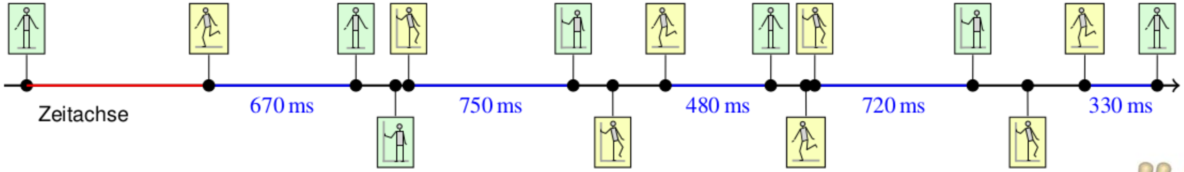


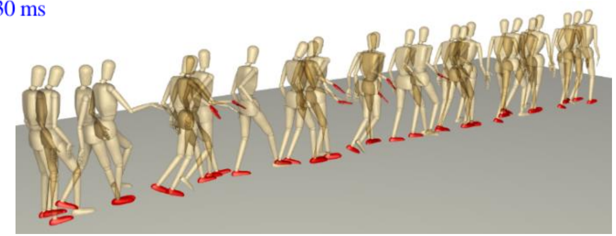
- Total of **388** motions processed
  - **Locomotion**
    - Upstairs/downstairs with handrail
    - Walk with handrail
    - Walk using table for supports
    - Kneeling up and down
    - Crawling

What Can We Do with It?

- **Generate whole-body multi-contact pose sequences**
- **Novel statistical approach** for planning multi-contact motions based on the taxonomy and knowledge extracted from **observing human motions**
- Representation of motions as a **sequence of poses** (**stance planning**)







Mandery, Christian, et al. "Using language models to generate whole-body multi-contact motions." 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE (2016)

Statistical Modelling of Pose Transitions (I)

- Statistical models employed:
  1. Modelling of pose transition probabilities using **n-gram model** :

$$P(p_t \mid (p_{t-4}, p_{t-3}, p_{t-2}, p_{t-1})) \qquad (\mathrm{N} = 5)$$

  2. Modelling of the average **center of mass displacement** for the execution of a given pose transition

- Both models are learned from the support pose sequences extracted by segmentation of human motion data

Statistical Modelling of Pose Transitions (II)

- **Linguistic approach** related to the idea of an **alphabet of motion**:
  - Poses are *words*
  - Multi-contact motions are *sentences*, consisting of *words* (poses)

- **Starting point: Textual representation** of pose sequences
  e.g.: `LeftFootRightFoot_1 LeftFoot_1 LeftFootRightFoot_2 RightFoot_4 ...`

- Textual representation can be used to learn a **n-gram model** which describes **probabilities of pose transitions**

Language Model to Generate Multi-Contact Motions

- **n-gram language model:** Statistical approach to learning conditional transition probabilities between whole-body shape poses
  - Observed shape poses are "words" and observed motions are "sentences"

$$P\left(p_t | (p_{t-4}, p_{t-3}, p_{t-2}, p_{t-1})\right) \qquad (n = 5)$$

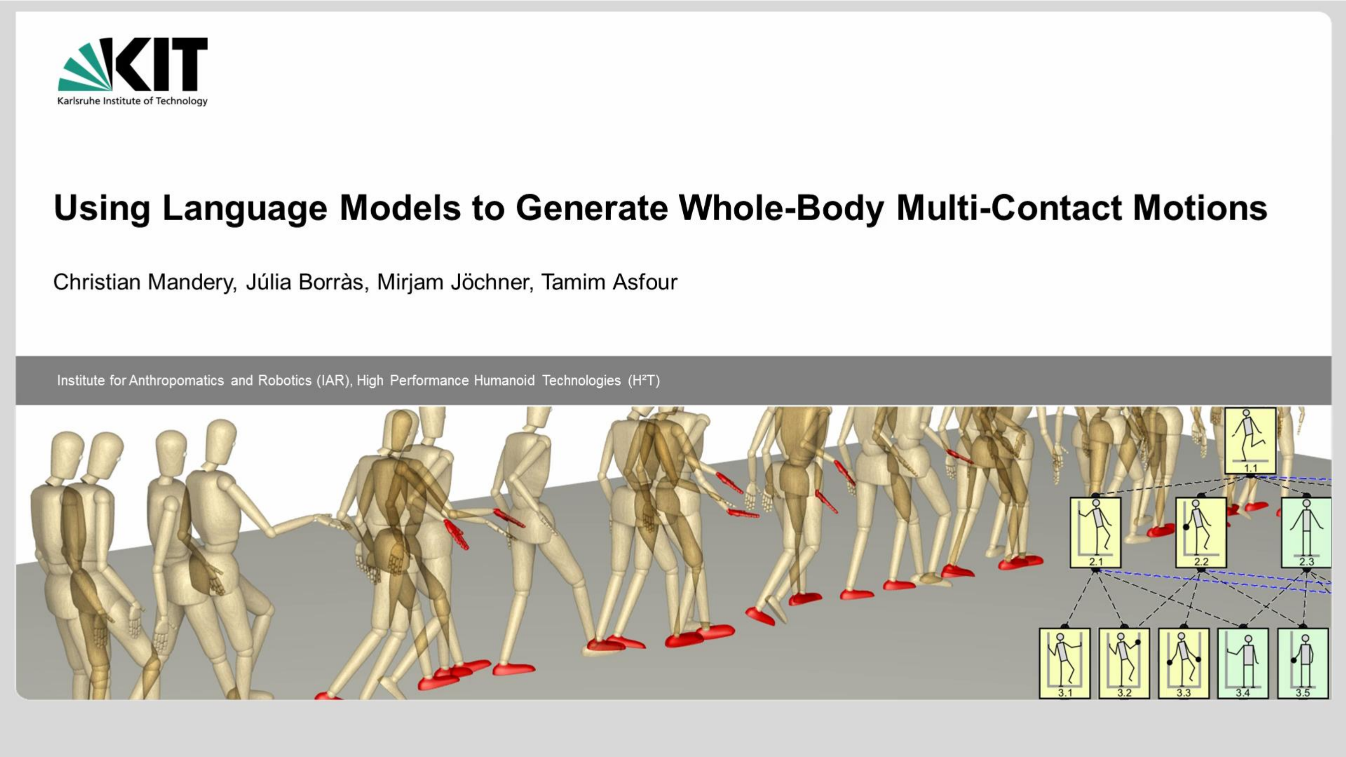
Here: **n = 5**, Witten-Bell smoothing

(determined empirically using grid search in parameter space: consider perplexities on test fold in 5-fold cross-validation)

- **Language model learned from motion capture data (segmented poses):**
  - 20 trials of 7 walking tasks each; 2813 poses in total (~20 per motion)
  - Automatic detection of poses

- **Spatial translation model:**
  - Considers only translation along one coordinate axis (valid for walking in a straight line!)
  - Average from all observed instances of a certain translation

Motion (Sentence) as Sequences of Poses (Words)



Motion as Sequences of Poses on ARMAR-4

Postural Synergies

Postural Synergies

Red: relevant for the exam

Karlsruher Institut für Technologie

- **Literature**
  - Santello, M., Flanders, M. and Soechting, J.F. “Postural Hand Synergies for Tool Use” *The Journal of Neuroscience*, 18.23 (1998): 10105-10115
  - Bicchi, A., Gabiccini, M. and Santello, M. “Modelling natural and artificial hands with synergies” *Philosophical Transactions of the Royal Society B*, 366 (2011): 3153-3161

Introduction

Red: relevant for the exam

- Questions:
  - How do humans grasp?
  - Do they control all the hand's DoF individually?
- Answer from human grasping experiments:
  - "Experimental evidence indicates that the simultaneous **motion and force** of the fingers are characterized by **coordination and covariation patterns** that **reduce** the number of independent degrees of freedom to be controlled." (Bicchi et al., 2011)

- In other words:
  - Not all finger joints are controlled independently when grasping an object.
  - Movements of the finger joints are strongly correlated.
  - Grasping movements are dominated by synergies in a (low-dimensional) postural space.
- What are **postural synergies**?
  - Postural synergies are the correlation of degrees of freedom in patterns of more frequent use.

Bicchi, A., Gabiccini, M. and Santello, M. "Modelling natural and artificial hands with synergies" *Philosophical Transactions of the Royal Society B*, 366 (2011): 3153-3161

Postural Synergies – Experiment (I)

Red: relevant for the exam

Karlsruher Institut für Technologie

- Human subjects were asked to perform grasp motions for various objects.
- No real objects were present, but the participants only imagined to grasp a large number of objects (n = 57) and moved the hand to a corresponding grasp configuration

Santello, M., Flanders, M. and Soechting, J.F. "Postural Hand Synergies for Tool Use" *The Journal of Neuroscience*, 18.23 (1998): 10105-10115

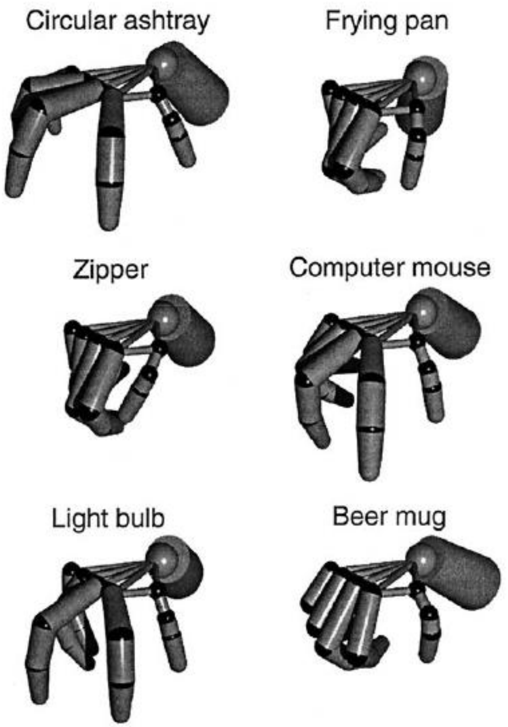
Table 1. List of objects used in the task

1. Apple	30. Hammer
2. Banana	31. Ice cube
3. Baseball	32. Iron
4. Beer bottle	33. Jar lid
5. Beer mug	34. Kitchen knife
6. Brick	35. Knob of a lid
7. Bucket	36. Knob of a stove
8. Calculator	37. Light bulb
9. Chalk	38. Milk carton
10. Cherry	39. Needle
11. Chinese tea cup	40. Notebook
12. Cigarette	41. Pen
13. Circular ashtray	42. Playing card
14. Coffee mug	43. Rope
15. Comb	44. Scissors
16. Compact disc	45. Screwdriver
17. Computer mouse	46. Stapler
18. Dictionary	47. Sugar cone
19. Dinner plate	48. Teaspoon
20. Dog dish	49. Telephone handset
21. Door key	50. Tennis racket
22. Door knob	51. Toothbrush
23. Drawer handle	52. Toothpick
24. Egg	53. Turtle
25. Espresso cup	54. Umbrella
26. Fishing rod	55. Wafer
27. Frisbee	56. Wrench
28. Frying pan	57. Zipper
29. Hair dryer	

Postural Synergies – Experiment (II)

- The hand movement was observed and measured by 15 sensors embedded in a glove (CyberGlove)
- Measurement sample rate 12 ms
- Each hand posture describes a joint angle configuration of the human hand approximated by a 15 DoF hand model.

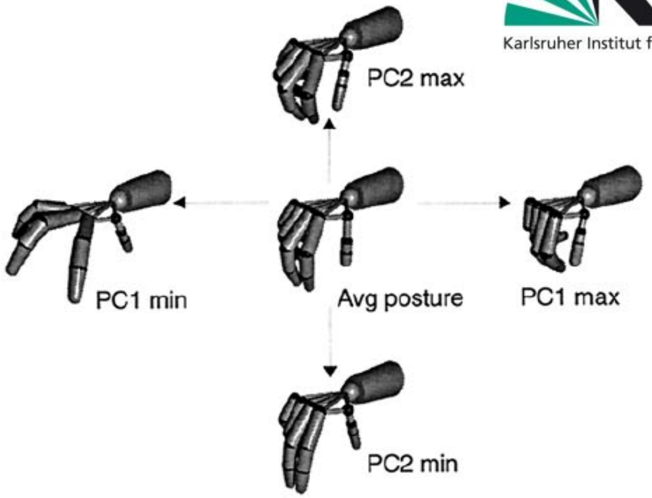
CyberGlove



Santello et al. 1998

Postural Synergies – Results (I)

- Principal Component Analysis on the data
- **Results (observations):**
  - During grasping, the hand moves in a low-dimensional subspace.
  - Considering only the first **two** principal components, **80%** of the variance in the data can be represented.
  - Using the first **three** principal components, **97%** of the variance can be represented.

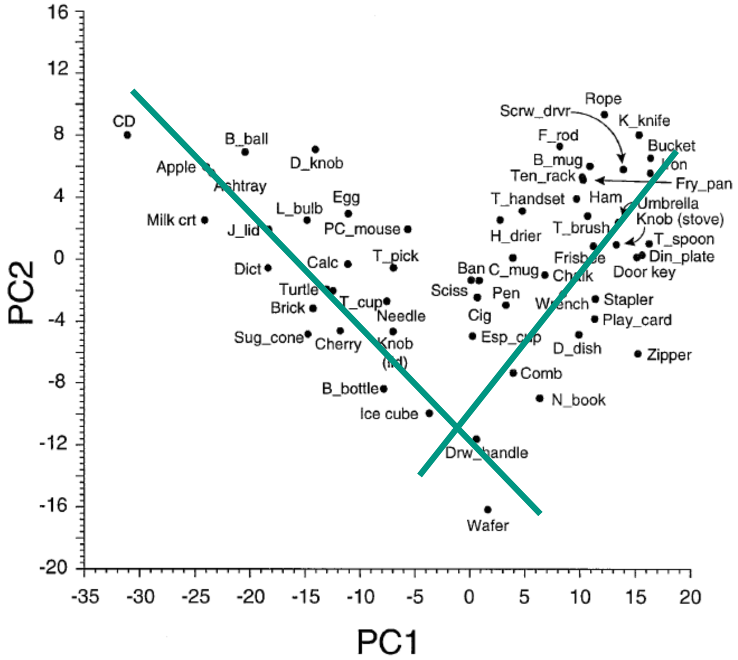


Santello et al. 1998

- Postural synergies defined by the first two principal components (PC1 and PC2)
- The hand posture at the center of the PC axes is the average of 57 hand postures for one subject
- Images rendered with the palm of the hand in the same orientation

Postural Synergies – Results (II)

- Distribution of hand postures in the plane of the first two principal components.
- The coefficients of the first two principal components are shown for each of the 57 objects for one subject.
- Note the lack of clustering and the distribution of the coefficients along two main axes.



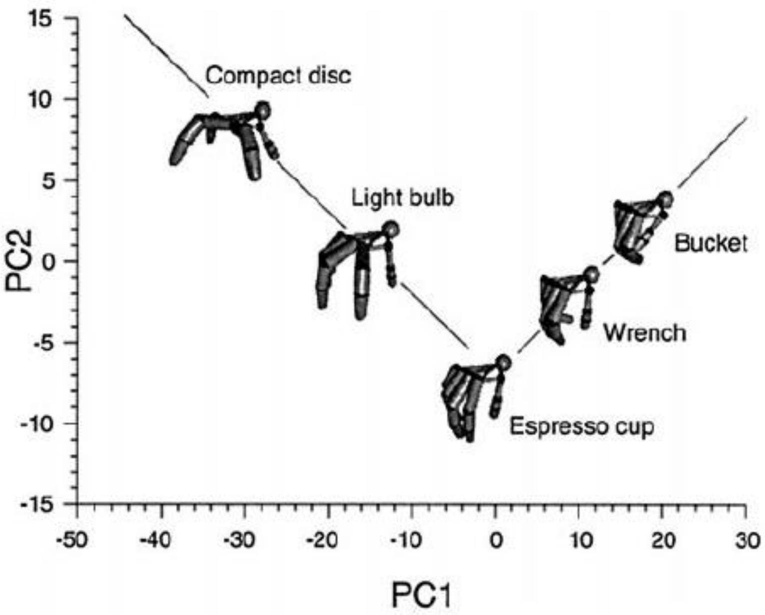
Santello et al. 1998

57 objects and one subject

Postural Synergies – Results (III)

- Distribution of hand postures in the plane of the first two principal components.
- The coefficients of the first two principal components are shown for each of the 57 objects for one subject.
- Note the lack of clustering and the distribution of the coefficients along two main axes.

Interpolation between various grasp postures



Postural Synergies – Subject Variance of the PCs

Subjects	PC_1	PC_2		PC_3	PC_4
FC	52.9	24.7	77.6	8.4	4.8
GB	49.5	37.6	87.1	4.8	4.6
MF	74.8	13.0	87.8	5.4	2.9
MS	79.3	10.0	89.3	5.0	2.2
UH	62.9	17.2	80.1	8.6	5.9

$PC_1 + PC_2$

Santello et al. 1998

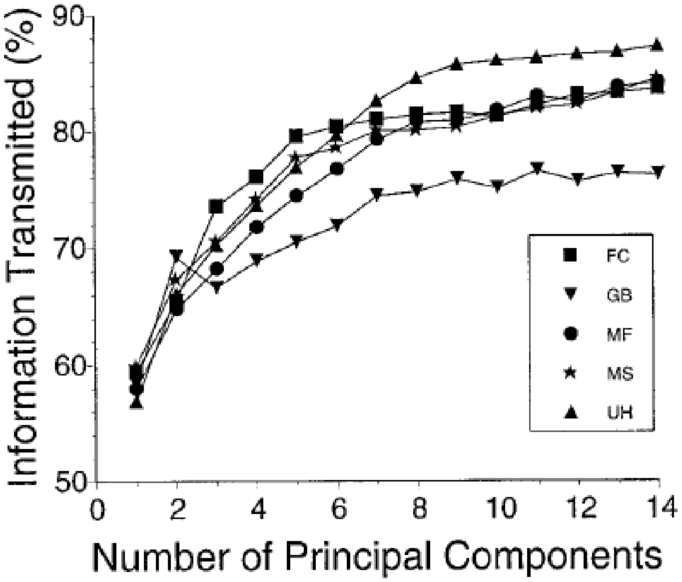
- The first three PCs account for ~ 90% of the variance (average over all subjects)
- The first two PCs account for ~ 84% of the variance (average over all subjects)
- This suggests a **significant reduction in the number of degrees of freedom (DOF) from 15 to 2 or 3**

Postural Synergies – How Many Effective DoF?

- The study shows also that there were also many instances in which pairs of joint angles were only **poorly correlated**, suggesting that there are **more than two effective degrees of freedom for the control of hand posture** and that several **higher-order PCs** would also be needed to represent this rather limited co-variation in joint angles
- There are two alternative solutions to this paradoxical result:
  - **higher-order PCs are needed** but represent noise (random variability) in the system
  - **higher-order PCs** do in fact contribute to discriminating among **hand shapes for different objects** → additional DoF controlled by the CNS
- Additional analysis needed!

Postural Synergies – Role of Higher-Order PCs (I)

- Reconstruction of the hand posture using an increasing number of PCs (PC1, PC2, … PC14); PC15 was nearly zero
- Determine **how much the representative information increased as the number of PCs increased**
  - If the **higher-order PCs represent noise**, the information about the object should not increase (may actually decrease) when higher-order PCs are used to define the hand posture
  - Conversely, if the **higher-order PCs do contribute to discriminating among hand shapes**, the information transmitted should increase as more PCs are included.

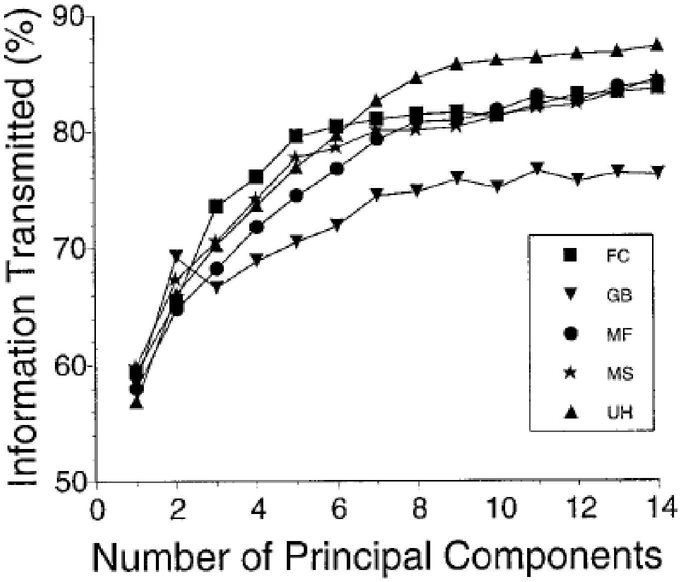


Santello et al. 1998

Postural Synergies – Role of Higher-Order PCs (II)

- The amount of information continued to **increase monotonically** up to at least the 5th or the 6th PC, even though these higher-order PCs contributed little to the variance

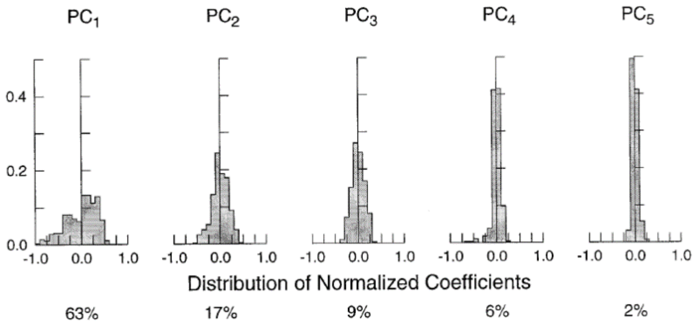
- Clearly, **more than two degrees of freedom are used** to mold the hand into the shape appropriate to grasp a particular object, and **the higher-order PCs do not simply represent random variability (noise)**



Santello et al. 1998

Postural Synergies – Role of Higher-Order PCs (III)

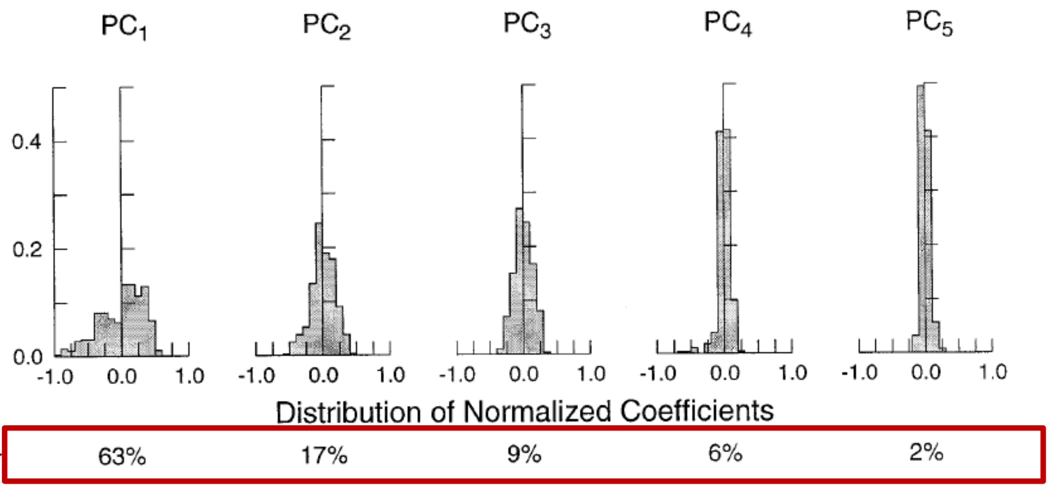
- Given that **higher-order PCs do not simply represent noise**, it is possible that the **hand postures associated with a few of the objects might be best represented by higher PCs**, i.e., that the amplitude of the higher-order PCs might be substantial for one or a few objects
  - Thus, the overall variance attributed to one PC might be small, but its contribution to a few postures might be large.
- If this were the case, the distribution of the PCs for the 57 objects would be multimodal and/or have a broad range. But this is not the case (see Figure)



Santello et al. 1998

Postural Synergies – Role of Higher-Order PCs (IV)

- Hence, **higher PCs do not seem to contribute substantially** to any one particular hand posture.
- These features were also **found in the other subjects**.
- This finding implies that the amplitudes of higher-order coefficients were generally small, irrespective of the object.

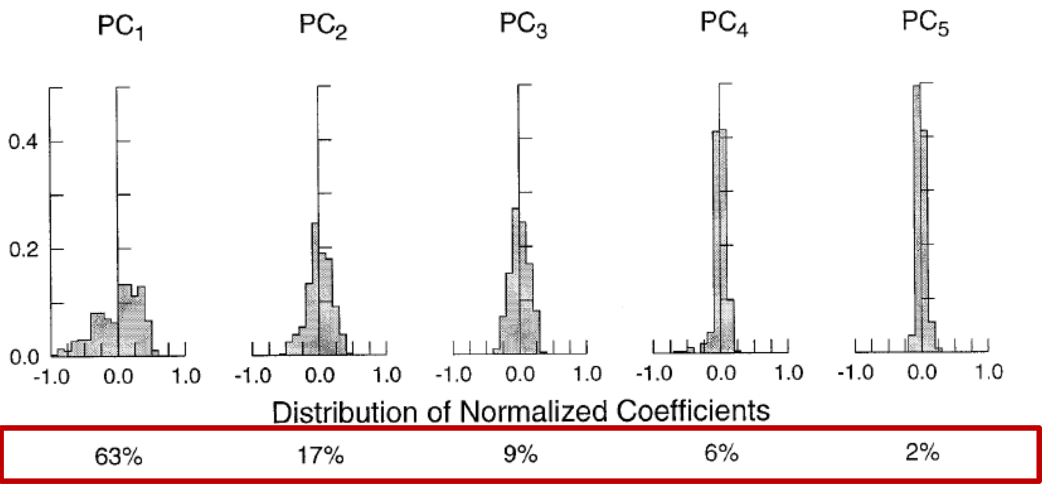


Santello et al. 1998

Variance

Postural Synergies – Role of Higher-Order PCs (V)

- Distribution of normalized amplitudes of the first five principal components.
- The amplitudes of the first five PCs have been normalized to the maximum (or minimum) value of the first PC. The data shown are for one subject (U.H.). Note that the amplitudes of the **3rd through the 5th PCs** are **not statistically normal, and not multimodal**, even though they contribute substantially to the information transmitted



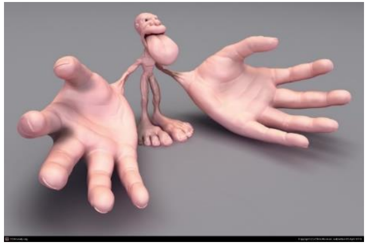
Santello et al. 1998

Variance

Discussion

This observation suggests the following interpretation.

- The control of hand shape is effected at **two levels**:
  - One **coarse control of hand shape** with a few synergies, and
  - a **finer level** that may be affecting all the joints.
- Because the higher-order principal components were very small and were not consistent from subject to subject, the study was not able to characterize this "finer level of control" more precisely.
- The higher-order PCs have coefficients that are distributed among all of the joint angles, suggesting that this finer control is also distributed.
- This hypothesis is consistent with the observation that a **disproportionate amount of sensorimotor cortical area** is devoted to the hand. It is also consistent with previous demonstrations of a tendency for coordinated motion of the fingers.



Conclusions of this Work (I)

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- No evidence for a clustering of the static postures for the various objects was found

- No straightforward relation: **object shape – hand shape**
  - **Similar object shapes** were often associated with grips that were quite **distinct** (i.e., precision vs power grips).

- This supports previous classifications of grasps, based on which finger(s) and which part(s) of the finger(s) contacts and exerts force on the object

Conclusions of this Work (II)

- Relationship between **static hand posture (i.e., kinematics) – control of contact force**
  - They are **not** independent, because the hand must be shaped properly so that the correct set of fingers makes contact with the object.
  - But there is **no one-to-one relation** between **posture** and **force control,** i.e., very different contact forces may be exerted with the hand in the same posture, depending on the object
- This is consistent with observations of neural activity in the hand area of primary motor cortex:
  - Monkeys controlling the grasp force of variously shaped objects showed that **1) the neural correlates of force and 2) the neural correlates of kinematics are dissociated**

Grasping Synergies

- Correlation of hand degrees of freedom in patterns of more frequent use (**postural synergies**)

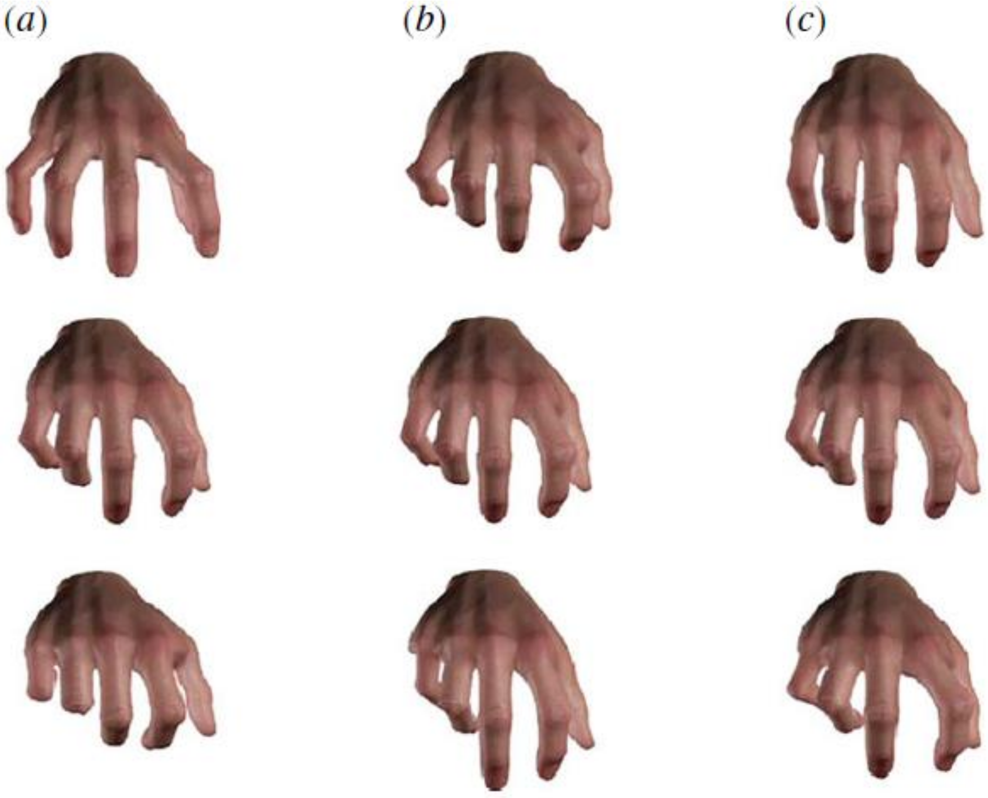
- No straightforward relation between **object shape and hand shape** (precision and power grasp on the same object)

- **No one-to-one relation** between **posture** and **force control** (different contact forces may be exerted with the hand in the same posture)

- How to extend applicability the synergy model to study force distribution in the actual grasp? → **soft synergy model (Bicchi et al. 2011)**

The First Three Synergies of the Hand

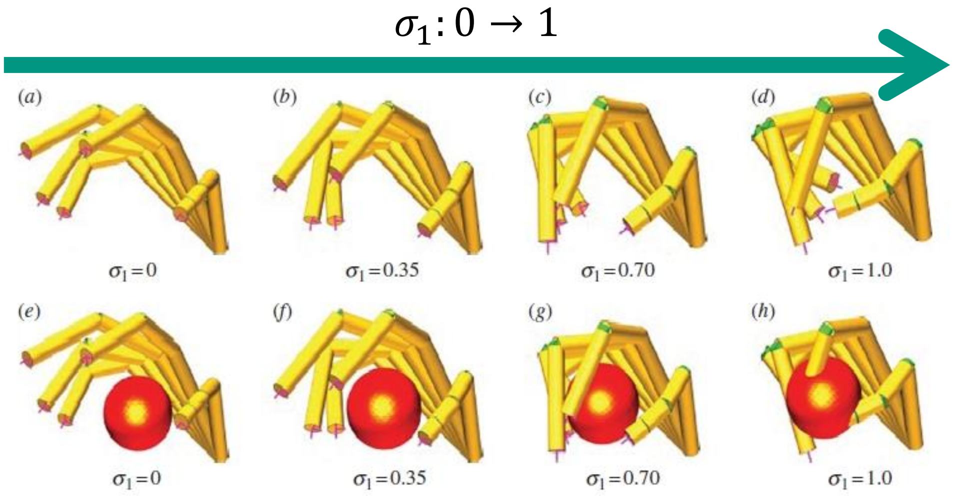
- The rows depict the first, second and third synergy of the human hand
- The PCs extracted from hand postures can be transferred to joint angle trajectories
- Hand closing motions can be designed by combining these trajectories of the different PCs



Bicchi, A., Gabiccini, M. and Santello, M. "Modelling natural and artificial hands with synergies" *Philosophical Transactions of the Royal Society B*, 366 (2011): 3153-3161

Problems with the Synergy Model

- Synergies can't be modeled as rigid manifolds.
- Example: Using the first synergy, when the hand closes around the object ($\sigma_1 : 0 \rightarrow 1$), it touches first with index and thumb at $\sigma_1 = 0.75$ and after that fingers penetrate the object
  - **Contact forces of the object not considered**
  - **Compliance in the hand is not considered**
- Consequently, a new model is necessary



Bicchi et al. 2011

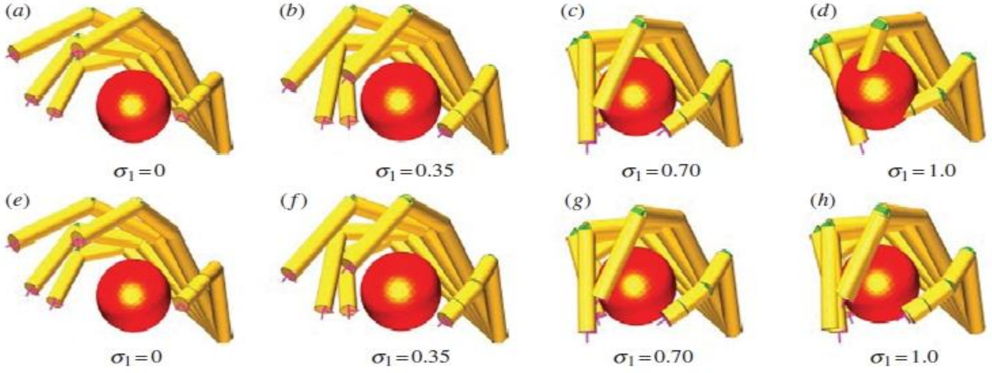
The Soft Synergy Model (I)

- Human hand (as an example):
  - Compliance in the human hand is introduced by the musculotendinous system.
  - **Redundancy** in the apparatus, together with its **nonlinear elastic characteristic** is used for changing the compliance of the agonist-antagonist pairs
- **Question:** How can a **model of elasticity** be introduced into the synergy model?
- **Answer:** Use a combination of **two force fields** to control the physical hand.
  - One force field is **attracting** the physical hand towards a virtual hand (which is shaped on the synergy manifold). The attraction forces are generated by the hand impedance.
  - The other force field is **repelling** the hand from penetrating the object at the contact points.

The Soft Synergy Model (II)

- The dynamical equilibrium between the two fields is found depending on the stiffness (more generally: mechanical impedance) of the hand actuation and control system.
  - Reference hand moves on the synergy manifold (a-d) and represent an attractor for the real hand.
  - Real hand is repelled by contact forces with the object (e-h).

$\sigma_1 : 0 \rightarrow 1$



Bicchi et al. 2011

Synergies in Force Distribution

- Questions:
  - Is the soft synergy model relevant to grasping?
  - Can the first few synergies suggested by Santello et al. (which were observed to generate a large part of pre-grasp postures) also explain the distribution patterns for grasp forces?

- Answer:
  - **Yes**. Application of the soft synergy model also allows making predictions on force distribution in manipulation (see experiment)

Experiment

- Associate each **postural synergy** through a numerical model of hand and object compliance to a **contact force pattern**.
- Combine the resulting force synergies linearly with weights in order to minimize a grasp cost index.
- The grasp index reflects the capability of the grasp to resist external forces while avoiding slippage of the object in the hand (force-closure) and also weighs factors such as required actuator torques.
- Examples:
  - Precision grasp of a cherry-like object
  - Power grasp of an ashtray

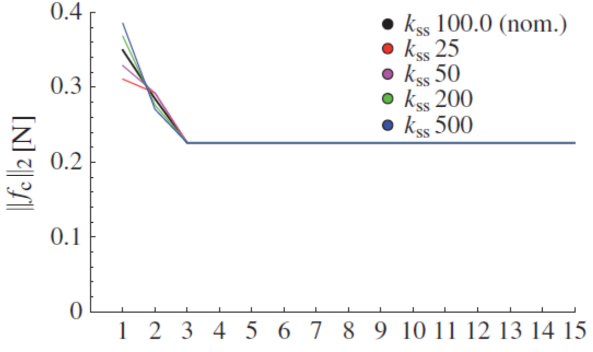
Application of the Soft Synergy Model to Grasping

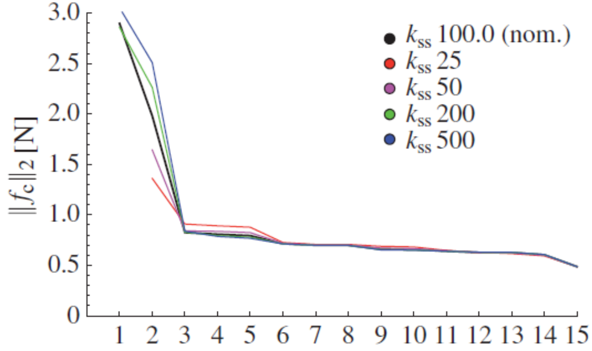
- In wireframe is the reference hand, moving according to the constraint manifold corresponding to the first three synergies.

Bicchi et al. 2011

Results

- The force-closure property of grasps strongly depends on which synergies are used to control the hand.
- Grasp cost index variations with increasing number of synergies involved, for different hand compliance values
- No improvement is observed beyond the first three synergies in the precision grasp case (top figure; cherry-like object), while continuous but small improvements are obtained in the whole-hand grasp case (bottom figure, ashtray).





Bicchi et al. 2011

Long-Term Goals of Research in Hand Synergies

- Long-term goal:
  - Define a set of synergies, ordered by increasing complexity
  - Define a correspondence between
    - a task (in terms of a number of different grasps, explorative actions and manipulations), and
    - the least number of synergies to make the task feasible.

- A hand for basic grasps only could use the first two or three synergies in the basis.

- A manipulative hand with fine motion control of single joints (such as a piano player's hand) may require coordination of many more synergies.

Eigengrasps

Eigengrasps – Introduction

- The **grasp planning problem** in robotics:
  - Find a hand pose and configuration (joint angle vector) relative to a known object such that the contact locations between hand and object prevent object motion relative to the hand, i.e. a stable grasp is achieved.
- This can be treated as an **optimization problem**:
  - Vary hand pose and configuration until distances between desired hand contact points and object surface are zero and a mechanical stability criterion is satisfied.
- However, the hand has:
  - 6 DoF pose
  - 21 DoF configuration/posture (in case of the human hand)
- Solving a **non-linear optimization problem in 27-dimensional space** may take very long.

Eigengrasps – Idea

Red: relevant for the exam

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- **Idea:**
  - Do not use the complete 21 DoF hand configuration for the optimization process.
  - Instead, **use only the first two hand synergies** obtained from human grasping observations.
  - Thus, the **27-dimensional** optimization problem is reduced to a **8-dimensional** optimization problem.
  - Theoretical justification: Most of the possible useful grasps should be found in the vicinity of a small set of points in configuration space.
- Ciocarlie et al. presented a grasp planning algorithm based on this idea and coined the term "**eigengrasps**“ for the principal components of the human grasp configuration data.

Ciocarlie, M., Goldfeder, C. and Allen, P. “Dimensionality reduction for hand-independent dexterous robotic grasping”, *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (2007): 3270-3275

H2T

Eigengrasps – Formalism (I)

- Let d be the total number of DoF of the hand and θ_i the i-th DoF, then a hand configuration $\boldsymbol{p}$ can be defined as

$$\boldsymbol{p} = [\theta_1, \theta_2, \dots, \theta_d] \in \mathbb{R}^d.$$

- Each eigengrasp e_i is a d-dimensional vector and can also be thought of as direction of motion in joint space:

$$\boldsymbol{e_i} = [e_{i,1}, e_{i,2}, \dots, e_{i,d}] \in \mathbb{R}^d$$

- The idea is now that the **eigengrasps $\boldsymbol{e_i}$ form a low-dimensional basis for grasp configurations**, and can be **linearly combined to closely approximate** most common grasping configurations.

Eigengrasps – Formalism (II)

- By choosing a basis comprising b eigengrasps, a hand configuration placed in the subspace defined by this basis can be expressed as a function of the **amplitudes $\boldsymbol{a_i}$** along each eigengrasp direction

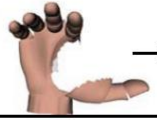
$$\boldsymbol{p} = \sum_{i=1}^{b} a_i \boldsymbol{e_i}$$

- A hand configuration is therefore completely defined by the amplitudes vector

$$\boldsymbol{a} = [a_1, \dots, a_b] \in \mathbb{R}^b.$$

Eigengrasps

- Similar to the human hand, eigengrasps for robotic hands can be defined by combining several DoF of the respective hand

Model	DOFs	Eigengrasp 1			Eigengrasp 2		
		Description	min	max	Description	min	max
Gripper	4	Prox. joints flexion			Dist. joints flexion		
Barrett	4	Spread angle opening			Finger flexion		
DLR	12	Prox. joints flexion Finger abduction			Dist. joints flexion Thumb flexion		
Robonaut	14	Thumb flexion MCP flexion Index abduction			Thumb flexion MCP extension PIP flexion		
Human	20	Thumb rotation Thumb flexion MCP flexion Index abduction			Thumb flexion MCP extension PIP flexion		

Ciocarlie et al. 2007

Eigengrasps – Optimization Problem

- In order to find stable grasps, one minimizes the energy function

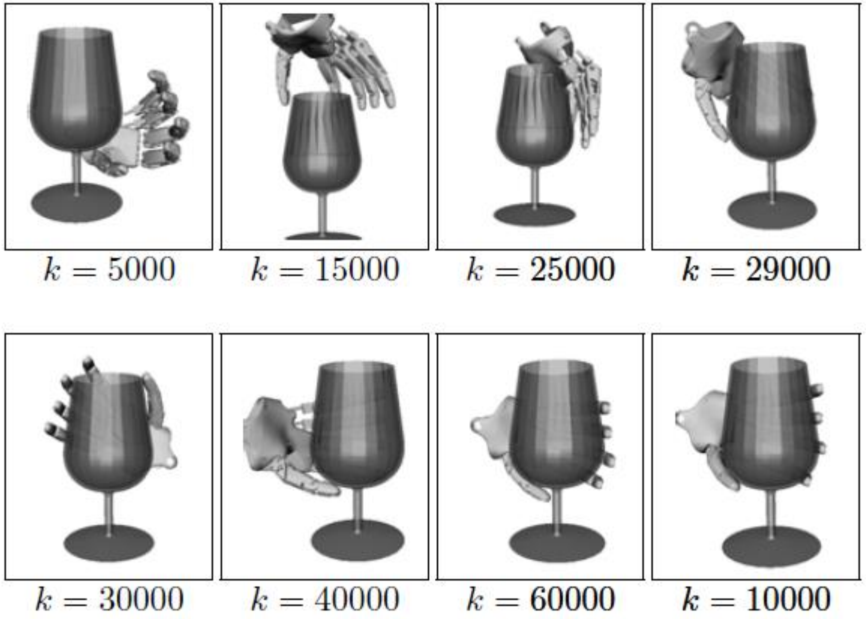
$$E = f(\boldsymbol{a}, \boldsymbol{w})$$

Ciocarlie et al. 2007

  - $\boldsymbol{a} \in \mathbb{R}^2$ is the vector of eigengrasp amplitudes
  - $\boldsymbol{w} \in \mathbb{R}^6$ is the vector describing the wrist pose
  - $f(.,.)$ is a function consisting of several components:
    - The sum of distances between the desired contact points on the hand and the object surface
    - The sum of angular differences between the orientation of the surface normals at the contact locations and the closest point on the object
    - A modified grasp quality measure based on the grasp wrench space
    - See (publicly available) source code of the *GraspIt!* simulator for further details: http://www.cs.columbia.edu/~cmatei/graspit/

Optimization Process

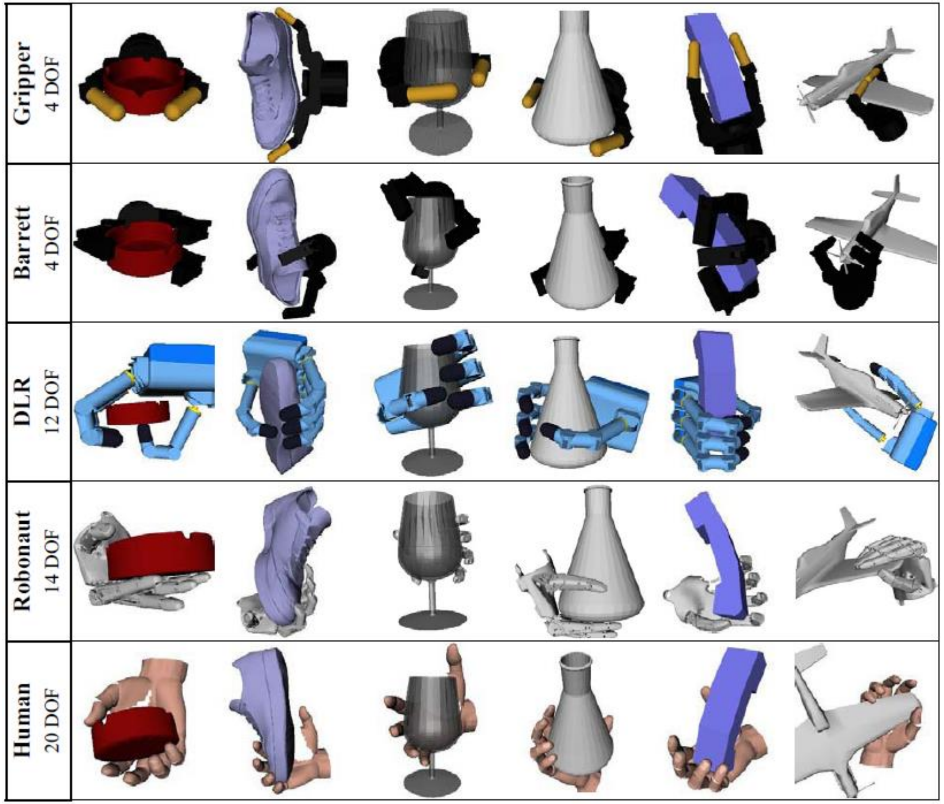
- Use simulated annealing as an optimization algorithm
- Example: Best state found after *k* iterations



Ciocarlie et al. 2007

Eigengrasps

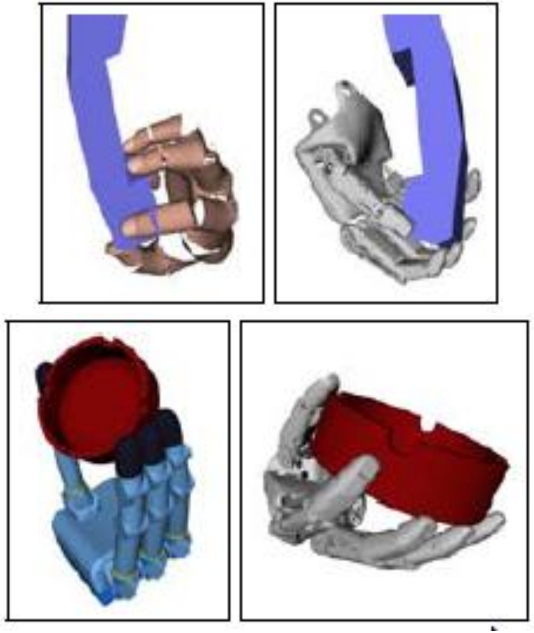
- Hand poses and configurations found by the optimization process for several hands and test objects



Ciocarlie et al. 2007

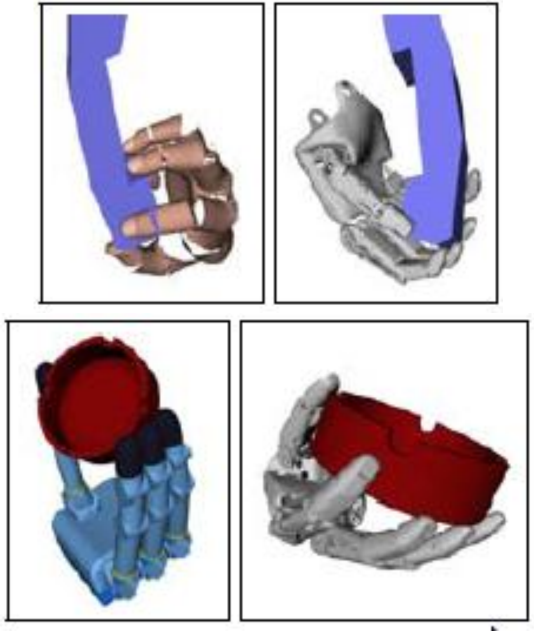
Eigengrasp Planning – Some Further Thoughts (I)

- Optimization in the eigengrasp space with only two principal components does not necessarily lead to hand configurations where all (most) finger segments are in contact with the object‘s surface.
- This is in line with the finding that the **higher synergies** are not simply noise but do in fact **represent details of the object‘s shape**.
- **Solution:** After a fixed number of iterations (or a certain period of time), stop the optimization process and close the finger joints until contact to the object prevents further motion.



Eigengrasp Planning – Some Further Thoughts (II)

- The algorithm **does not work well with non-convex objects**.
- The algorithm can be modified towards finding precision grasps by considering only desired contact points at the fingertips (see picture).



Ciocarlie et al. 2007

Implementation of Synergies in Robotics

Literature

Red: relevant for the exam

- Brown C. Y. and Asada, H. "Inter-Finger Coordination and Postural Synergies in Robot Hands via Mechanical Implementation of Principal Components Analysis", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (2007): 2877 - 2882

Building Robot Hands Based on Postural Synergies

- Do we really need (want) to independently control 21 DoF in a robotic hand?
  - Example: Shadow hand, …
- Engineer's perspective:

  The more motors in the hand...

  ... the more expensive the hand

  ... the heavier the hand (load on the robot arm!)

  ... the harder to control
- A different approach:
  - Use only as many motors as necessary.
  - Use a **mechanical implementation of postural synergies**
- This is part of a whole area of research: **underactuated hands**

© Shadow Robot Company (2020)

Mechanical Implementation of Hand Synergies

- Each desired posture (configuration) of the robot hand is represented by a posture vector:

$$\boldsymbol{P_i} = \left[z_1 \ldots z_j \ \ldots z_n\right]^T$$

- The elements z_j of the posture vector are the **linear tendon displacements** required to create the posture.
- Given N posture vectors, we define the posture matrix:

$$\boldsymbol{P} = \begin{bmatrix} \boldsymbol{P_1^T} \\ \vdots \\ \boldsymbol{P_i^T} \\ \vdots \\ \boldsymbol{P_N^T} \end{bmatrix}$$

Mechanical Implementation of Hand Synergies (I)

- Principal Components Analysis (PCA) lets us rewrite the posture matrix as the product of two smaller matrices:
  - one matrix consisting of the **principal component vectors** and
  - one matrix consisting of the **weights for those vectors**.
- Similar to singular value decomposition (see Brown and Asada 2007)
  - First, calculate the covariance matrix of $\boldsymbol{P}$.
  - Next, find the **eigenvectors** of the covariance matrix.
  - These are the principal components of $\boldsymbol{P}$. Their associated eigenvalues, ranked from largest to smallest, represent the relative importance of each component (i.e. the variance in the data explained by the respective component).
  - Since these principal components can be used to reconstruct the entire posture matrix, we call them **eigenpostures**.

Mechanical Implementation of Hand Synergies (II)

- If we choose to use only a few of the eigenpostures, then we can still approximate the posture matrix with reasonable accuracy.
- Here, we use only **two principal components**, so:

$$\boldsymbol{P} \approx \widehat{\boldsymbol{P}} = \begin{bmatrix} q_{1,1} & q_{1,2} \\ & \vdots & \\ q_{i,1} & q_{i,2} \\ & \vdots & \\ q_{N,1} & q_{N,2} \end{bmatrix} \begin{bmatrix} \boldsymbol{e}_1^T \\ \boldsymbol{e}_2^T \end{bmatrix} + \begin{bmatrix} \bar{z}_1 & \cdots & \bar{z}_n \\ \bar{z}_1 & \cdots & \bar{z}_n \\ & \vdots & \\ & \vdots & \\ \bar{z}_1 & \cdots & \bar{z}_n \end{bmatrix}$$

- The values $q_{i,k}$ are scalar weights.
- The vectors $\boldsymbol{e_k}$ are the eigenpostures.
- The additional term on the right is a **zero-offset** common to all postures (the average posture in the set)

Mechanical Implementation of Hand Synergies (III)

- Now we can rewrite each posture vector as:

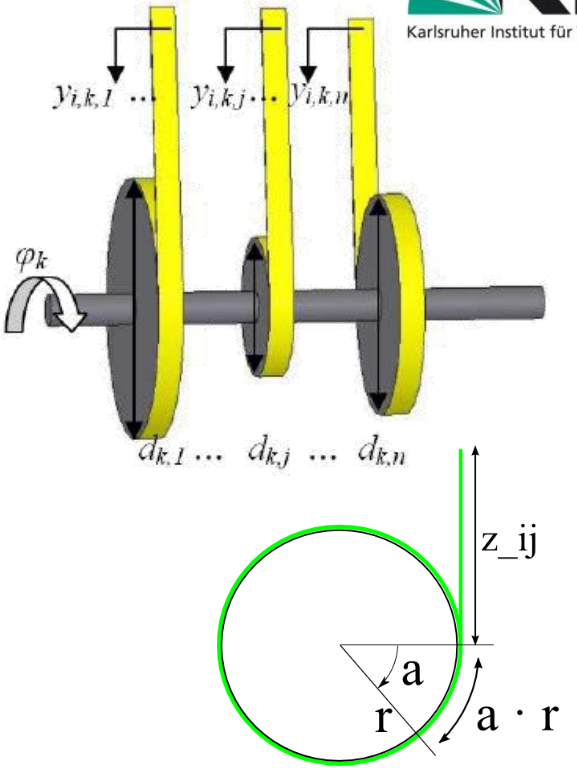
$$\boldsymbol{P_i} \approx q_{i,1}\boldsymbol{e_1} + q_{i,2}\boldsymbol{e_2} + \bar{\boldsymbol{z}}, \qquad \text{where} \qquad \bar{\boldsymbol{z}} = [\bar{z}_1 \dots \bar{z}_j \dots \bar{z}_n]$$

- **Goal: Find a way to realize this equation through mechanical means!**

- Problems to be solved in this context:
  - How to actuate a vector multiple $q_{i,k}e_k$?
  - How to mechanically add two vector quantities?
  - How to account for the zero offset $\bar{z}$?

How to Actuate a Vector Multiple?

- We can use the individual elements of $\boldsymbol{e_k} = [d_{k,1} \ldots d_{k,j} \ \ldots d_{k,n}]$ as the diameters of pulleys fixed on a shaft (see figure)
- $q_{i,k}$ is represented in the angle of rotation of the shaft, $\phi_{i,k} = 2q_{i,k}$.
- The tendon displacements $y_{i,k,j}$ equal the elements of $q_{i,k}\boldsymbol{e_k}$.
- If any of the values $d_{k,j}$ are negative, we can account for this by wrapping tendons in opposite directions.



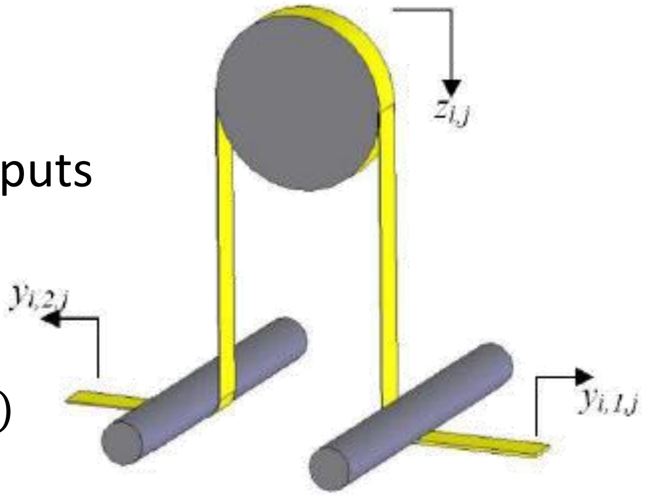
Brown and Asada 2007

How to Mechanically Add Two Vector Quantities?

- Add two scalar values by the mechanism in the figure.
- The pulley in the figure is free to translate in the vertical direction.
- This configuration also winds up scaling the output, so that: $z_{i,j} = \frac{1}{2}(\mathrm{y}_{\mathrm{i,1,j}} + \mathrm{y}_{\mathrm{i,2,j}})$
- Attach one of these mechanisms to each of the outputs $\mathrm{y}_{\mathrm{i,k,j}}$ from the mechanism on the previous slide.
- Then the vector output becomes:

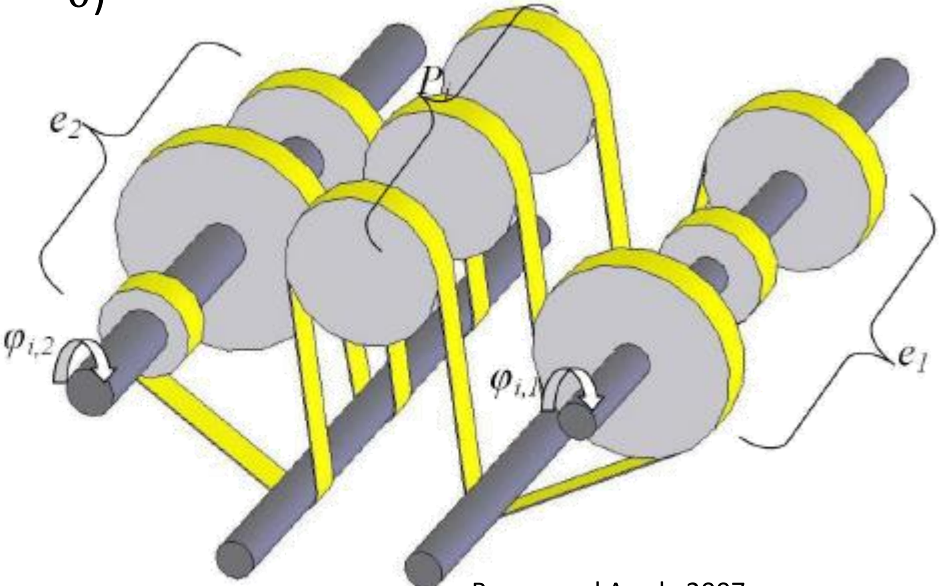
$$[z_{i,1} \dots z_{i,n}] = \frac{1}{2}([\mathrm{y}_{\mathrm{i,1,1}} \dots \mathrm{y}_{\mathrm{i,1,n}}] + [\mathrm{y}_{\mathrm{i,2,1}} \dots \mathrm{y}_{\mathrm{i,2},n}])$$

$$[z_{i,1} \dots z_{i,n}] = \frac{1}{2}(q_{i,1}\boldsymbol{e_1} + q_{i,2}\boldsymbol{e_2})$$



Putting Everything Together

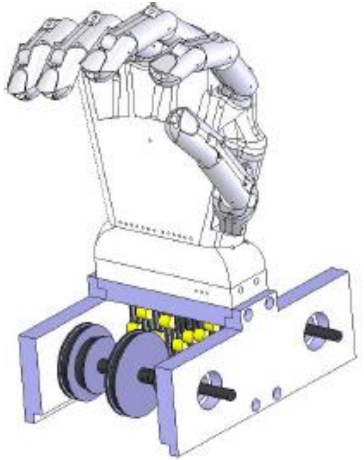
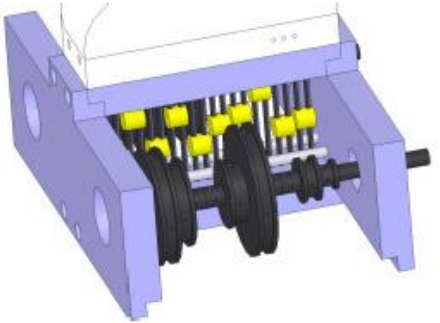
- How to account for the zero offset value $\bar{z}$?
  - Simply adjust the tendon lengths so that $[z_{i,1} \dots z_{i,n}] = \bar{z}$ when the shafts are in their zero position ($\Phi_1 = \Phi_2 = 0$)
- The complete mechanism:



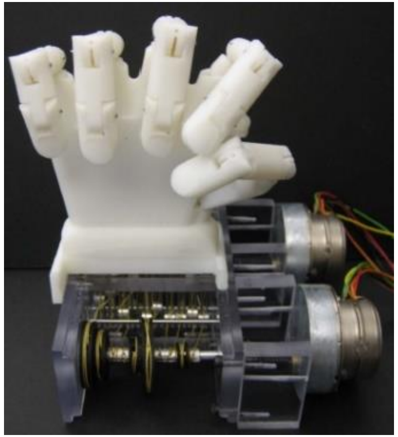
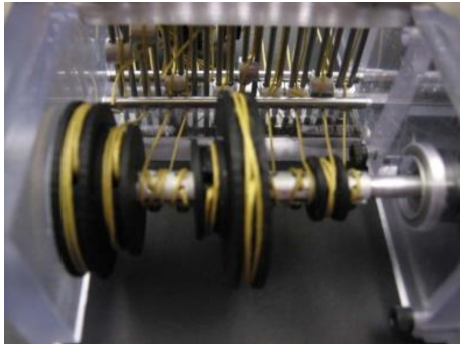
Brown and Asada 2007

The Resulting 17 DoF 5-Fingered Robotic Hand

- The eigenposture mechanism

- Sliding pulley details and tendon routing

Brown and Asada 2007

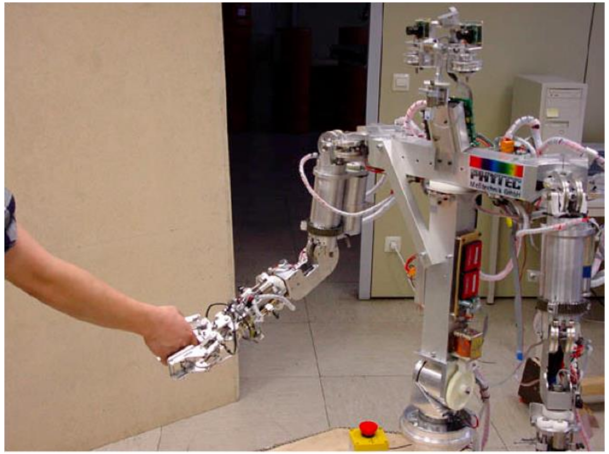
The TUAT/Karlsruhe Humanoid Underactuated Hand

Underactuation

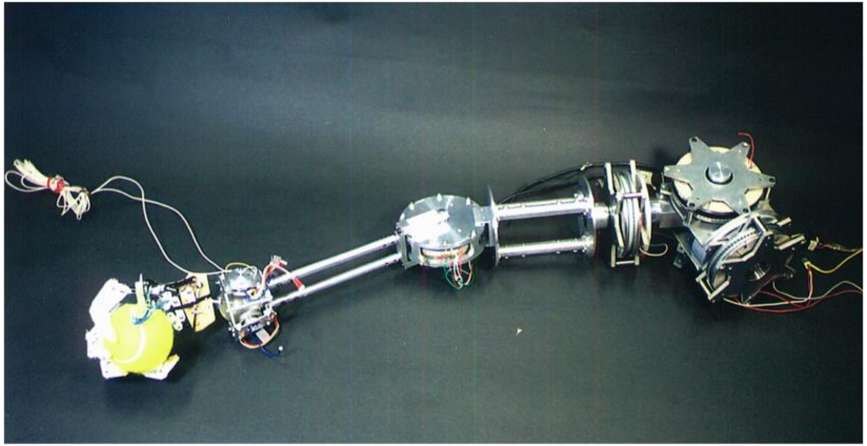
- Underactuation expresses the property of a system to have an input vector of smaller dimension than the output vector

- In robotics, it means having fewer actuators than degrees of freedom (DoF)
  - Simple control
  - Adapt to the shape of the object
  - Mechanical intelligence

The TUAT/Karlsruhe Humanoid Underactuated Hand



Humanoid Robot ARMAR
Univ. of Karlsruhe, Germany



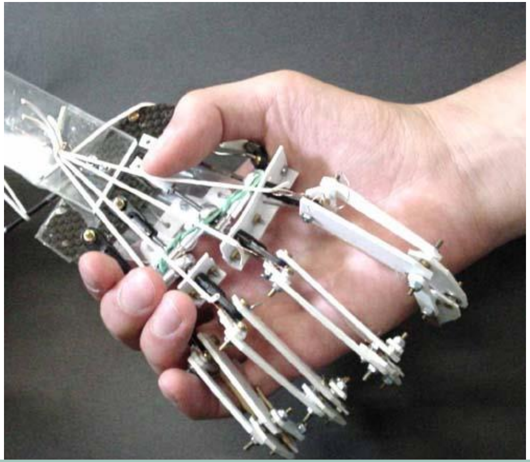
Artificial arm by using spherical ultrasonic motor
Tokyo Univ. of Agriculture and Technology
(東京農工大学／TUAT)

Joint work: Naoki Fukaya and Tamim Asfour

Fukaya, N., Toyama, S., Asfour, T. and Dillmann, R. (2000) "Design of the TUAT/Karlsruhe Humanoid Hand", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*

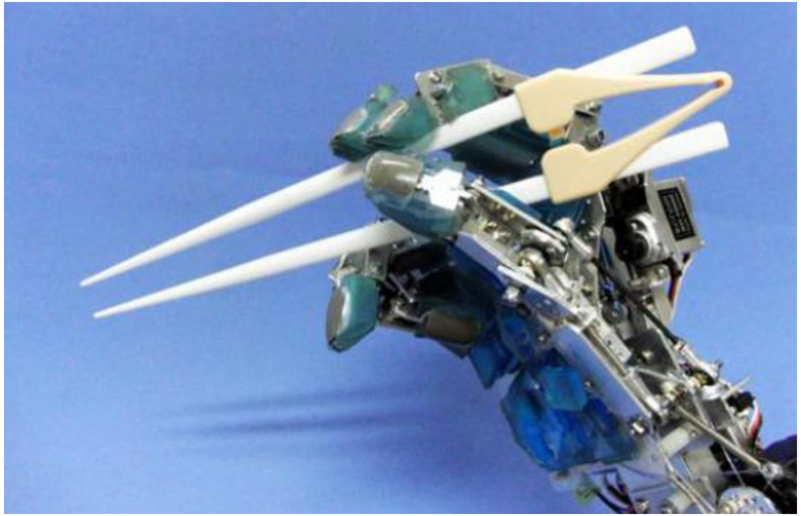
The TUAT/Karlsruhe Humanoid Hand (I)

Red: relevant for the exam



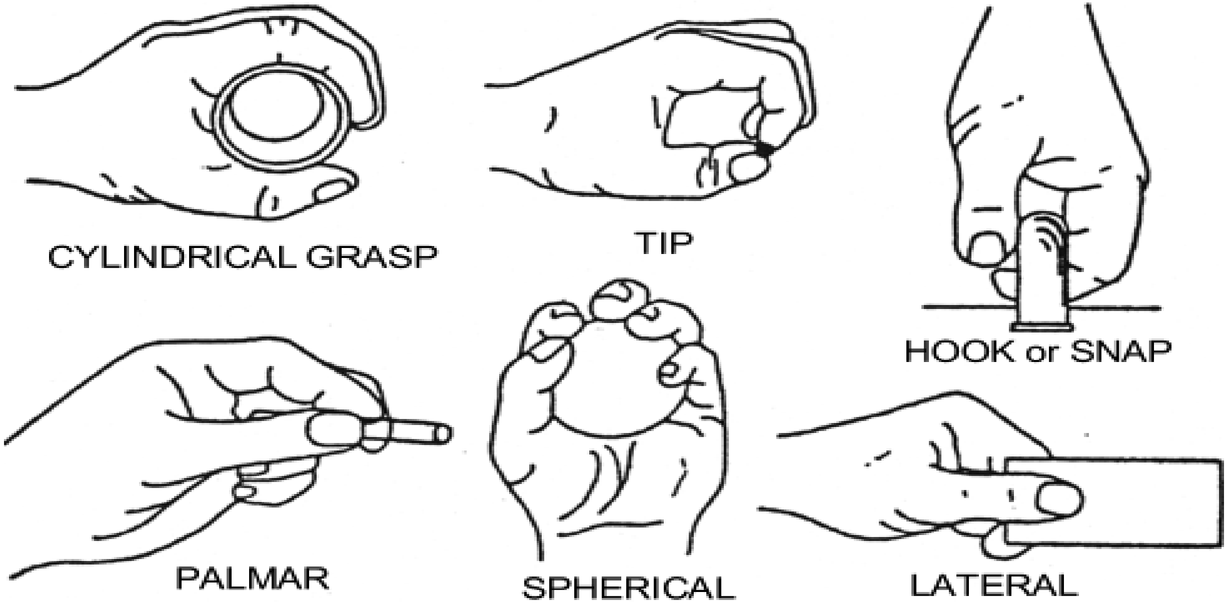
The core idea is the "Mechanism"

1. Light weight, similar size, similar motion
2. Only one actuator
3. No need for sensors, simple operation
4. Self-make a best gripping shape
5. Self adjustment of fingertip force
6. No need for feedback control



Fukaya, N., Asfour, T., Dillmann, R. and Toyama, S. "Development of a Five-Finger Dexterous Hand With Feedback Control: The TUAT/Karlsruhe Humanoid Hand", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (2013): 4533-4540

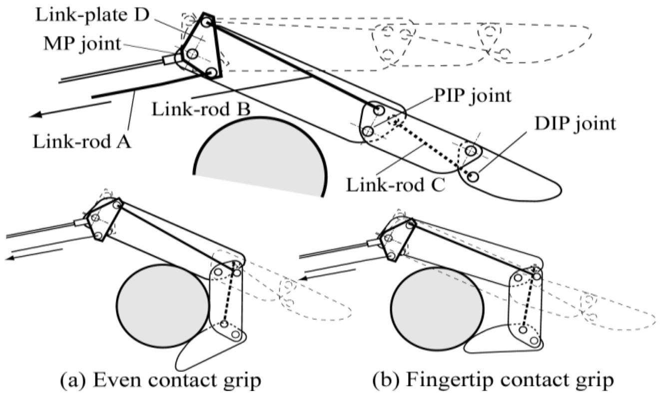
The TUAT/Karlsruhe Humanoid Hand (II)



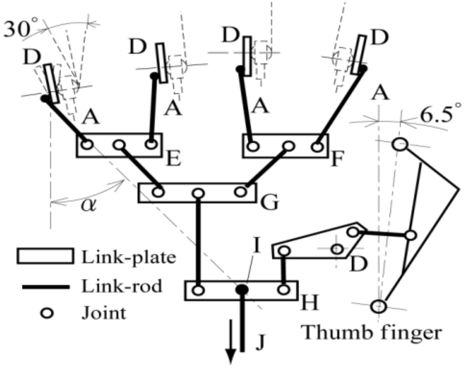
Keller et al. 1947

The TUAT/Karlsruhe Humanoid Hand (III)

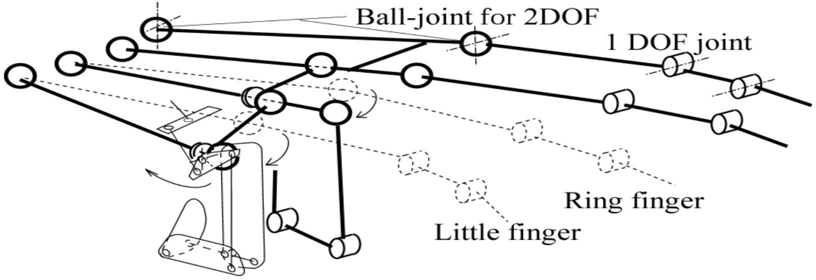
Finger link mechanism for finger



TUAT/Karlsruhe hand mechanism



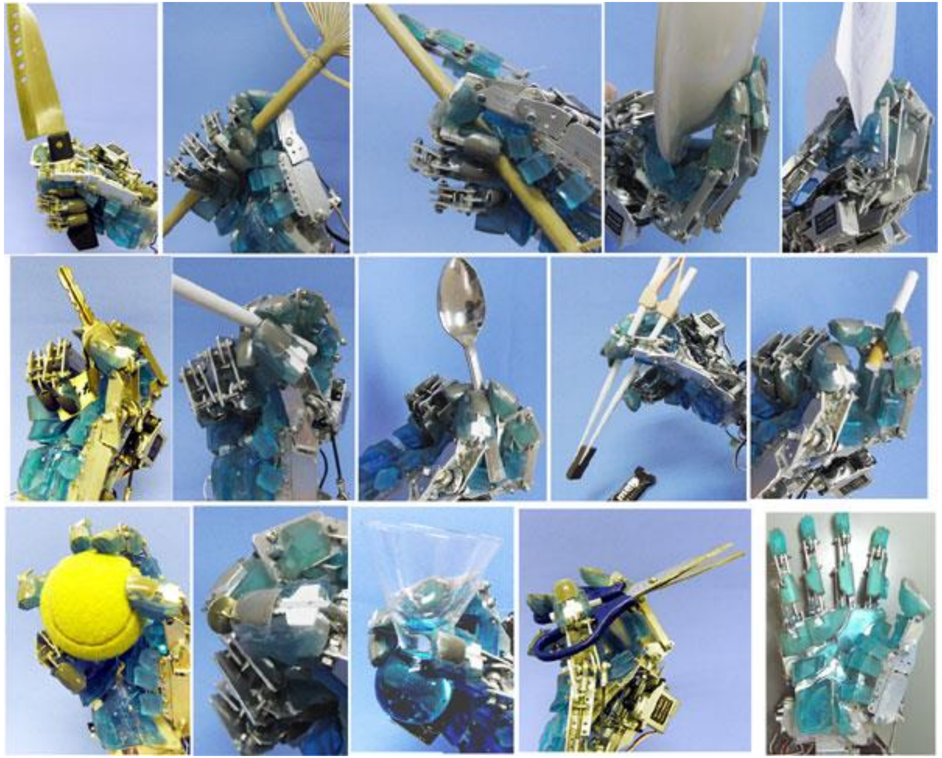
Palm moving mechanism



Fukaya et al. 2000

Latest Version (2013)

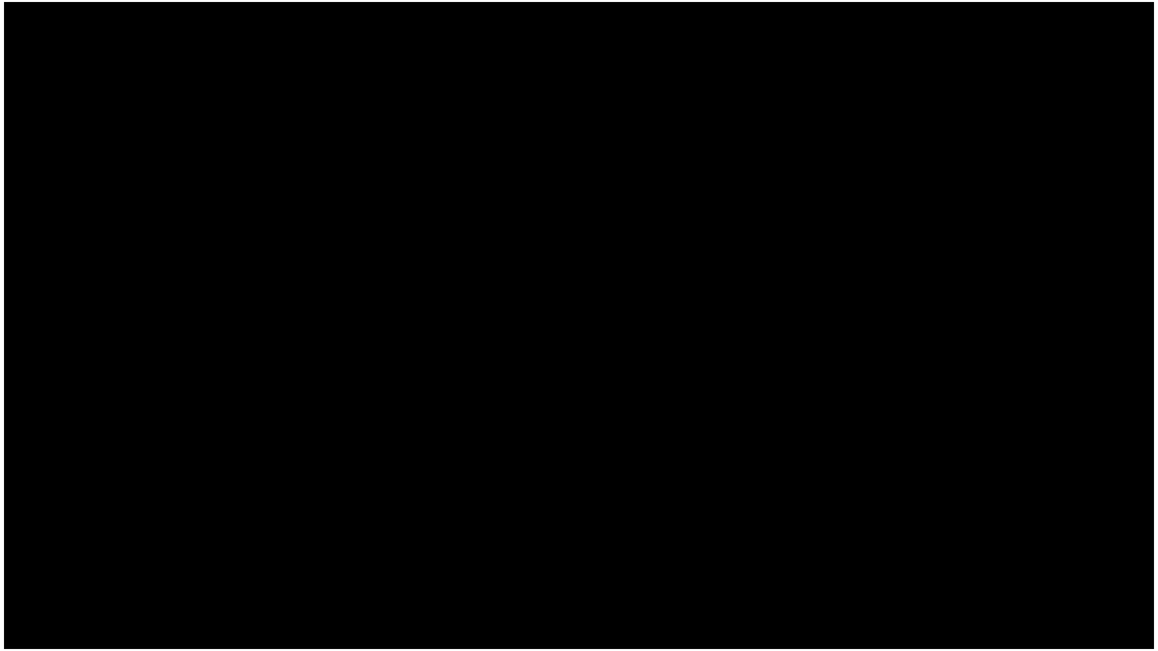
- This hand realizes Cutkosky's taxonomy and 14 kinds of operations of daily life
- It operates by one large servo motor and 6 small auxiliary servo motors.
- Needs no feedback control, touch sensor and complex control system



Fukaya et al. 2013

The TUAT/Karlsruhe Humanoid Hand (IV)

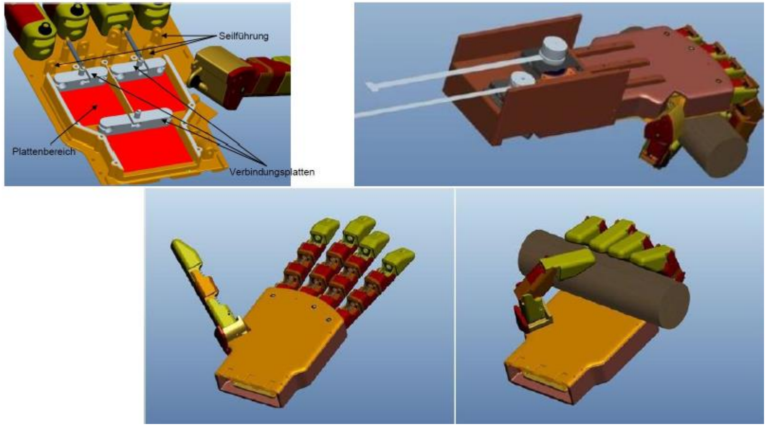
- Further development by **Naoki Fukaya**

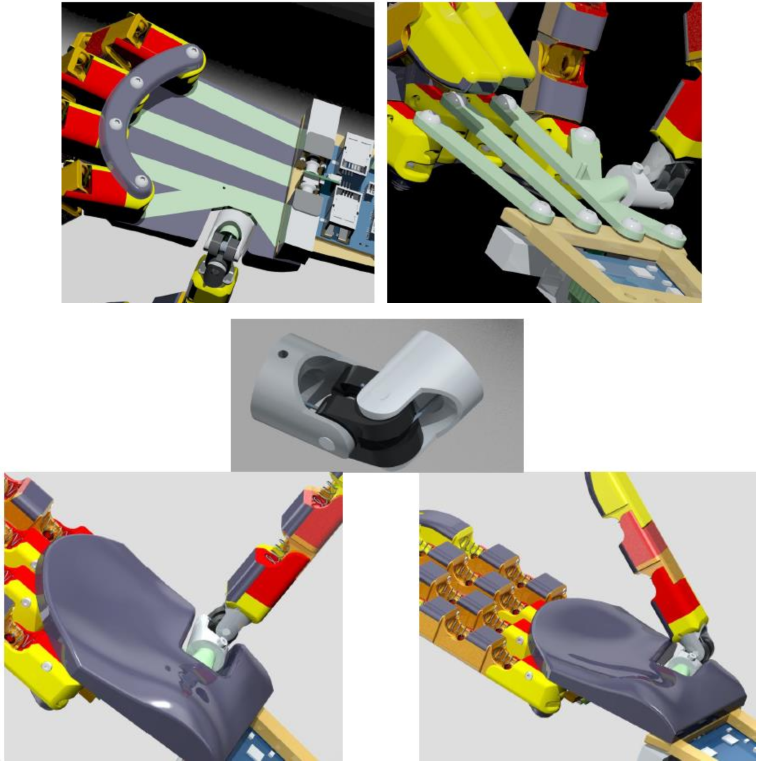


Fukaya et al. 2013

The TUAT/Karlsruhe Humanoid Hand

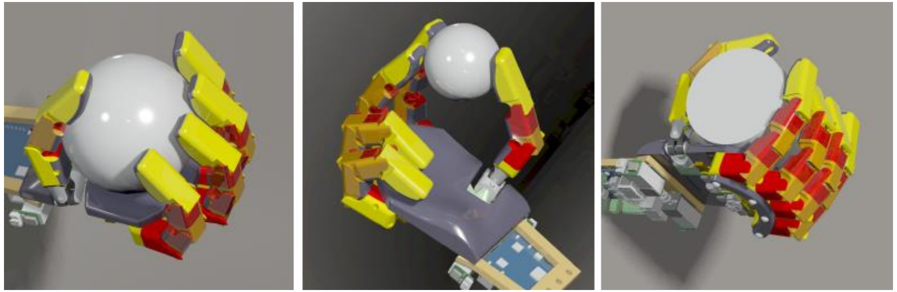
Further development at KIT for 3D printing

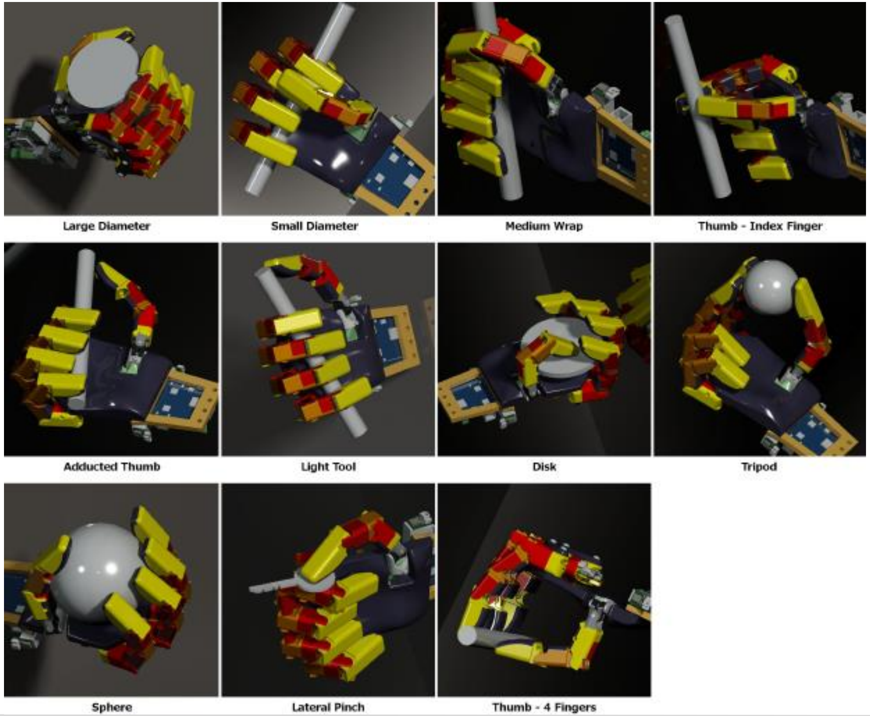




The TUAT/Karlsruhe Humanoid Hand

Further development at KIT for 3D printing

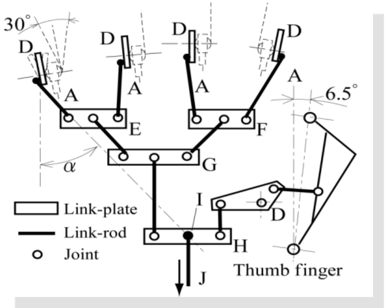




The KIT Prosthetic Hand

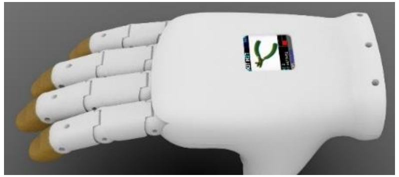
Red: relevant for the exam

- Personalized prosthetic hands with semi-autonomous grasping abilities

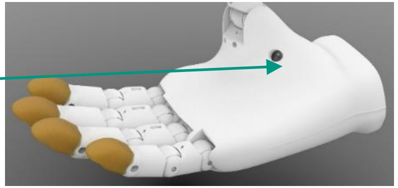


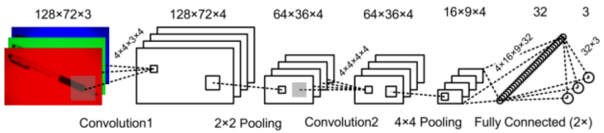
Fukaya et al. 2000

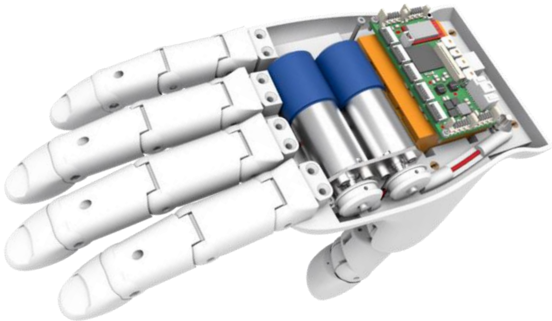
TUAT-Karlsruhe hand mechanism



Camera

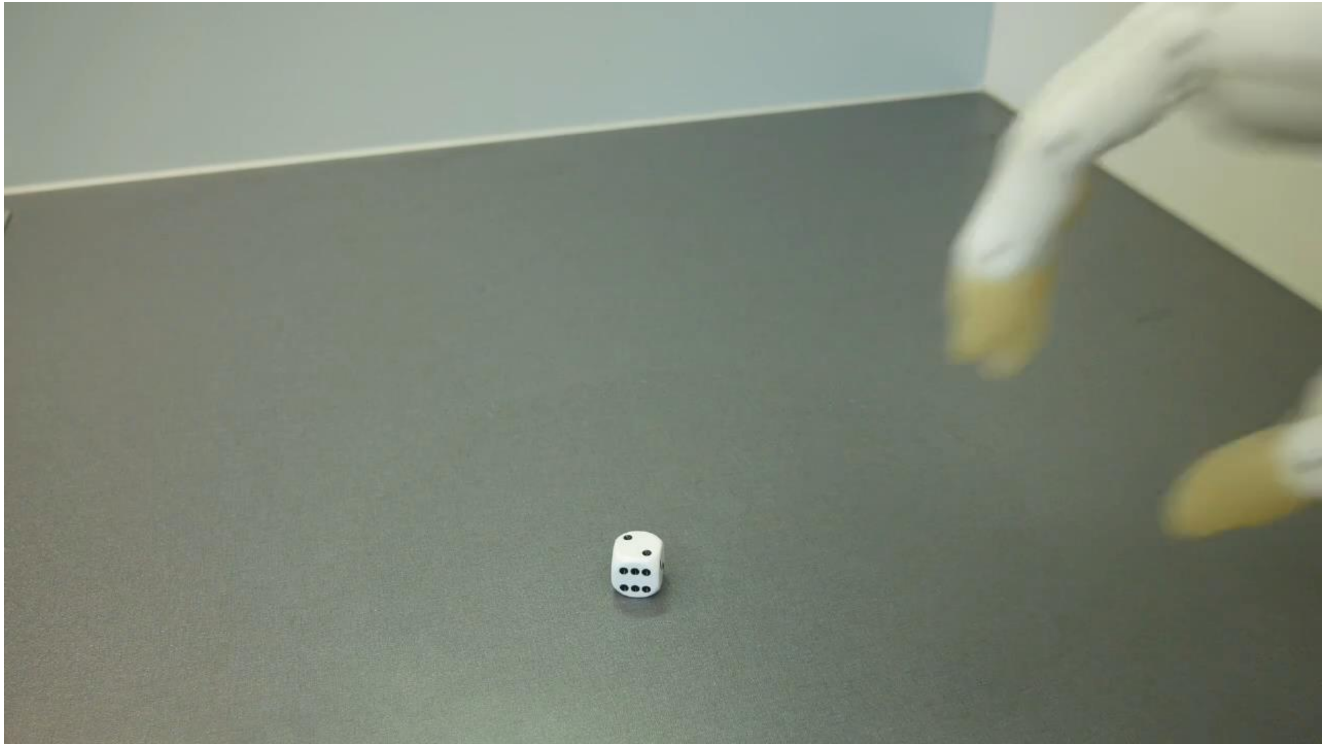






Weiner, P., Starke, J., Hundhausen, F., Beil, J. and Asfour, T., "The KIT Prosthetic Hand: Design and Control", *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, (2018):3328-3334

Intelligent Grasping



KIT Male and Female Prosthetic Hands (I)

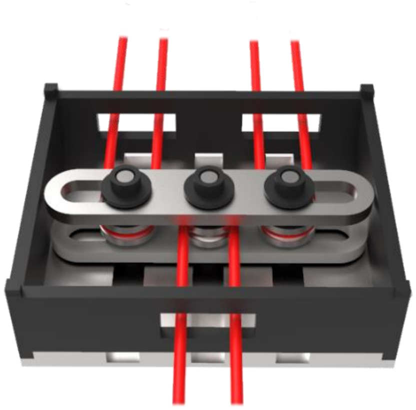
- Prostheses sized according to the 50th percentile male/female hand
- Scalable in all dimensions according to the able hand
- Parts are 3D-printed using selective laser sintering in durable plastic
- 10 degrees of freedom:
  - One motor for thumb flexion
  - One motor for flexion of all fingers

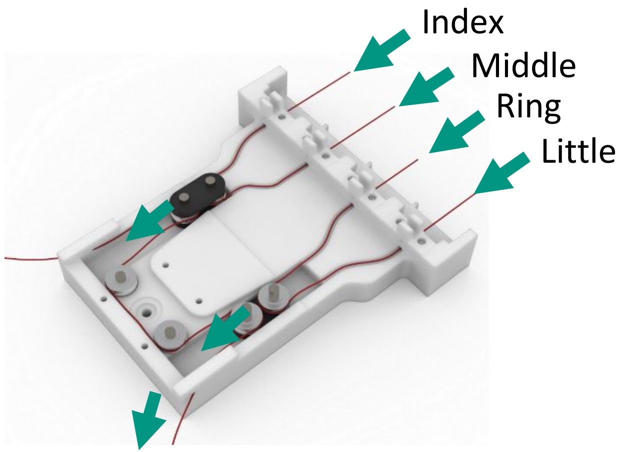
KIT Male and Female Prosthetic Hands (II)

	Male	Female
Palm length	111 mm	100 mm
Palm width	87 mm	77 mm
Palm depth	30 mm	28 mm
Thumb	75 mm	62 mm
Index	85 mm	77 mm
Middle	94 mm	88 mm
Ring	90 mm	83 mm
Little	74 mm	67 mm

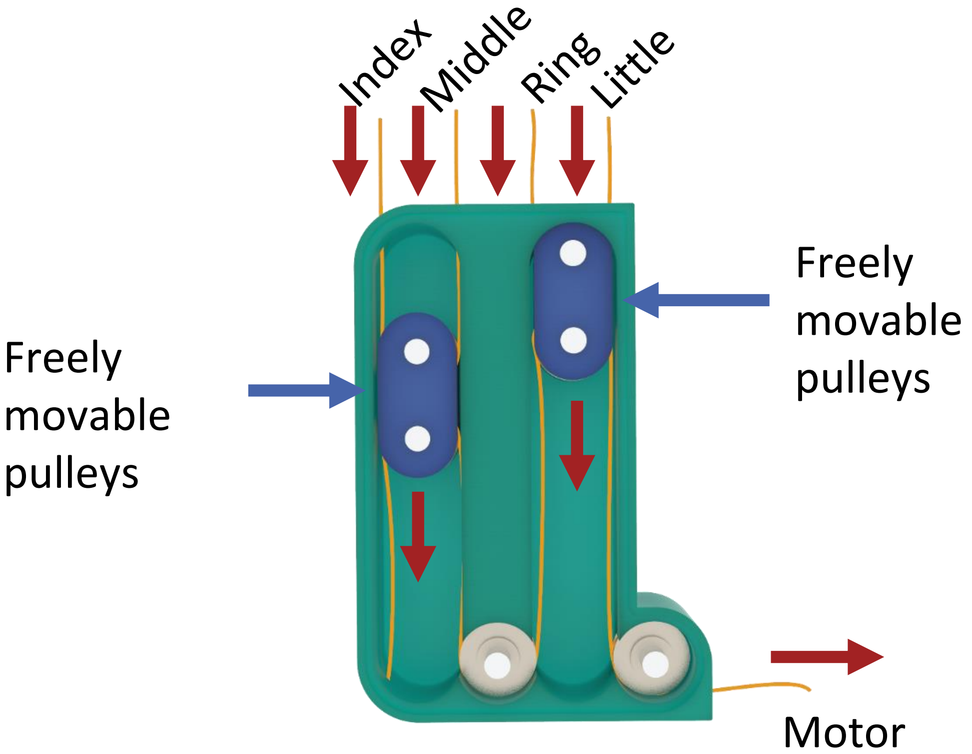
Underactuated Mechanism (I)

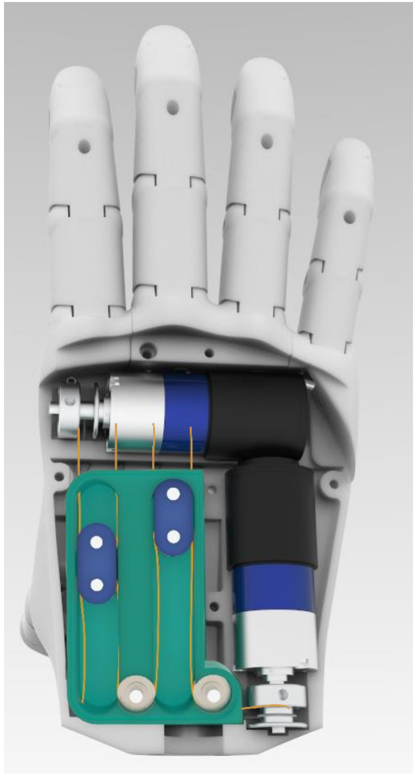
- All four long fingers are actuated by one motor
- Finger joints are driven by tendons
- Motor force is distributed among the fingers by an underactuated mechanism
  - Whipple tree with pulley block (male version)
  - Double pulley block (female version)





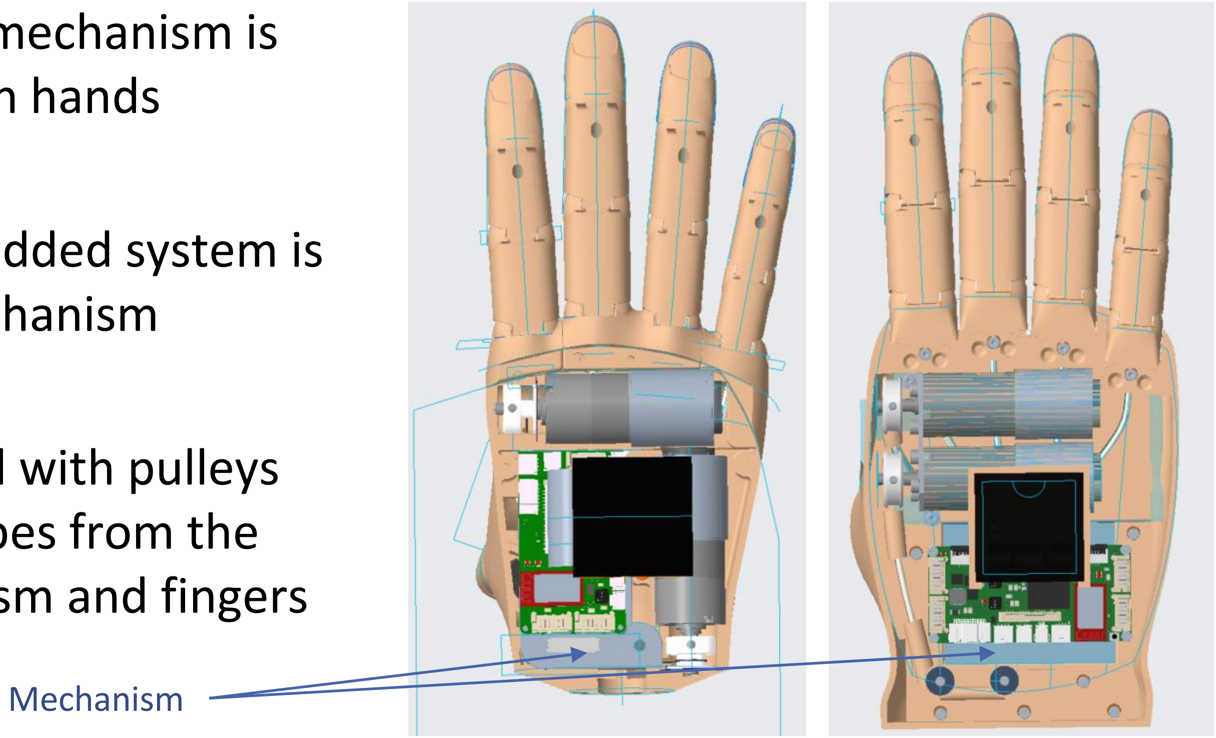
Underactuated Mechanism (III)





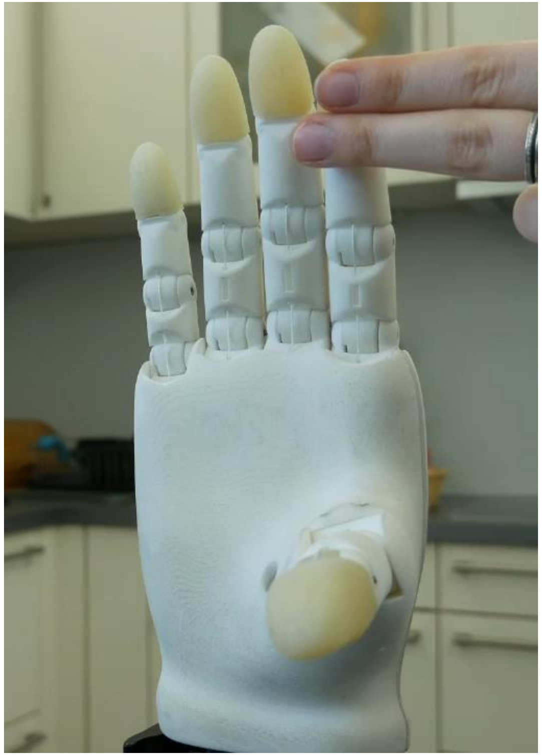
Underactuated Mechanism (IV)

- An underactuated mechanism is integrated into both hands
- A PCB for the embedded system is stacked on the mechanism
- Tendons are routed with pulleys and low-friction tubes from the motors to mechanism and fingers



Underactuated Mechanism (V)

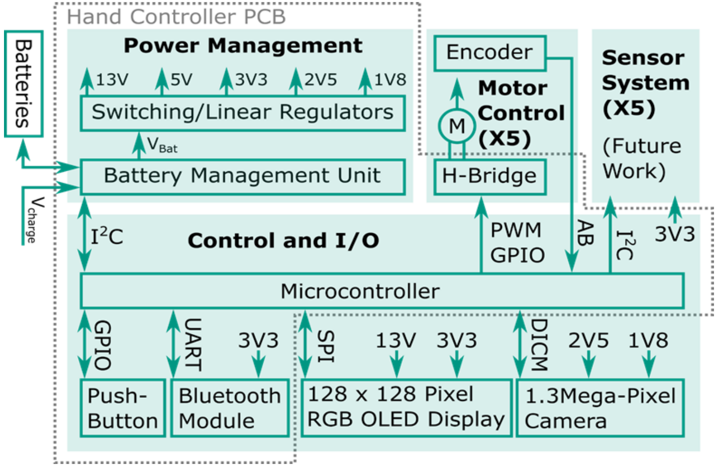
- The mechanism allows for adaptive underactuation
- Individual joints and fingers can move, while others are blocked
- Fingers wrap around arbitrarily shaped objects



Weiner et al. 2018

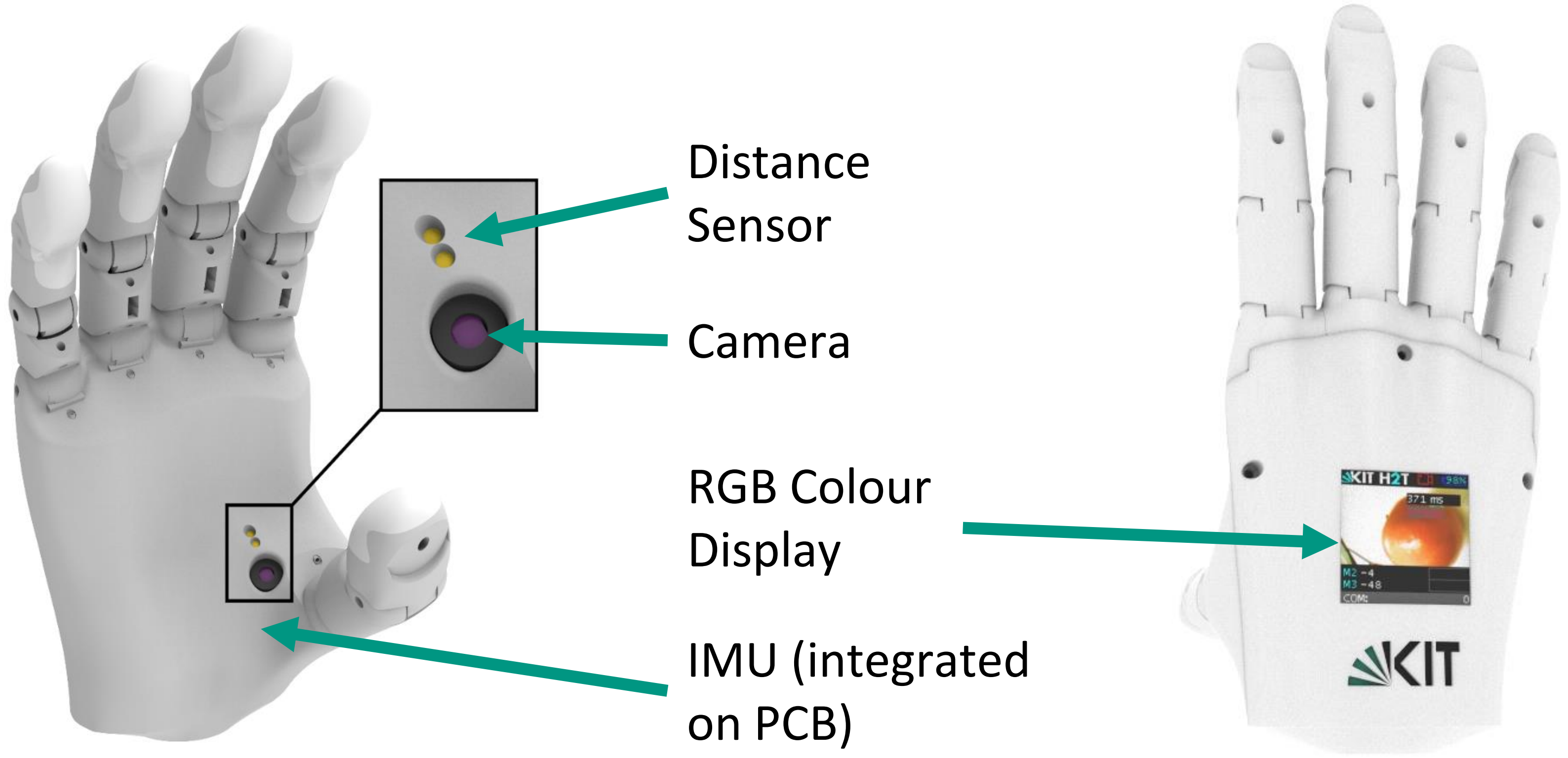
Embedded System

- Microcontroller system (ARM, 400MHz) is embedded into the hand
  - Integrates an **IMU** (female version) and interfaces for **camera** and **display**
  - **Processing** of sensor values
  - **Embedded vision** and deep convolutional neural networks
  - **Control** of all functions and motors
  - Wireless communication with **Bluetooth LE**
  - Enables **multichannel feedback**
  - **30 x 50 mm** in size (female version)
- User does not need any external device for intelligent functions



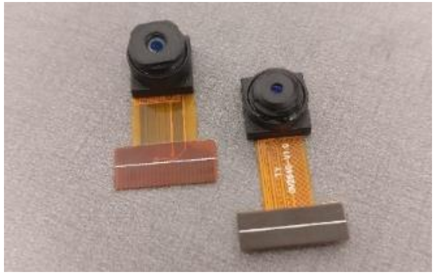
Weiner et al. 2018

Multimodal Sensor System and Display



Multimodal Sensor System

- An **IMU** is integrated into the hand
  - Allows to estimate the prosthesis' pose
  - Can be used as a user input device: recognition of simple gestures

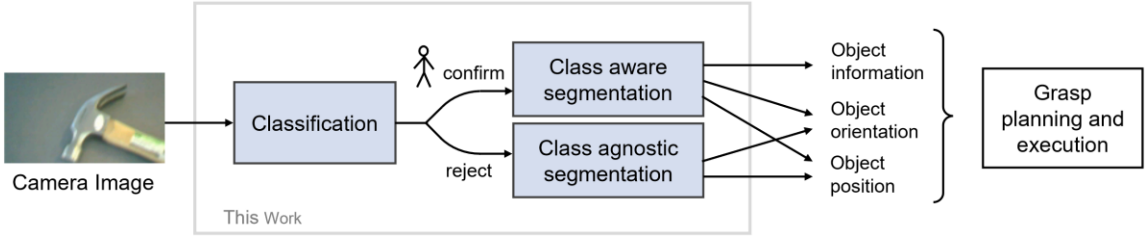


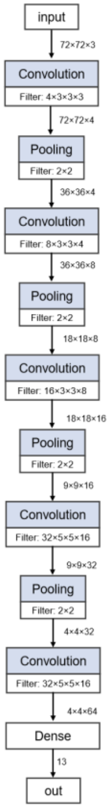
- A **distance sensor** is mounted next to the camera
  - Time of flight distance sensing → no influence of ambient light/object reflectance
  - Allows to estimate the distance to the image plane

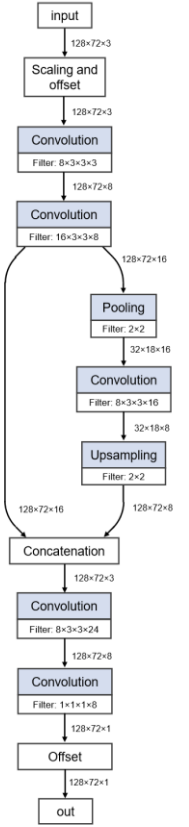
- The **RGB camera** is installed in the palm of the prosthesis
  - It is directly connected to the embedded system

Semi-Autonomous Grasping with Deep CNNs

- Training of a DCNN with images taken by the camera
- Object recognition (daily objects) with a DCNN implemented on the embedded system
- Finger pre-shaping and grasp force can be autonomously selected based on the recognized object

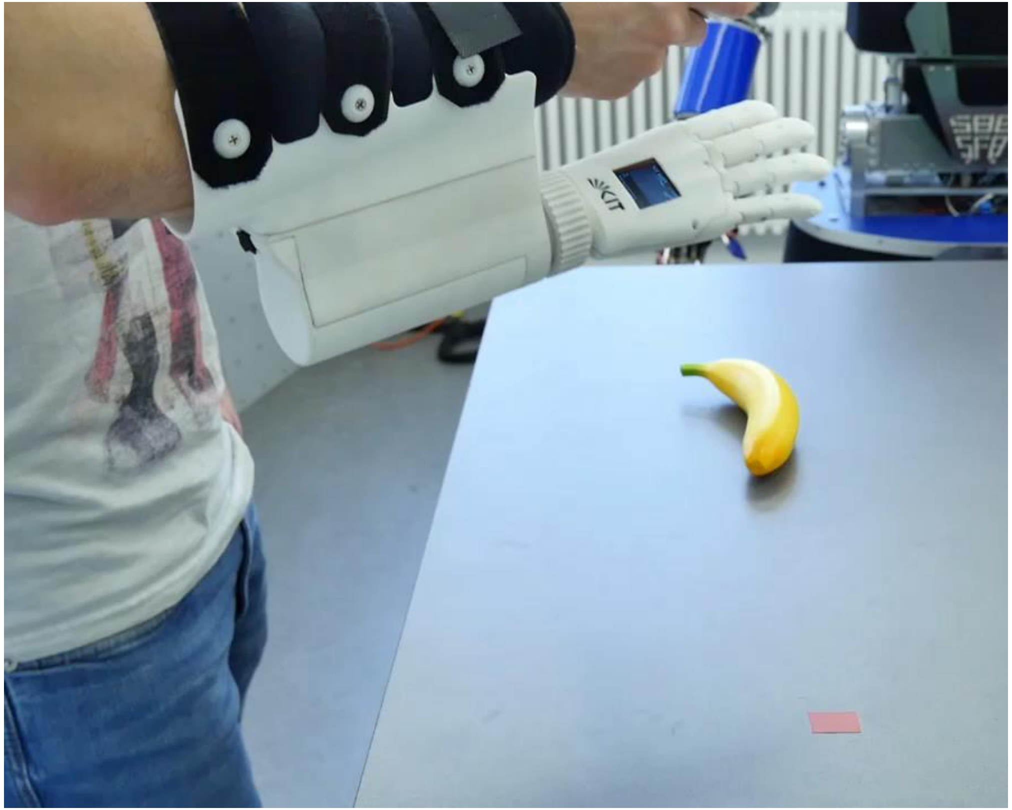






Hundhausen, F., Megerle, D. and Asfour, T., "Ressource-Aware Object Classification and Segmentation for Semi-Autonomous Grasping with Prosthetic Hands", *IEEE/RAS International Conference on Humanoid Robots (Humanoids),* (2019): 215-221

Semi-Autonomous Grasp Control



The TUAT/Karlsruhe Hand and the KIT Hands

Publications

Red: relevant for the exam

- Fukaya, N., Asfour, T., Dillmann, R. and Toyama, S., “Development of a Five-Finger Dexterous Hand without Feedback control: the TUAT/Karlsruhe Humanoid Hand”, *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2013): 4533-4540
- Fukaya, N., Asfour, T., Dillmann, R. and Toyama, S., “Design of the TUAT/Karlsruhe Humanoid Hand” *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2000): 1754-1759
- Weiner, P., Starke, J., Hundhausen, F., Beil, J. and Asfour, T., ”The KIT Prosthetic Hand: Design and Control” *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (2018): 3328-3334
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Chapter 3 – Outline Grasping

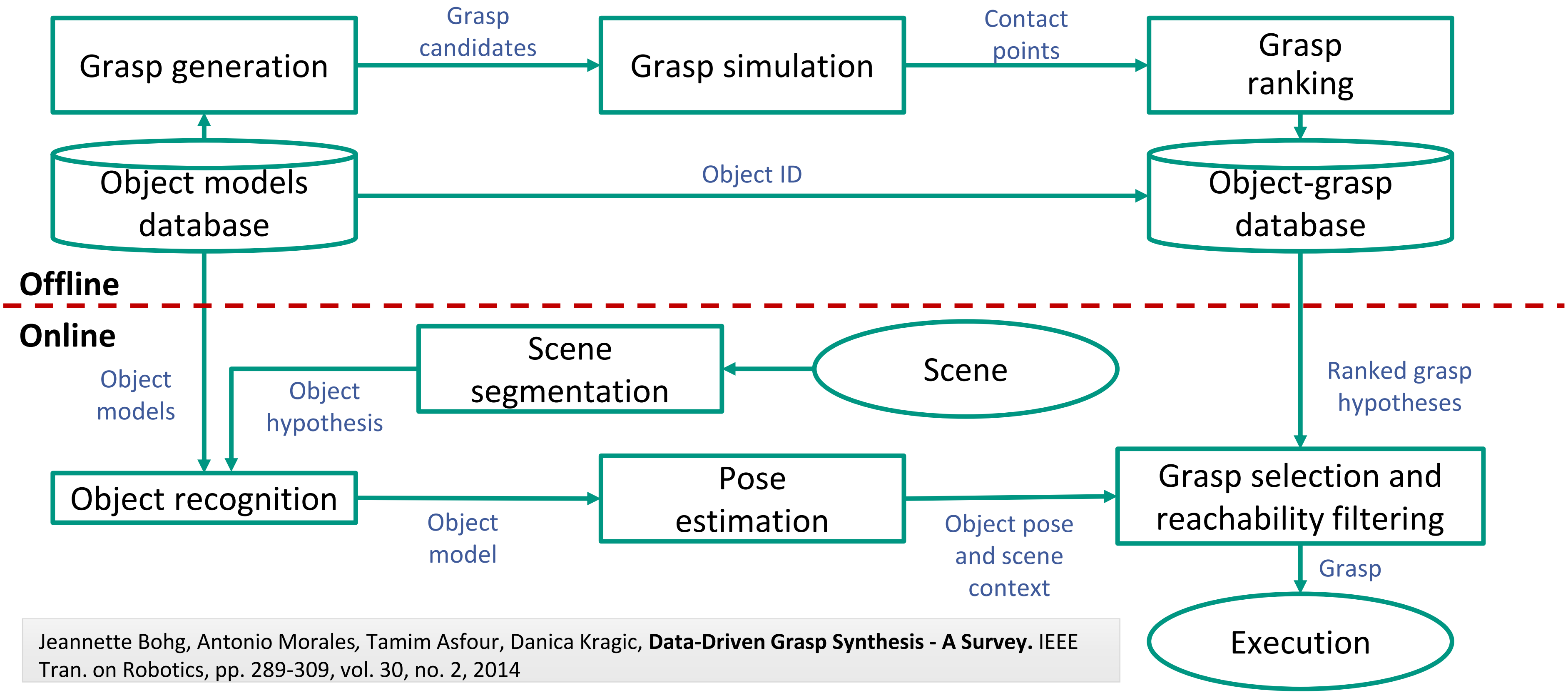
- Fundamentals and Definitions
  - Grasp Analysis and Grasp Synthesis
  - Grasp Contact
- Human Hand Models
- Grasping in Humans
  - Neuroscience of Grasping
- Grasping Taxonomies
  - Cutkosy, Kamkura, Feix, Bolluck & Dollar
  - KIT Taxonomy for Whole-Body Grasps
- Postural Synergies and Eigengrasps
  - Implementation of Synergies in Robotics
  - The TUAT/Karlsruhe Underactuated hands
- **Grasping Known, Familiar and Unknown Objects**

Grasping Known Objects

Grasping Objects: Outline

- Grasping known objects
  - Recap (see "lecture Robotics I")
- Grasping familiar/similar objects
  - Concepts
  - Different approaches
  - Part-based grasp planning for familiar/similar objects
- Grasping unknown objects
  - Concepts
  - Approximating unknown object shape
  - From low-level features to grasp hypotheses

Grasping Known Objects: Typical Flow-Chart



Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

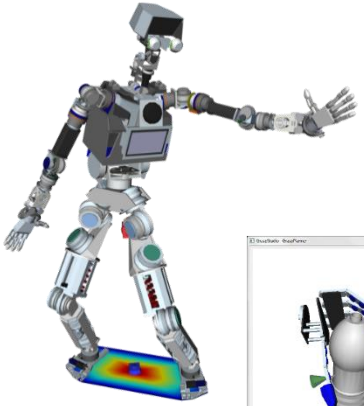
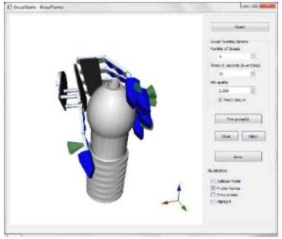
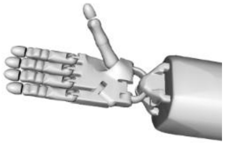
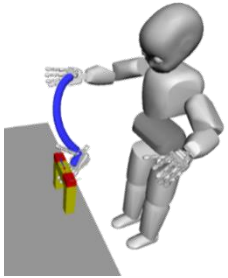
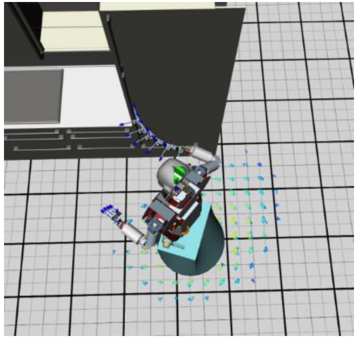
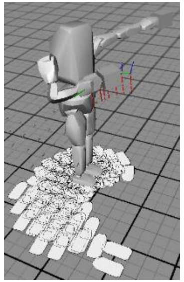
KIT Object database

Representation	Source	Usage
Point cloud	Object Modeling Center	Part based grasping
Triangle mesh	Point cloud, simplified	Collision detection and visualization
Textured mesh	Additional textures	Visualization (vision simulation possible)
Vision data	Real images, synth. views	Object detection and localization

http://h2t-projects.webarchiv.kit.edu/Projects/ObjectModelsWebUI/

Grasp Simulator - Simox

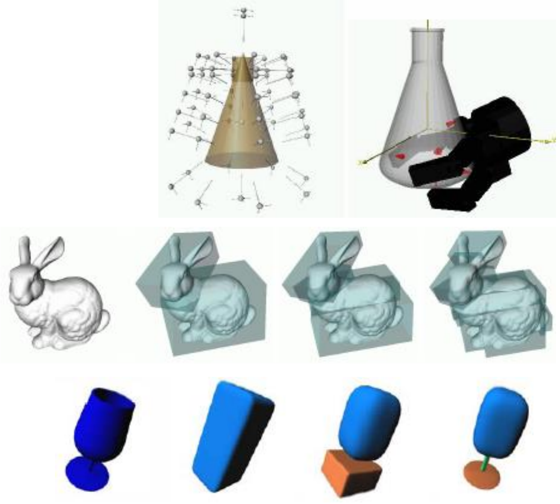
- **Developed at H^{2}T**
  - Open Source (LGPL)
  - C++
  - Robot Independent:
    ARMAR-III, ARMAR-4, iCub, ….
- **Structure**
  - *VirtualRobot*: Kinematic simulation of complex (multi) robot systems
  - *Saba*: Motion Planning
  - *GraspStudio*: Grasp Planning
  - *SimDynamics*: Dynamics Simulation
- **Sources**
  - *https://gitlab.com/Simox/simox*
- **Wiki**
  - *https://gitlab.com/Simox/simox/wikis/home*

Known: Grasp Synthesis on Object Parts

- **Question**: How to generate good grasp candidates?

- Approaches for different segmentation methods
  - **Shape primitives**
    Manual segmentation into primitives
    (e.g. boxes, cylinders, spheres, cones)
  - **Box decomposition**
    Automatic segmentation into boxes
  - **Superquadrics**
    Automatic segmentation into superquadrics
  - **Medial axis transformation**
    Use only spheres
  - **Surface normals**



See lecture “Robotics I”

Grasping Familiar Objects

Grasping Objects: Outline

- Grasping known objects
  - Recap (see “lecture Robotics I”)
- Grasping familiar/similar objects
  - Concepts
  - Different approaches
  - Part-based grasp planning for familiar/similar objects
- Grasping unknown objects
  - Concepts
  - Approximating unknown object shape
  - From low-level features to grasp hypotheses

Grasping Familiar Objects: Concept

- Identify categories of objects with **common characteristics/features**
  - **Visual:** texture, shape, spatial constellation
  - **Semantic:** Functionality, affordances, task

- Train grasps on a set of **known objects (or known object parts)**
  - Store features and generated grasps (feature-grasp relations)
  - Use learning mechanisms for generalization

- Grasp new but **familiar/similar objects**
  - Categorize the new object
  - Recall grasp hypothesis of objects in the same category
  - Adapt grasp hypothesis to new object

- Optional: Update database with new data

Grasping Familiar/Similar Objects: Approaches

- **Discriminative** approaches
  - Learn the decision boundary between classes
  - Learn a discriminative function to separate positives (good) and negatives (bad) grasps
  - Use low-level 2D and/or 3D features
- Grasp **synthesis by comparison**
  - Find the most similar object in the database
  - Adapt good grasps for that object
- Grasp **synthesis by shape deformation**
  - Learn shape deformation for each object class
  - Use deformation to transfer grasps from database
- **Generative models** for grasp synthesis
  - Learn the distribution of grasps for each class
  - Use model (learned distribution) to generate grasps directly
- **Category-based** grasp synthesis
  - Use object categories and semantics to determine similarity

Generative vs. Discriminative

Generative classifiers

- Gaussian Mixture Model (GMM)
- Naïve Bayes
- Bayesian Networks (BN)
- Markov Random Fields
- Variational Autoencoder
- Generative Adversarial Network (GAN)

Discriminative Classifiers

- Logistic regression
- Scalar Vector Machine (SVM)
- Nearest Neighbour
- Conditional Random Fields (CRFs)

Generative or Discriminative

- Neural Networks (NN)
- Hidden Markov Models (HMM)

Discriminative Approach: Rao et al. 1/2

- Goal: Learn which parts of the scene are **graspable** or **ungraspable**

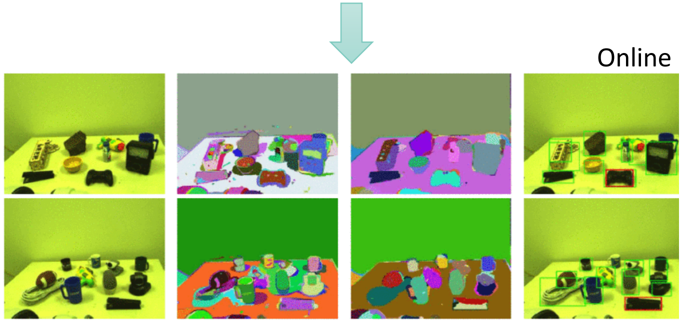
- Preprocessing: Segmentation
  - Segmentation based on depth information

- Feature vector
  - Color information (LAB color space)
  - Variance in depth and height of segments (3D)
  - Width and height of segments (2D)

- Learning mechanism
  - Support Vector Machine (SVM) with Gaussian Radial Basis Function (RBF) kernel

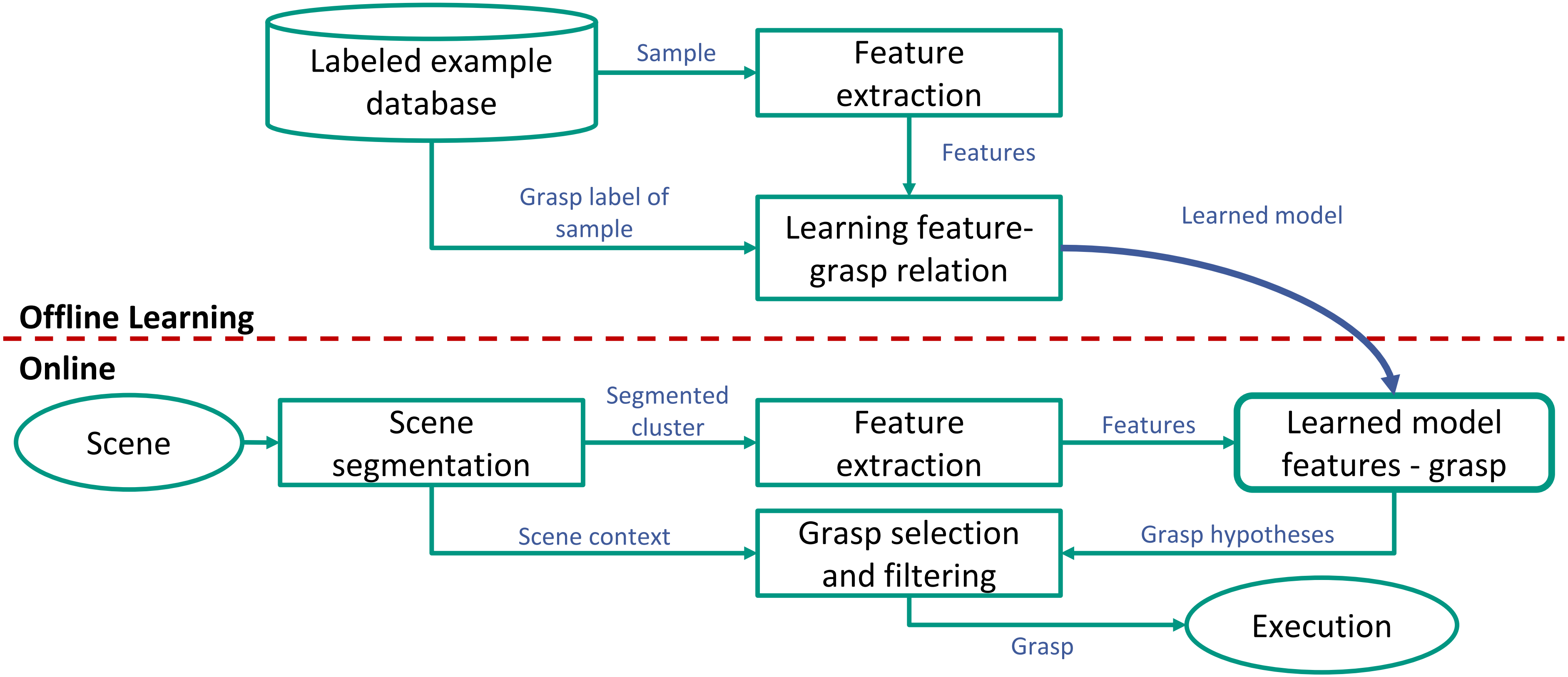
Offline Learning

Online



D. Rao, Q. V. Le, T. Phoka, M. Quigley, A. Sudsang, and A. Y. Ng, **Grasping novel objects with depth segmentation**, in Proc. IEEE/RSJ, Int. Conf. Intell. Robots Syst., 2010

Discriminative Approach: Rao et al. 2/2



Grasp Synthesis by Comparison

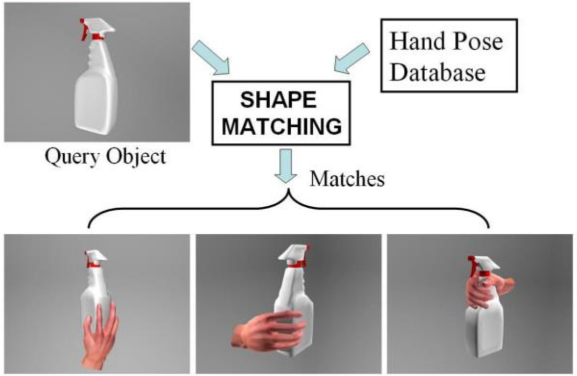
- Find the most similar object (part) in the database
- Use the associated grasps to generate good grasp hypotheses
- Examples
  - **Synthetic data**
    - Requirement: 3D object models (for exemplary and familiar objects)
    - Use 3D models to calculate similarity
    - Transfer grasp to familiar/similar object
  - **Real sensor data**
    - Use object representation from sensor data
    - Execute on real robot
    - Learn from past and new grasp experiences

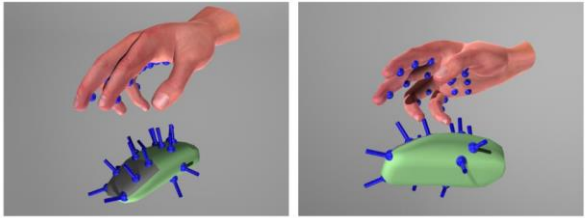
Synthetic Data: Li and Pollard

- Grasp synthesis as a **shape matching** problem
  - Offline: create database with hand poses
  - Online: Query matching hand pose for an object

- Hand pose database
  - **Contact points** and **normals**
  - On hand and known object

- Shape matching process
  - Query: new object model
  - Find: Hand pose with matching/similar contact points and normals

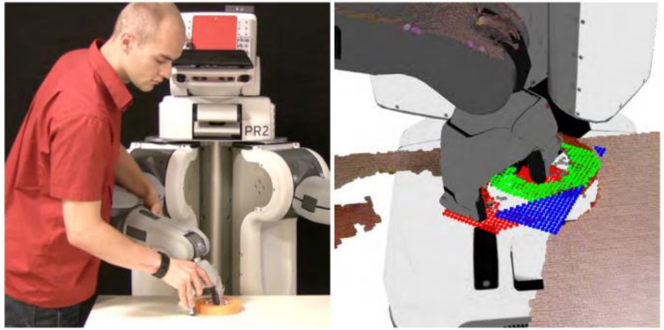


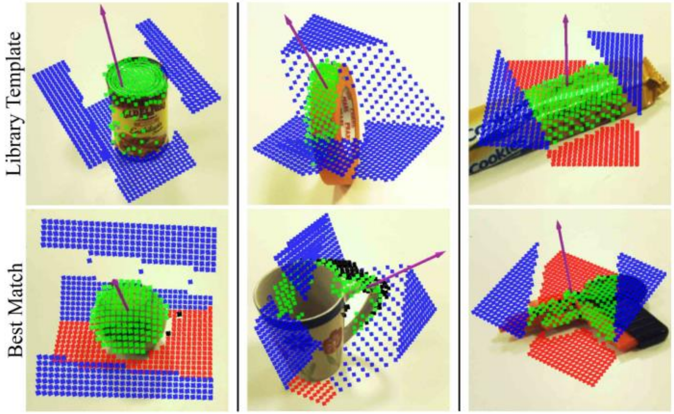


Y. Li and N. Pollard, **A Shape Matching Algorithm for synthesizing humanlike enveloping grasps**, in Proc. IEEE/RAS Int. Conf. Human. Robots (Humanoids), Dec. 2005, pp. 442–449.

Real Sensor Data: Herzog et al. 1/3

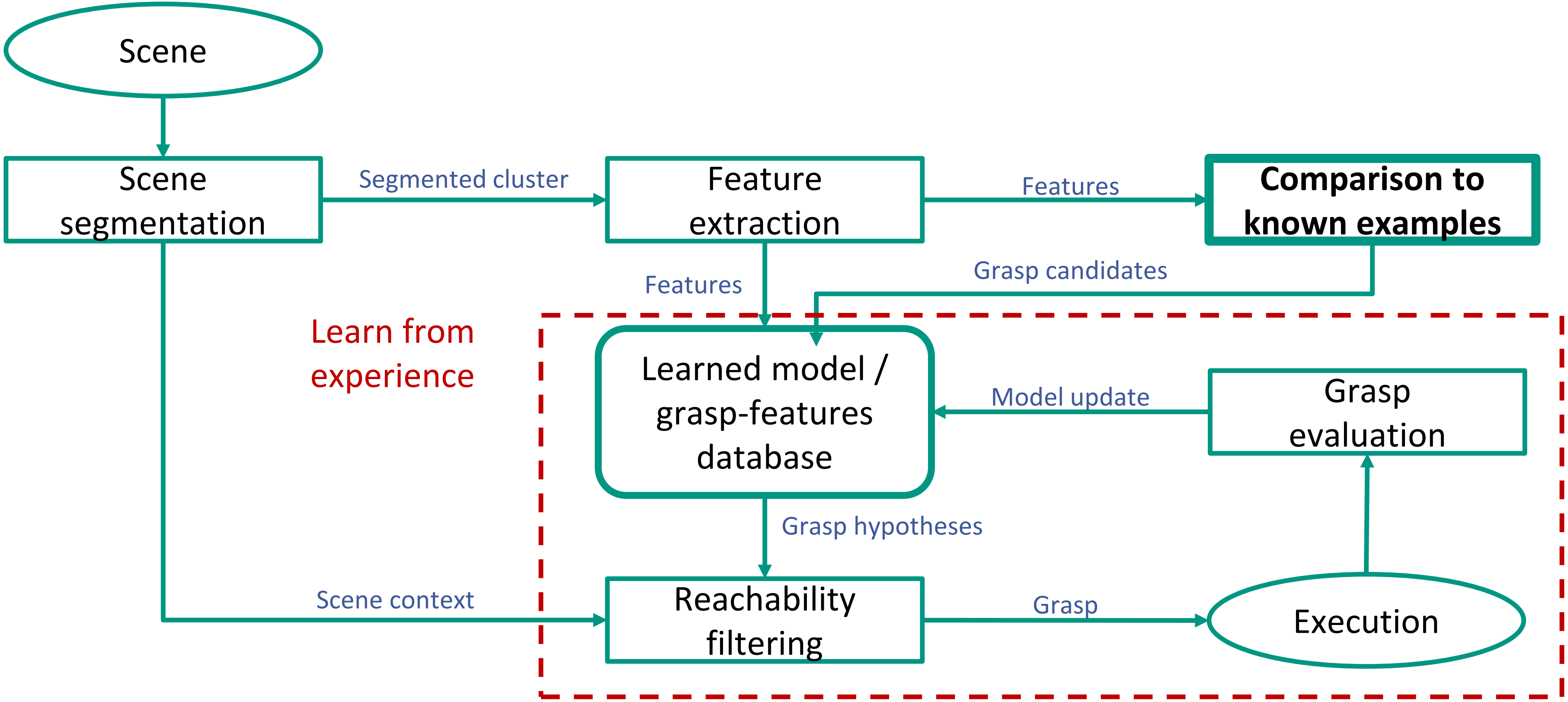
- Training data
  - Programming by demonstration
  - Generate templates from **demonstrated grasps**
- Template
  - **Local shape descriptor** for a possible grasp pose
  - templates encode object height maps that are sampled from various height-axes
  - Generated from 3D depth data
- Matching
  - Find **best matching template** according to the local shape



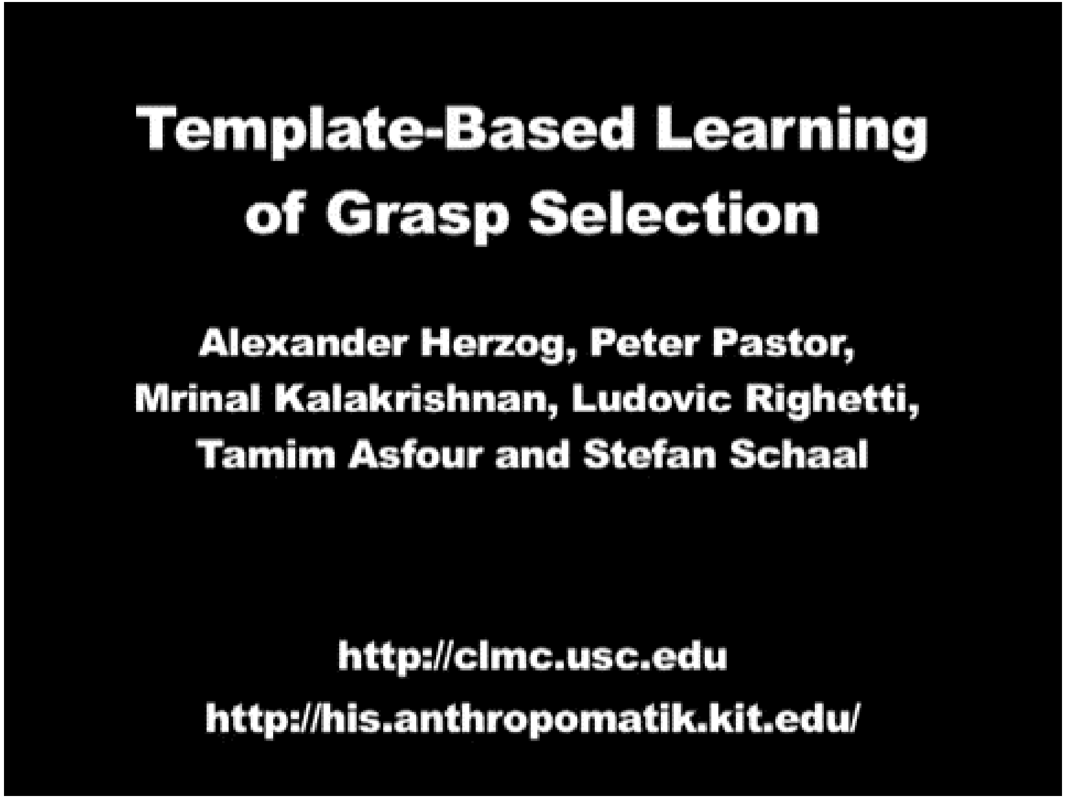


A. Herzog, P. Pastor, M. Kalakrishnan, L. Righetti, T. Asfour, and S. Schaal, **Template-based learning of grasp selection**, in Proc. IEEE Int. Conf. Robotics and Automation, 2012, pp. 2379–2384.

Real Sensor Data: Herzog et al. 2/3

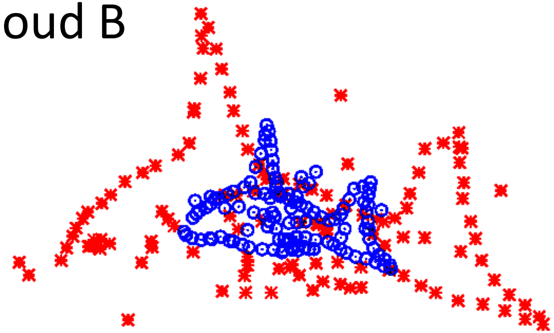


Real Sensor Data: Herzog et al. 3/3



Grasp Synthesis by Shape Deformation: Rodriguez et al. 1/3

- Based on Coherent Point Drift (CPD). CPD determines a transformation to deform point cloud A into point cloud B
- Offline Phase (per object class)
  - Set of different object models per class
  - Creates a latent shape space for the models
- Online Phase
  - Object detection and segmentation
  - Use latent shape space to adapt grasps to the detected object

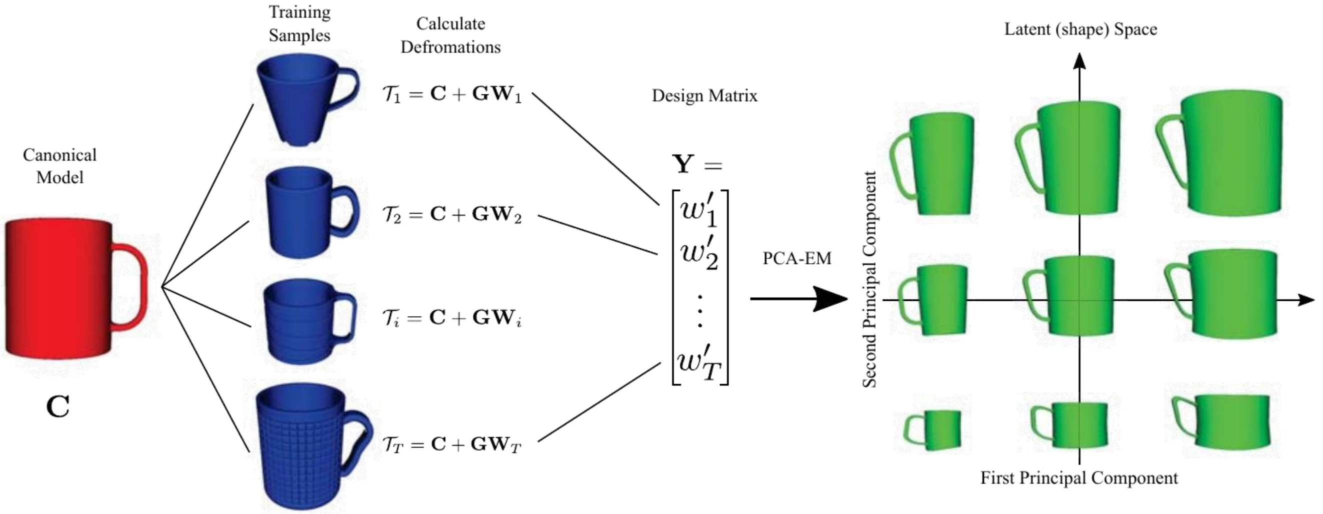


https://en.wikipedia.org/wiki/File:Cpd_fish_rigid.gif (CC-BY-SA 3.0)

D. Rodriguez, C. Cogswell, S. Koo, and S. Behnke, **Transferring Grasping Skills to Novel Instances by Latent Space Non-Rigid Registration**, in Proc. IEEE Int. Conf. Robot. Autom., 2018

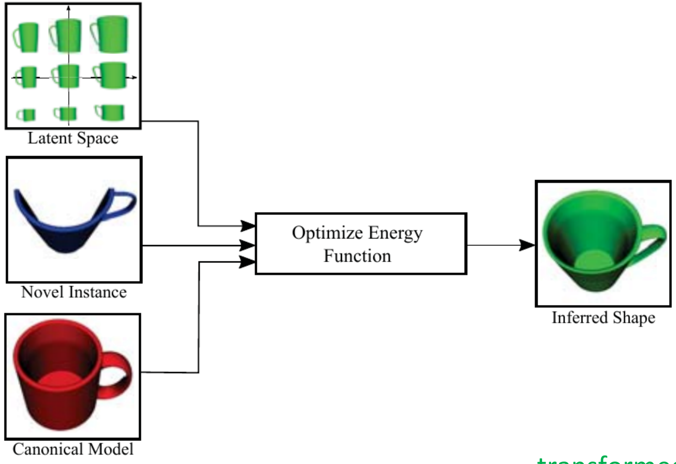
Grasp Synthesis by Shape Deformation: Rodriguez et al. 2/3 – Offline Phase

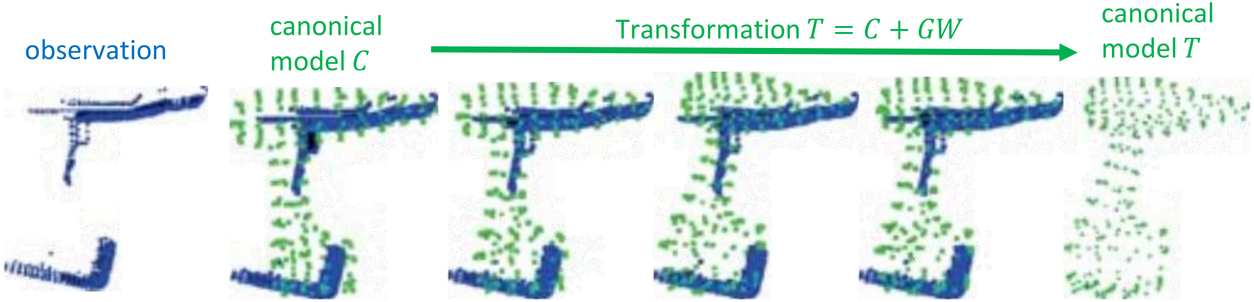
- Input: different object models of the same class (full point cloud)
- Select one object model as canonical model C → C, G
- Calculate Deformations for all models → T_i, W_i
- Turn W_i into row vectors, normalize them (zero-mean, unit-variance) → w'_i
- Stack them to form Y
- PCA on Y
- Take first n components as latent shape space



Grasp Synthesis by Shape Deformation: Rodriguez et al. 3/3 – Online Phase

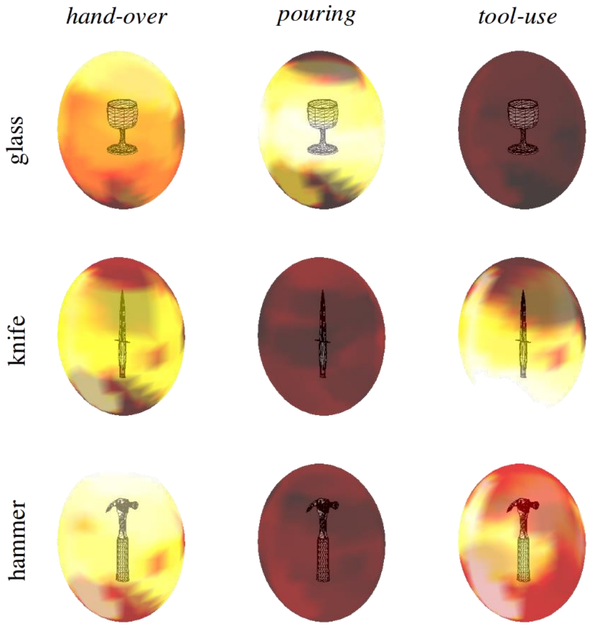
- Requires object detection and instance segmentation in advance
- Input: Canonical model, latent shape space, observed point cloud
- Use Estimation Maximization (EM) to determine W for the observed point cloud
- Use CPD to transform grasping trajectories from C to T





Generative Models for Grasp Synthesis: Song et al.

- Infer grasp configuration for an object given a **specific task**
- Joint distribution of variables is modelled as **Bayesian network**
- Training data:
  - Grasp examples generated in grasping simulator (GraspIt!)
  - Annotated with task-specific quality metrics
- Improved structure learning
  - Nonlinear dimensionality reduction



Ranking of approach vectors
Brighter: Higher rank

D. Song, C. H. Ek, K. Hübner, and D. Kragic, **Multivariate discretization for bayesian network structure learning in robot grasping**, in Proc. IEEE Int. Conf. on Robotics and Automation, 2011

Category-Based Grasp Synthesis

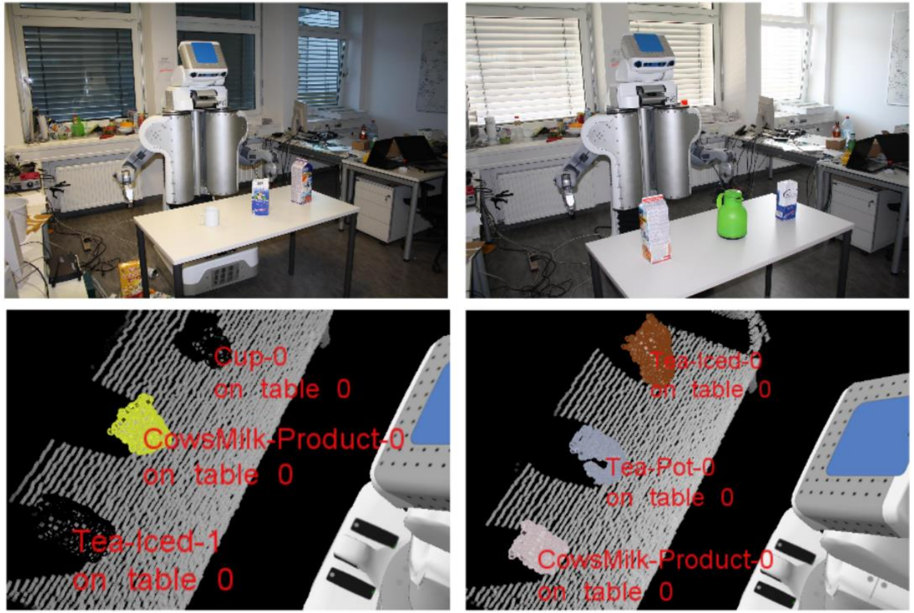
- Previous approaches:
  - Similar low-level features → Similar grasp

- **Idea:** Similarity on **semantic level**
  - Different shape or appearance
  - Same functional category (affordances)
  - But can be grasped in a similar way

- Category is not known
  - Category needs to be determined
  - **Classification of objects** based on features

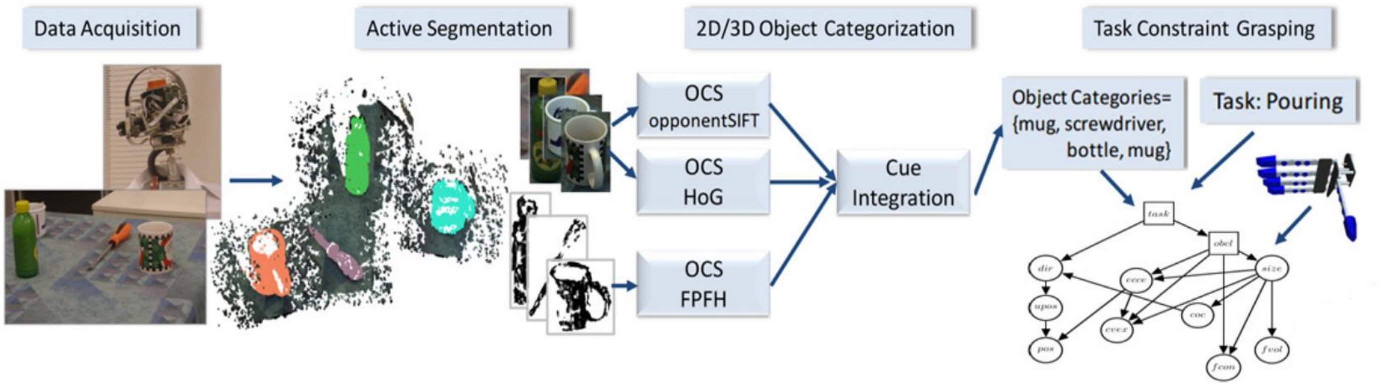
Category-Based Grasp Synthesis: Marton et al.

- Features based on
  - Segmented point cloud
  - Segmented image region
- Object classification
  - Bayesian network
  - Fixed set of categories
- Only detection of categories
  - No grasp synthesis



Z. C. Marton, D. Pangercic, N. Blodow, and M. Beetz, **Combined2-D–3-D categorization and classification for multimodal perception systems**, Int. Journal of Robotics Research, vol. 30, no. 11, pp. 1378–1402, 2011.

Category-Based Grasping: Madry et al.



- Classification based on multi-model visual descriptors
- Also uses task information
- Bayesian network generates hand configuration

M. Madry, D. Song, and D. Kragic, **From object categories to grasp transfer using probabilistic reasoning**, in Proc. IEEE Int. Conf. on Robotics and Automation, 2012, pp. 1716–1723.

Task-based grasp adaptation

Part-Based Grasp Planning for Familiar Objects

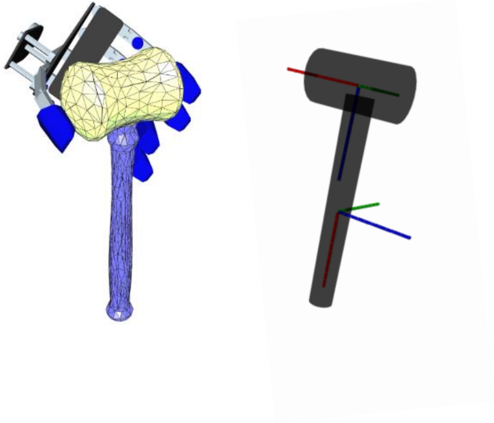
Red: relevant for the exam

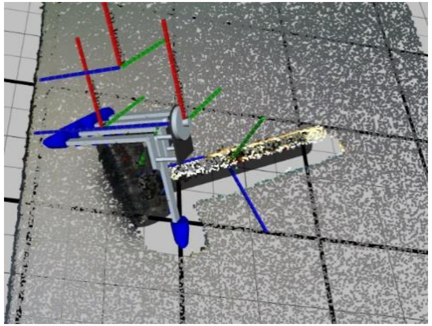
- Goal
  - **Generalized grasping information** for familiar objects
  - Grasps can be used for familiar objects and **partly known objects**
- Offline learning
  - **Train** grasps on multiple familiar object models
  - Identify promising grasps with **transferability success measure**
- Online
  - **Transfer** grasps to similar novel objects

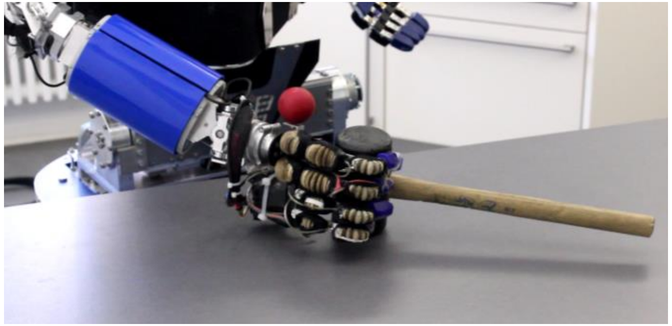
Vahrenkamp, N., Westkamp, L., Yamanobe, N., Aksoy, E. E. and Asfour, T., Part-based Grasp Planning for Familiar Objects, IEEE/RAS International Conference on Humanoid Robots (Humanoids), pp. 919-925, Nov, 2016

Part-Based Grasp Planning for Familiar Objects

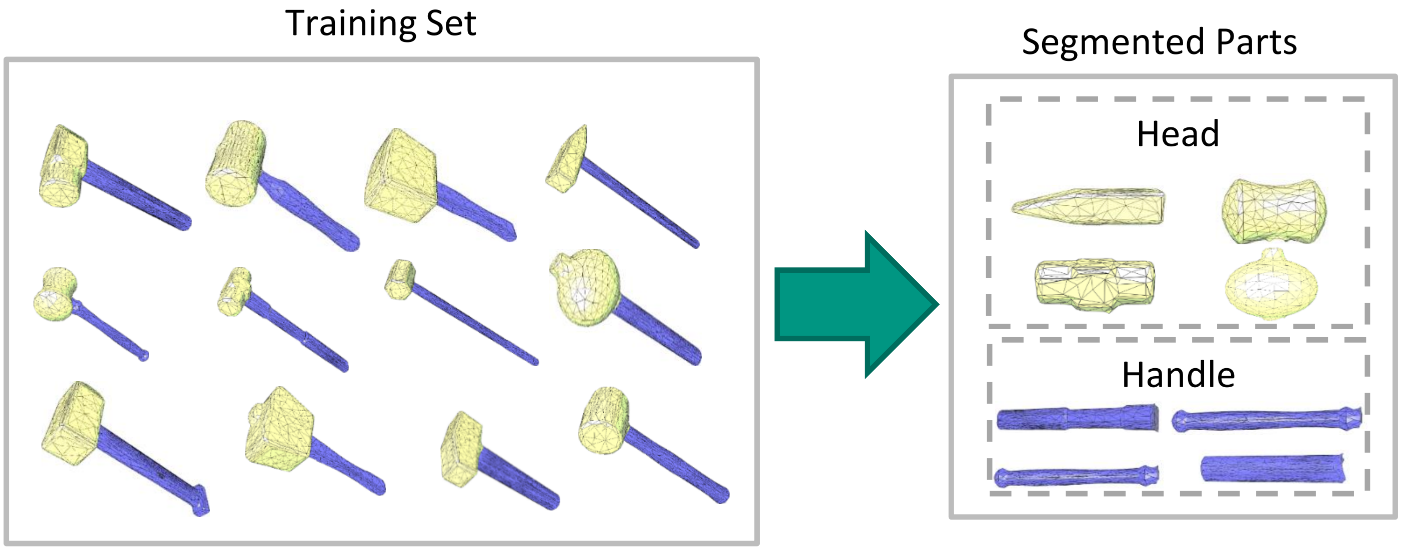
- Offline learning
  - Step 1: Object shape segmentation
  - Step 2: Labeling with task-related information
  - Step 3: Plan grasps on object parts planning
- Online execution
  - Localization and approximation of object parts
  - Grasp transfer to novel object





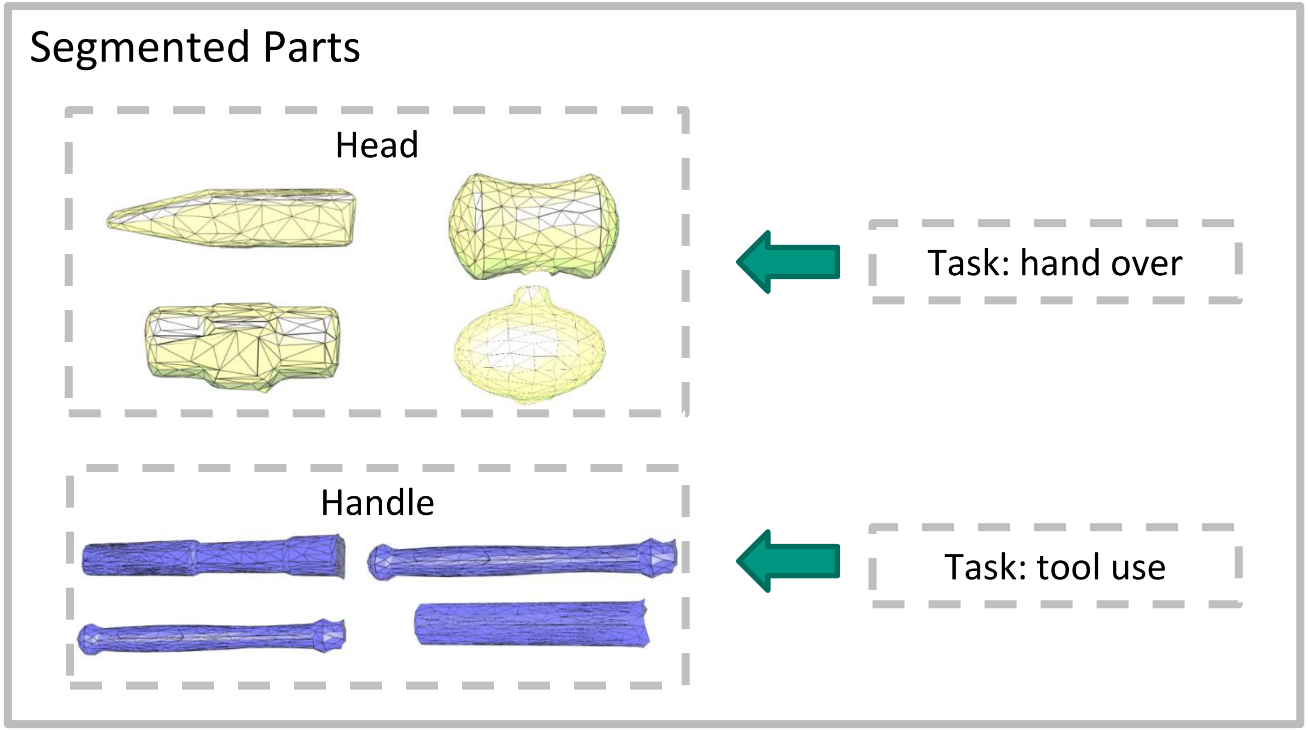


Offline Step 1: Object Shape Segmentation

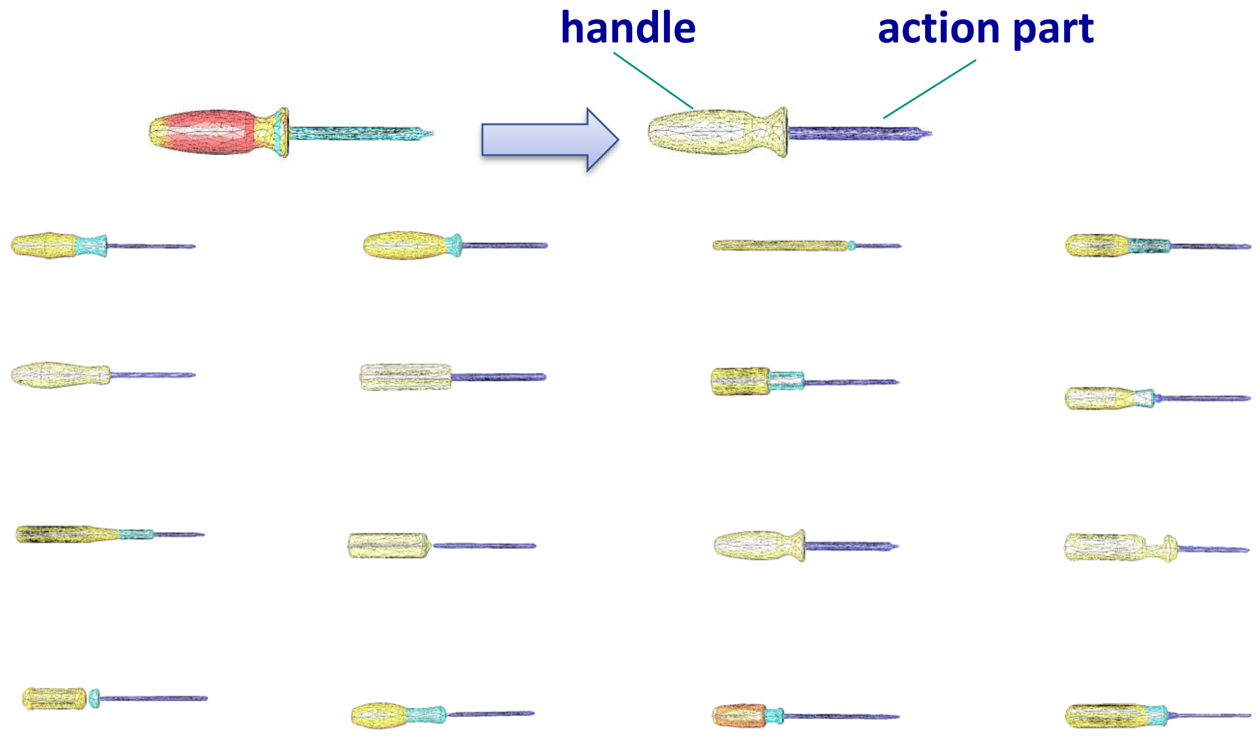


Mesh segmentation based on Shape Diameter Function (SDF), (Shapira et al., 2008);
SDF maps volumetric information onto the surface boundary mesh

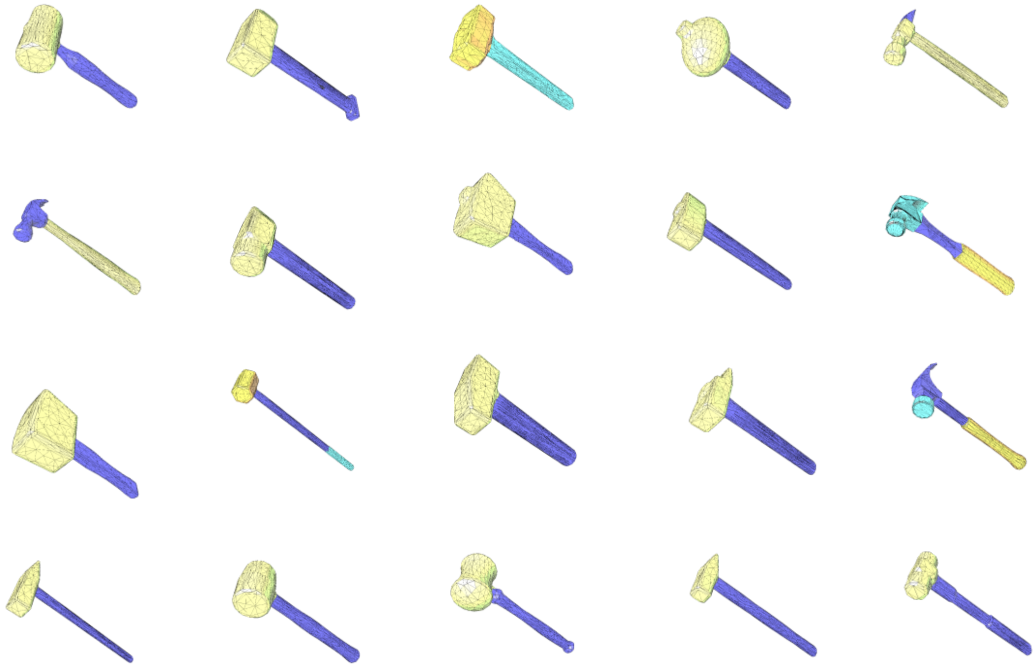
Offline Step 2: Labeling with Task-related Information



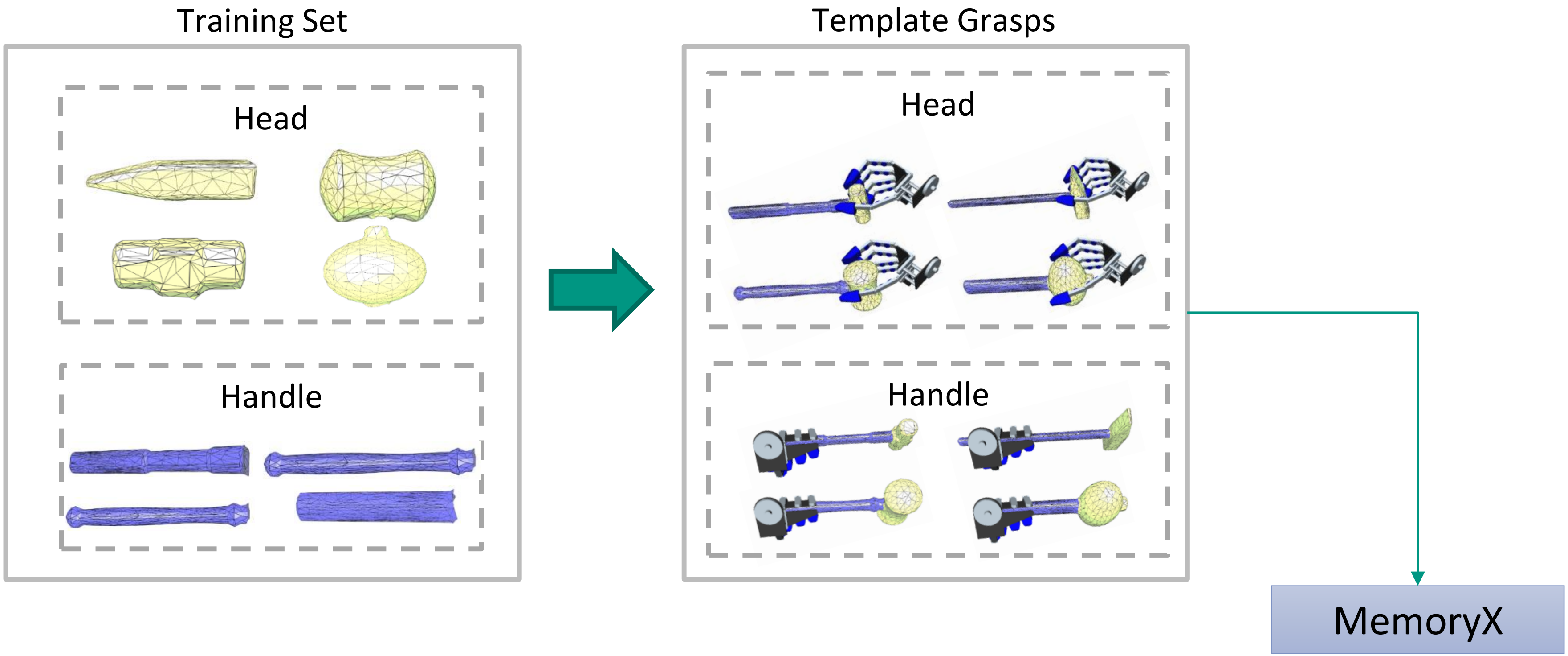
Training Objects: Category Screwdriver



Training Objects: Category Hammer

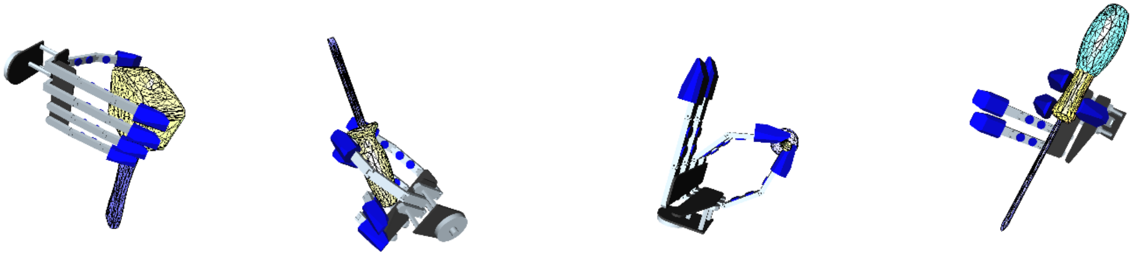


Offline Step 3: Part-Based Grasp Planning



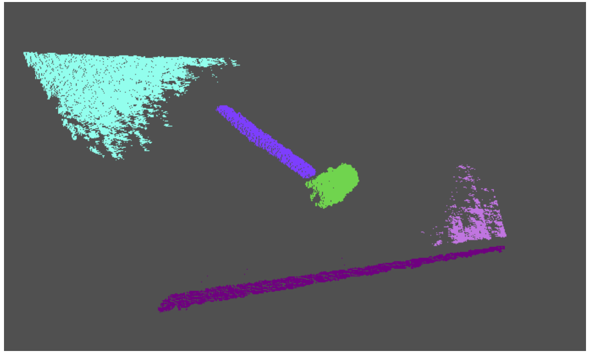
Planning Grasps for an Object Category

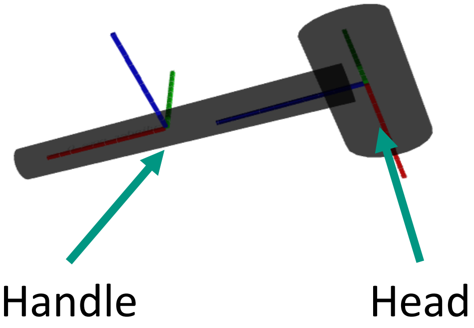
- Plan grasps on object parts
  - Identify “good” grasps on all parts within an object category
  - Power and precision grasps
- Grasp evaluation based on
  - Wrench Space Grasp Quality
  - Force Closure measure
- Local optimization
  - Optimize grasping pose w.r.t. grasp quality on all training objects



Online: Localization and Approximation of Object Parts

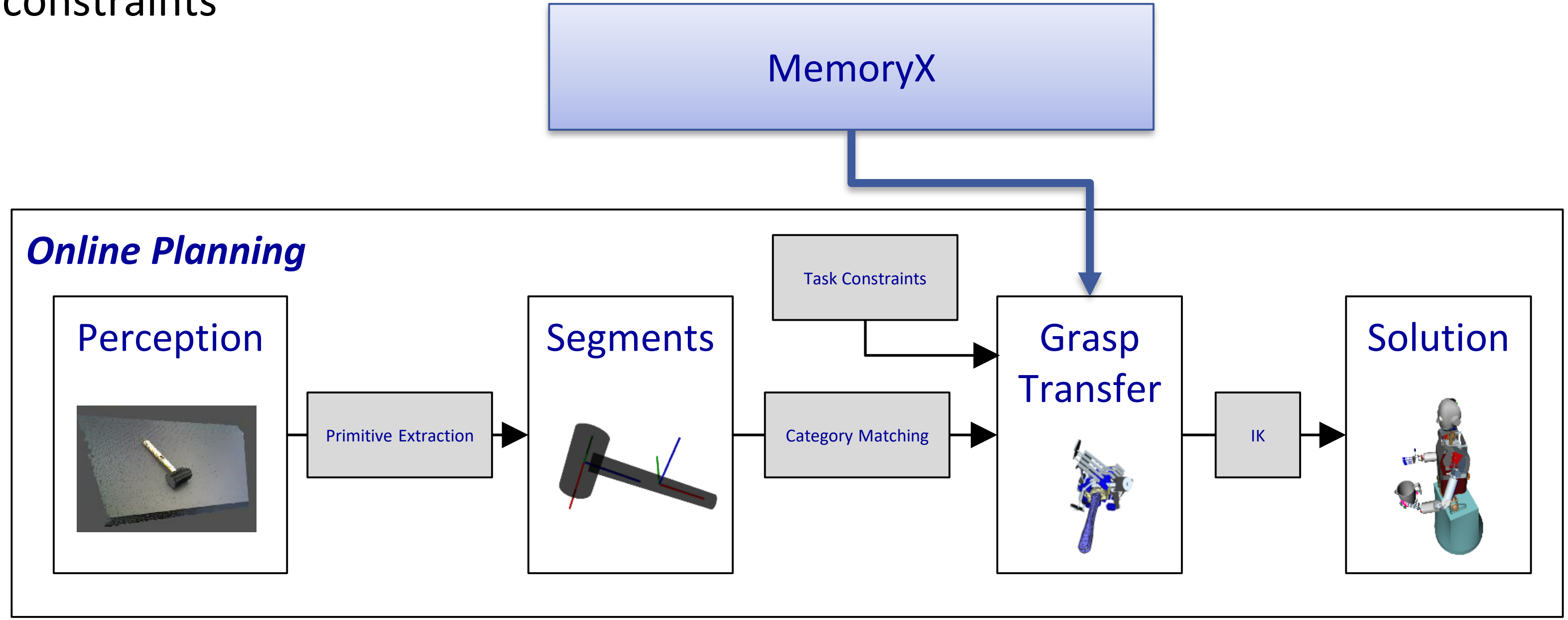
- Input: RGBD data (point cloud)
- Segmentation
  - Identify the object
  - Segment object parts
- Classification
  - Classify each object part
  - Label the parts





Online: Grasp Transfer to Novel Object 1/2

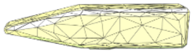
- Identify if a perceived object belongs to a trained object category
- Apply trained grasps on novel object while taking into account task constraints



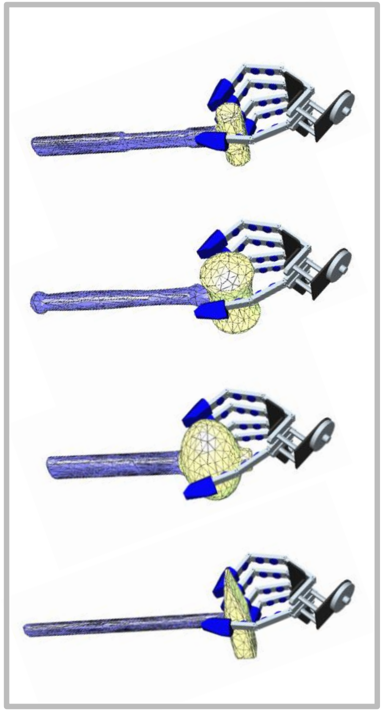
Online: Grasp Transfer to Novel Object 2/2

Task Constraints

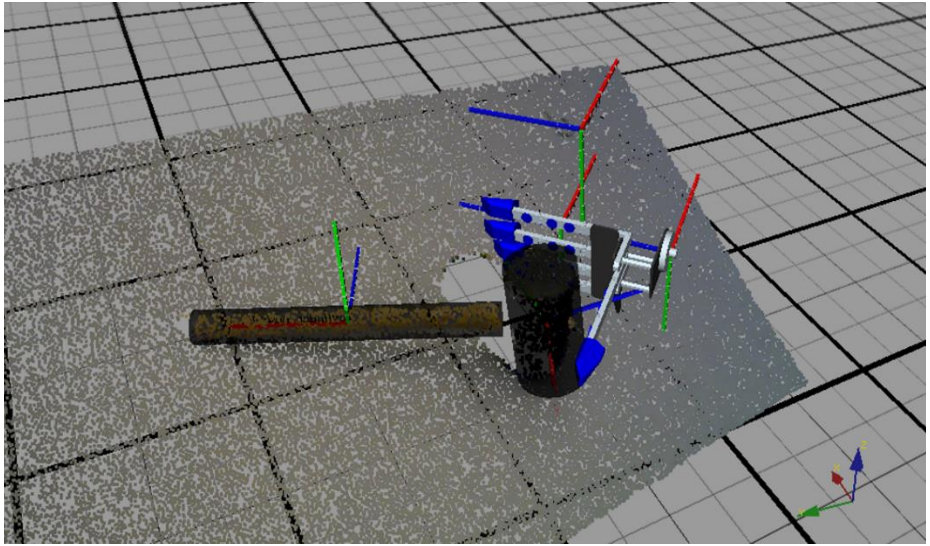
Object Part Selection



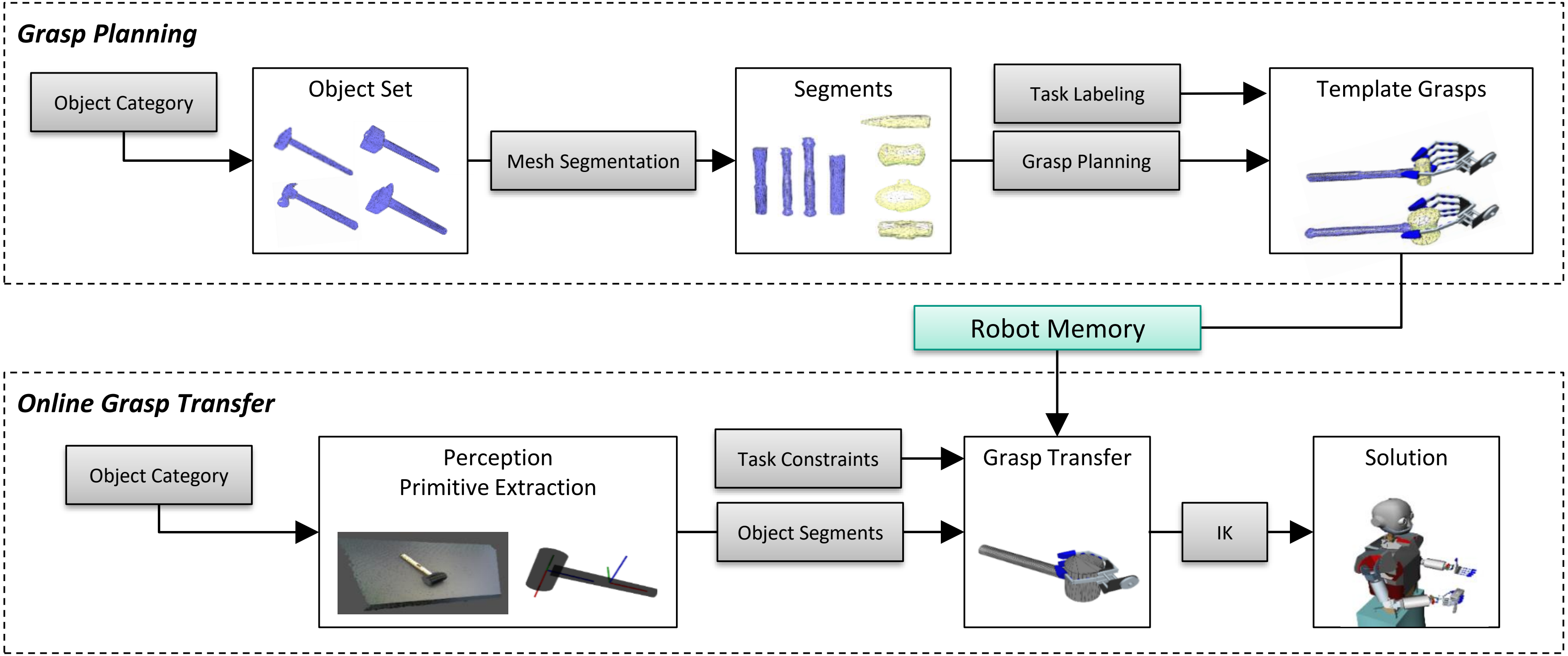
Template Grasps



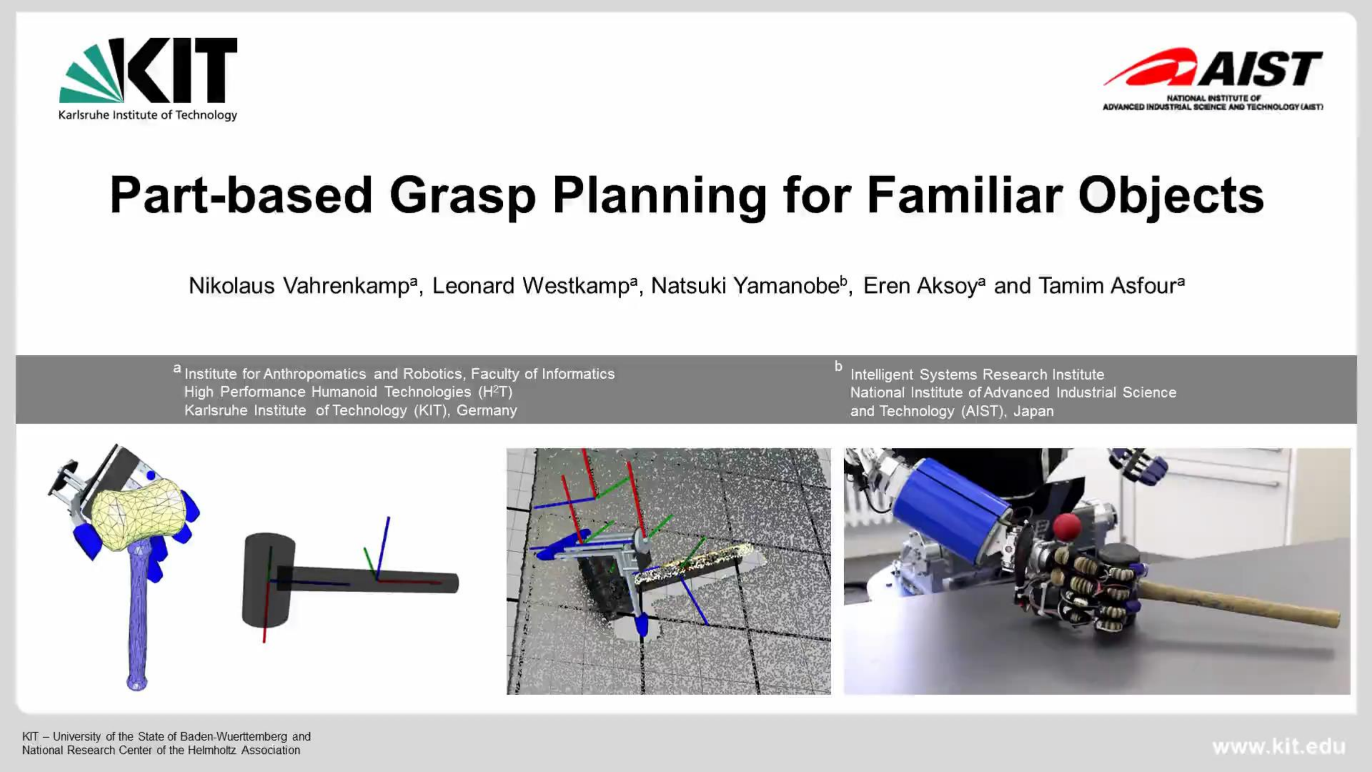
Grasp Transfer



Part-Based Grasp Planning: Architecture



Part-based Grasp Planning



Grasping Unknown Objects

Grasping Objects: Outline

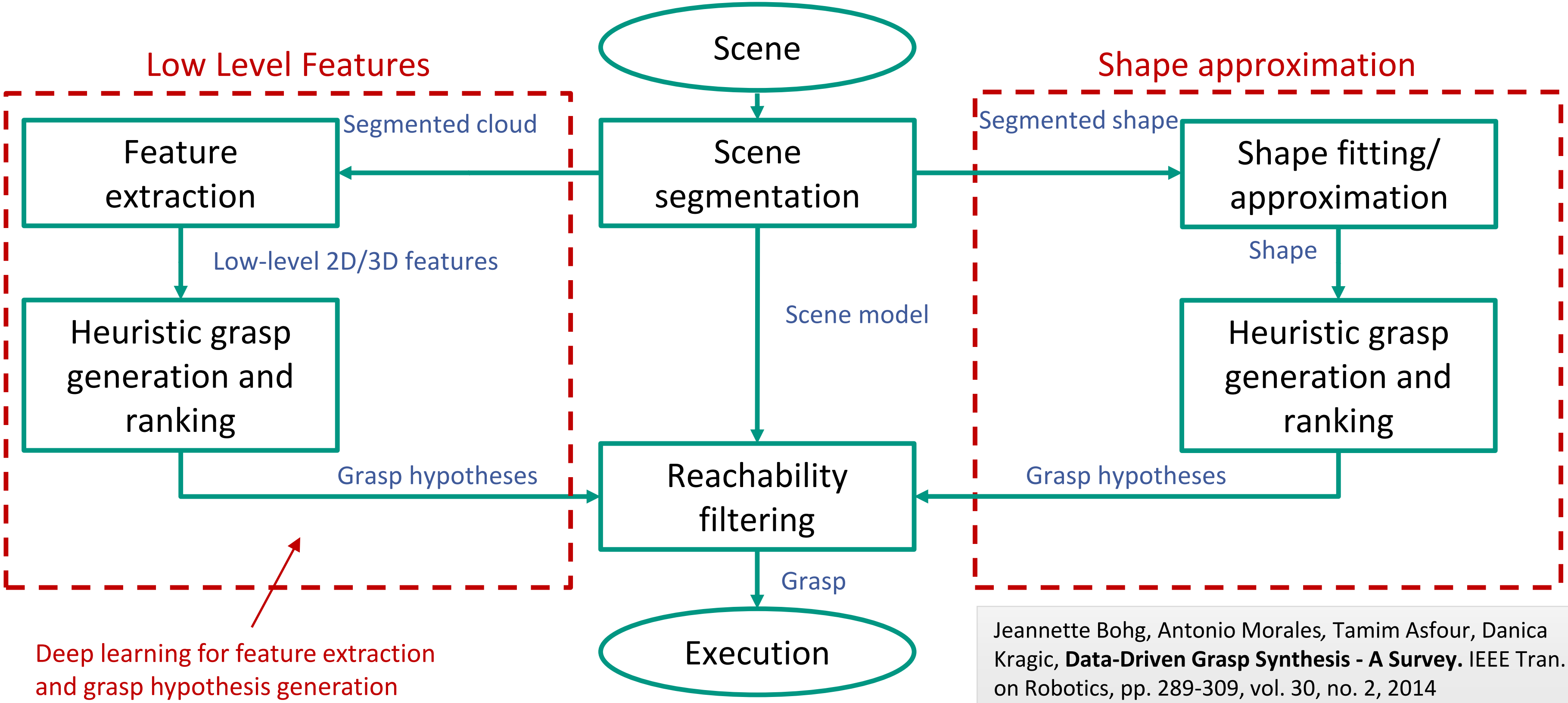
- Grasping known objects
  - Recap (see “lecture Robotics I”)
- Grasping familiar objects
  - Concepts
  - Different approaches
  - Part-based grasp planning for familiar objects
- Grasping unknown objects
  - Concepts
  - Approximating unknown object shape
  - From low-level features to grasp hypotheses

Grasping Unknown Objects: Concept

- How to grasp unknown objects?
  - Object model is not available
  - No access to similar objects or grasp experiences
- Mapping: Noisy sensor data → Grasp hypotheses
- Approaches can be divided into two methods
  - Approximating unknown object shape
  - From low-level features directly to grasp hypotheses

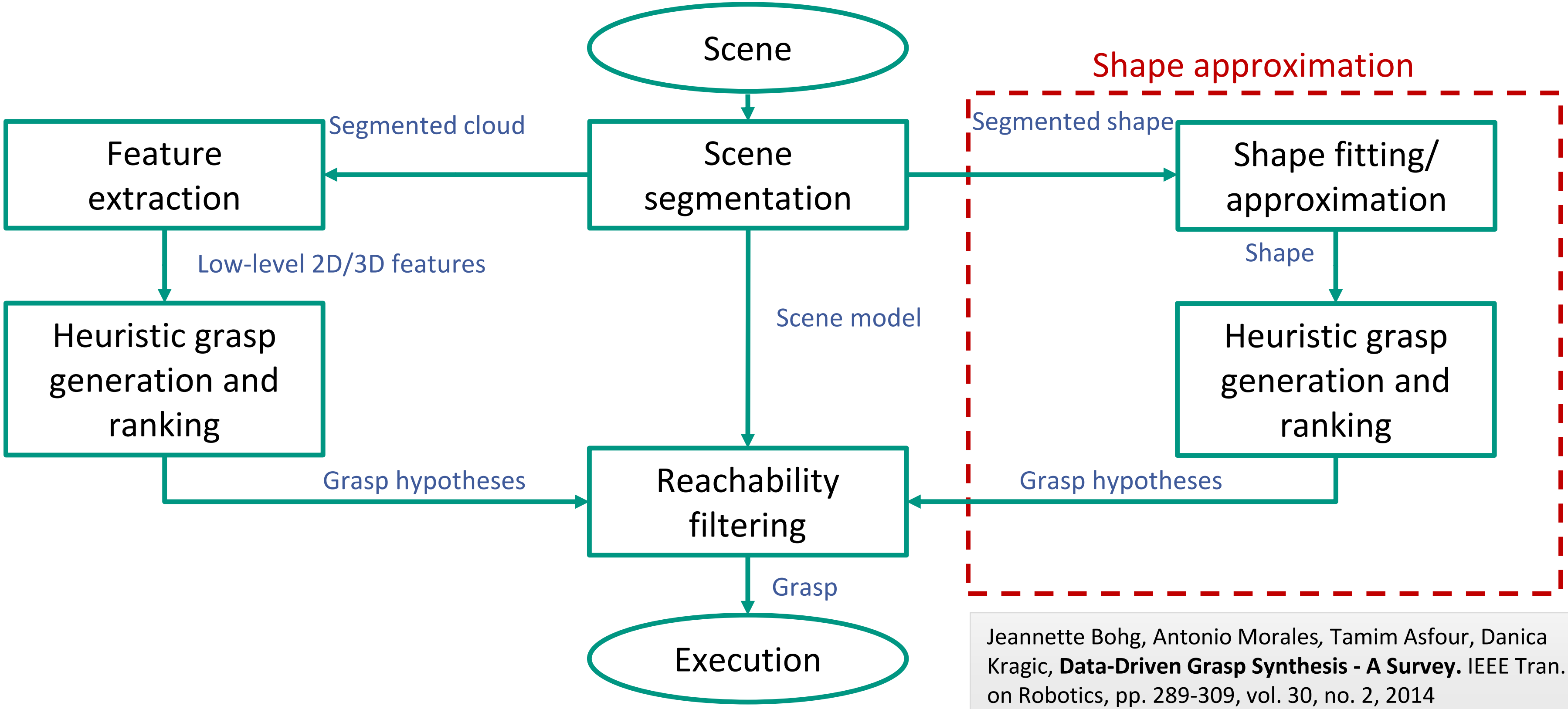
- Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014
- Rhys Newbury, Morris Gu, Lachlan Chumbley, Arsalan Mousavian, Clemens Eppner, Jürgen Leitner, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, Dieter Fox, Akansel Cosgun. **Deep Learning Approaches to Grasp Synthesis: A Review.** IEEE Transactions on Robotics, 2023

Grasping Unknown Objects: Flow-Chart



Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

Grasping Unknown Objects: Flow-Chart



Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

Approximating Unknown Object Shape

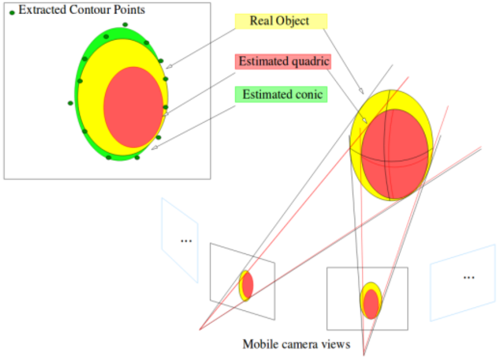
- Idea
  - Approximate object shape using shape primitives
  - Plan grasp on approximated shape

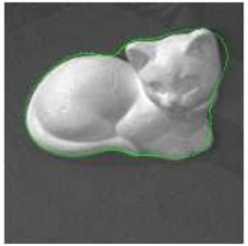
- Input can be
  - Monocular images
  - Stereo images
  - RGBD data (point cloud)

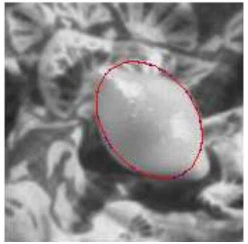
- Shape approximation methods
  - Quadrics
  - Local normal estimation
  - Mesh construction (using symmetry)

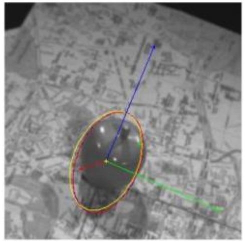
Approximation using Quadrics: Dunes et al.

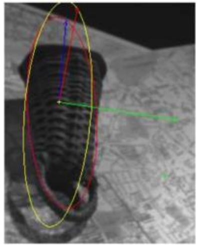
- Find a quadric that approximates at best the shape of the object
- Features: object minor axis, its centroid position and its rough size
- Use of active vision:
  - Gather **multiple views** of the object
  - Minimize uncertainty of parameters
  - Determine the next best view







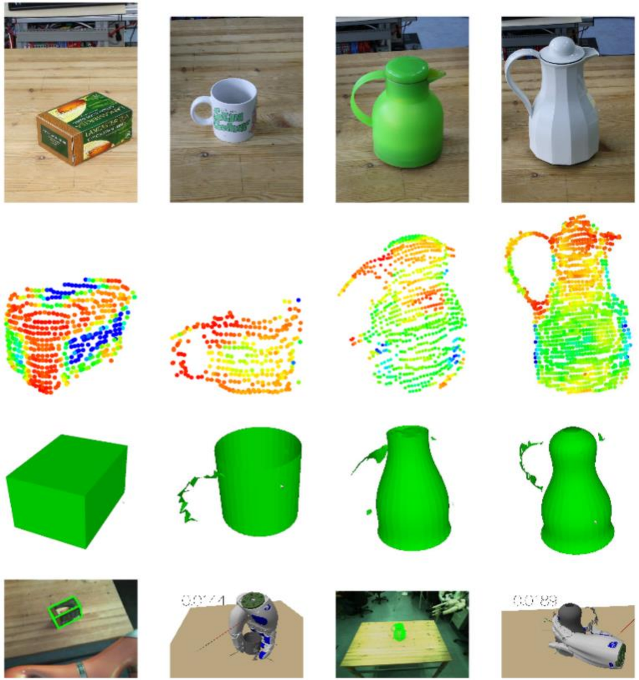




C. Dunes, E. Marchand, C. Collowet, and C. Leroux, **Active Rough Shape Estimation of Unknown Objects**, in IEEE Int. Conf. on Intelligent Robots and Systems (IROS), 2008, pp. 3622–3627.

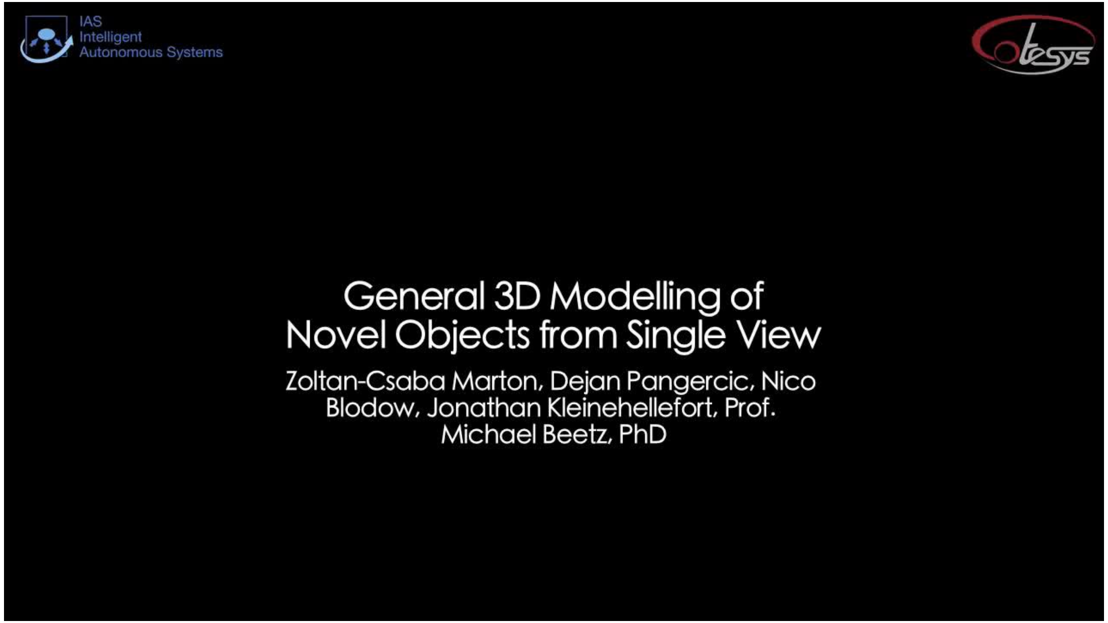
Approximation on Point Clouds: Marton et al.

- Input: Point cloud
- Initial step:
  - Estimation of **surface normal** and **minimal curve radius** for each point from **one single view**
- Different surface estimation methods are tested:
  1. Fit boxes and cylinders
  2. Detect revolution surfaces
  3. Triangulate free form surfaces
- Grasp planning on estimated object surface



Z. C. Marton, D. Pangercic, N. Blodow, J. Kleinehellefort, and M. Beetz, **General 3D Modelling of Novel Objects from a Single View**, in IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2010, pp. 3700 – 3705.

Approximation on Point Clouds: Marton et al.



https://www.youtube.com/watch?v=ZS3ZH7GTCwk

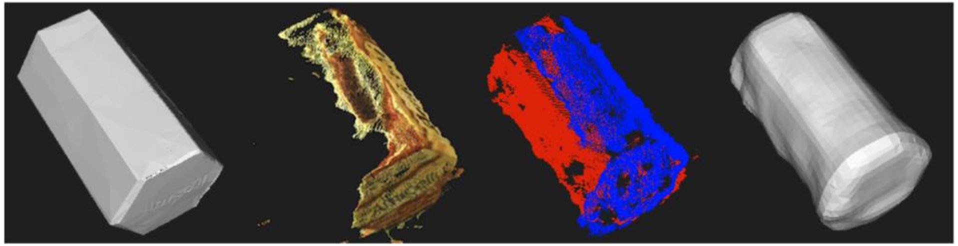
Z. C. Marton, D. Pangercic, N. Blodow, J. Kleinehellefort, and M. Beetz, **General 3D Modelling of Novel Objects from a Single View**, in IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2010, pp. 3700 – 3705.

Shape Completion Based on Symmetry: Bohg et al.

- Detect planar reflection symmetry in point cloud
  - Each point *P* can be uniquely associated with a second point *Q* by reflection on the opposite side of a **symmetry plane**
  - Iteratively improve and test hypothesis for symmetry plane

- Object shape completion
  - Create a mesh based on original and mirrored points
  - Use **Poisson reconstruction** to create a mesh (estimate normal using kd-tree based method)

- Plan grasps on the completed object shape



J. Bohg, M. Johnson-Roberson, B. León, J. Felip, X. Gratal, N. Bergström, D. Kragic, and A. Morales, **Mind the Gap – Robotic Grasping under Incomplete Observation**, in IEEE Int. Conf. on Robotics and Automation (ICRA), 2011.

Shape Completion Based on Symmetry: Bohg et al.

https://www.youtube.com/watch?v=jskDy2IfQr4

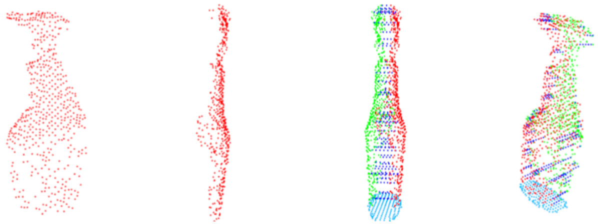
J. Bohg, M. Johnson-Roberson, B. León, J. Felip, X. Gratal, N. Bergström, D. Kragic, and A. Morales, **Mind the Gap – Robotic Grasping under Incomplete Observation**, in IEEE Int. Conf. on Robotics and Automation (ICRA), 2011.

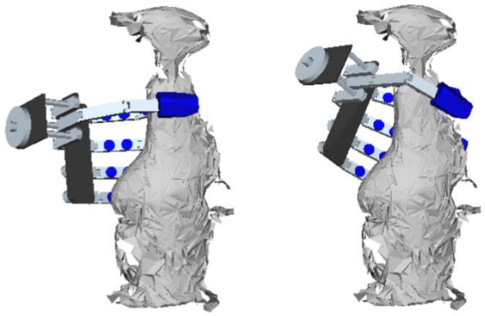
Shape Completion: Schiebener et al.

- Similar to (Bohg et al. 2011) we assume that a symmetry plane of the object is perpendicular to the supporting surface
  - **Difference:** several hypotheses for the supporting surface
- Only planar reflection symmetry

  → Still holes in the point cloud

  → Additional completion steps
- Sides of the object
  - Projection into the camera plane
  - Subdivide image into horizontal segments
  - Find minimal and maximal point in horizontal direction
  - Connect with mirrored points
- Bottom of the object
  - Use supporting plane

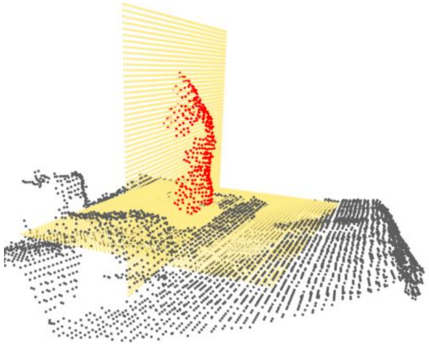


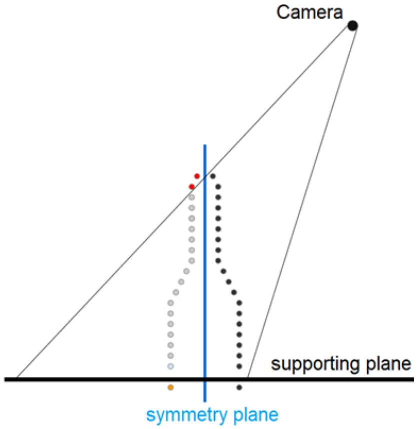


Schiebener, David, et al. **Heuristic 3D object shape completion based on symmetry and scene context**. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2016

Finding symmetry planes (Schiebener et al.)

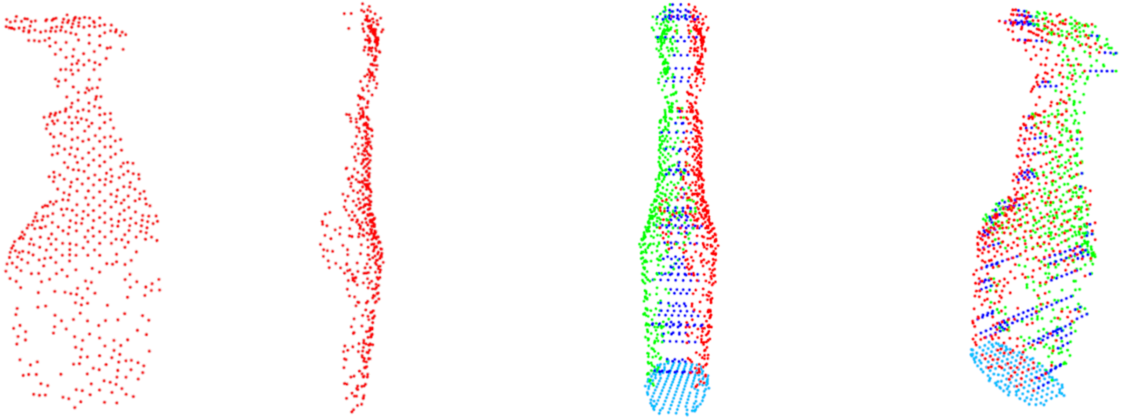
- **Proposed approach:** Symmetry assumption plus information about scene context
  - Estimate possible support surfaces based on neighboring points around the segmented object
  - Search for best symmetry plane perpendicular to these support surfaces
- Generate symmetry plane candidates
  - Mirror object points on them
  - Rate them based on visibility criteria
- Mirrored points may
  - Coincide with the original points
  - Lie behind the original points
  - Lie in front of the object
  - Lie besides the object



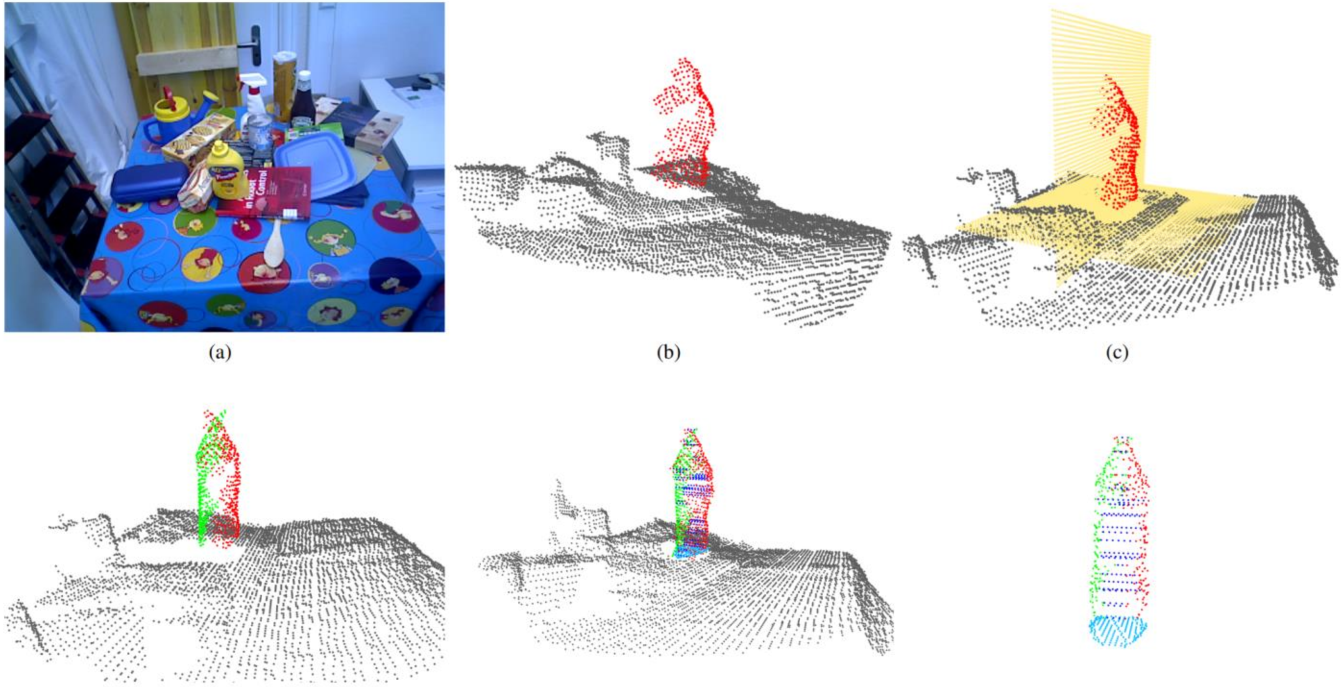


Object shape completion (Schiebener et al.)

- Completed point cloud results from
  - **Mirroring** at the symmetry plane (green)
  - Regular samples in intersection of estimated support plane and **bottom part** of the object (light blue)
  - Along **edges**: Straight lines from the front to the back side in the depth direction (dark blue)



Object shape completion (Schiebener et al.)

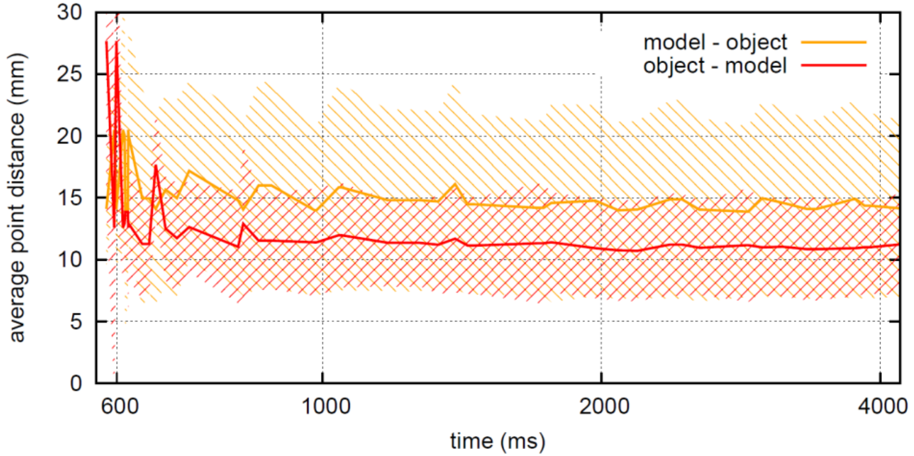


(a) (b) (c)

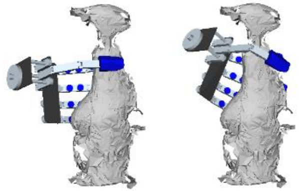
(d) (e) (f)

Shape completion results (Schiebener et al.)

- Complete shapes obtained from segmentation
- Mean distance between completed shape and ground truth model, depending on calculation time

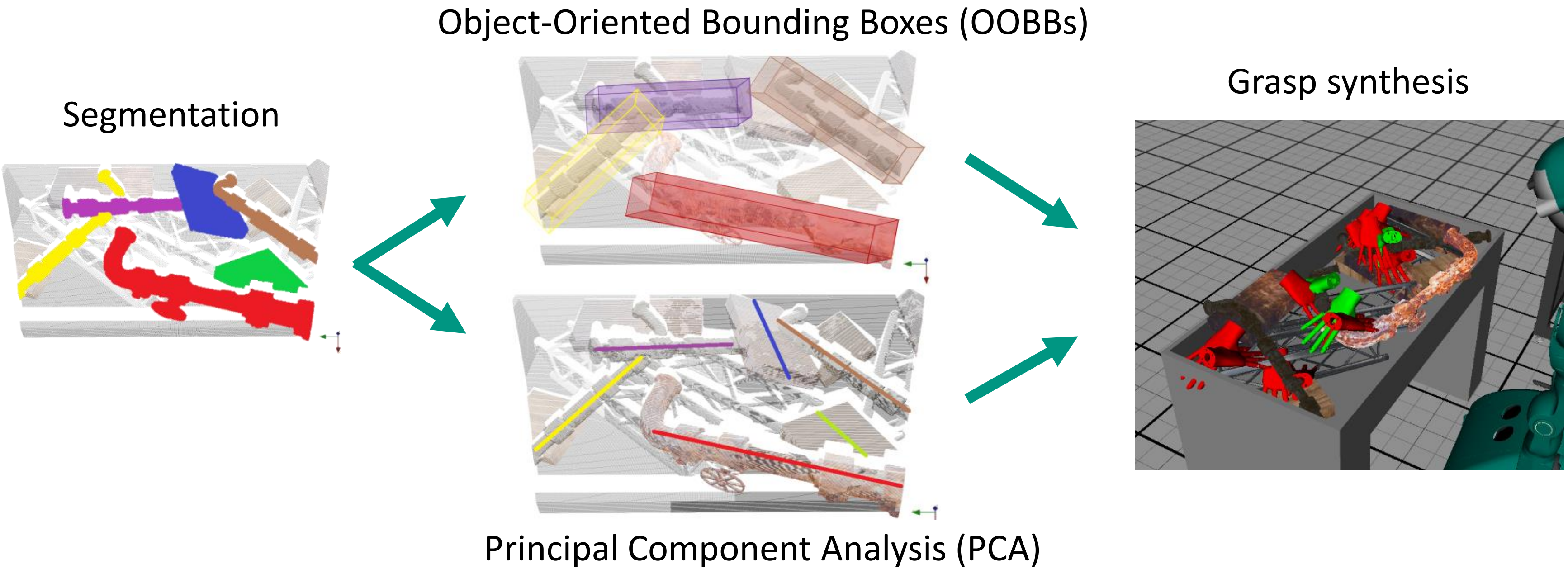


- Completed shape allows grasp planning, but inaccuracies must be expected and handled

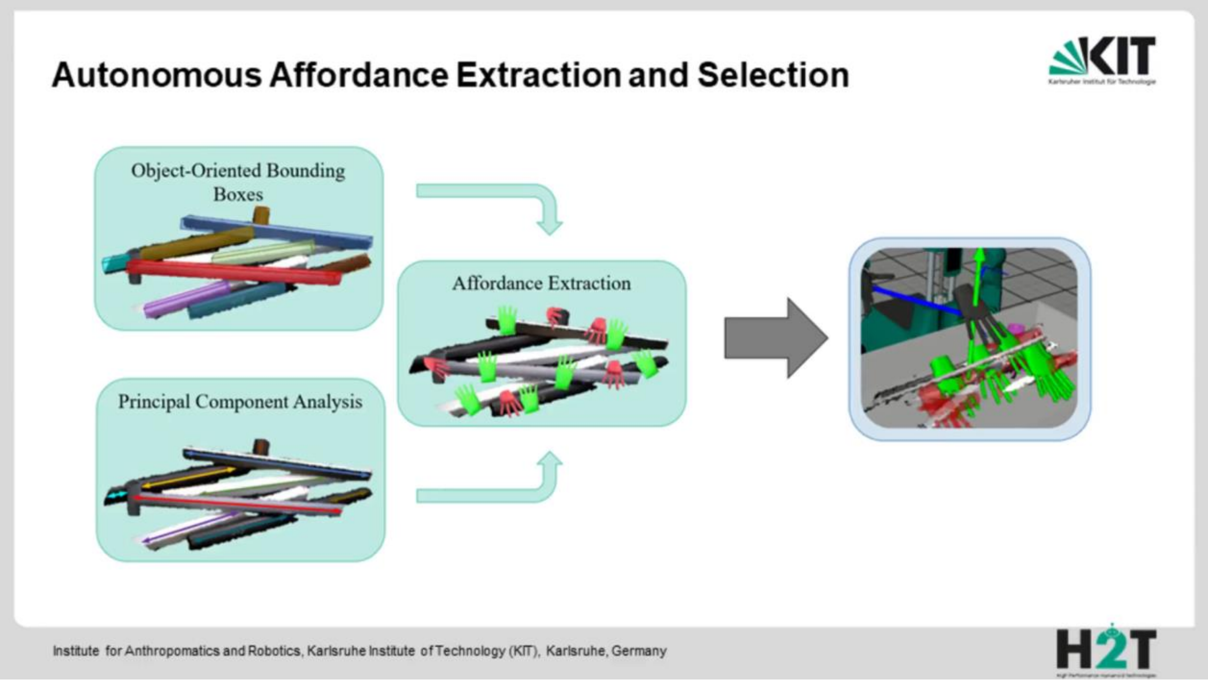


Grasp Synthesis using Primitive Fitting and PCA

- **Preprocessing:** Point Cloud filtering and region growing segmentation
- **Grasp synthesis** using primitive fitting and principal component analysis

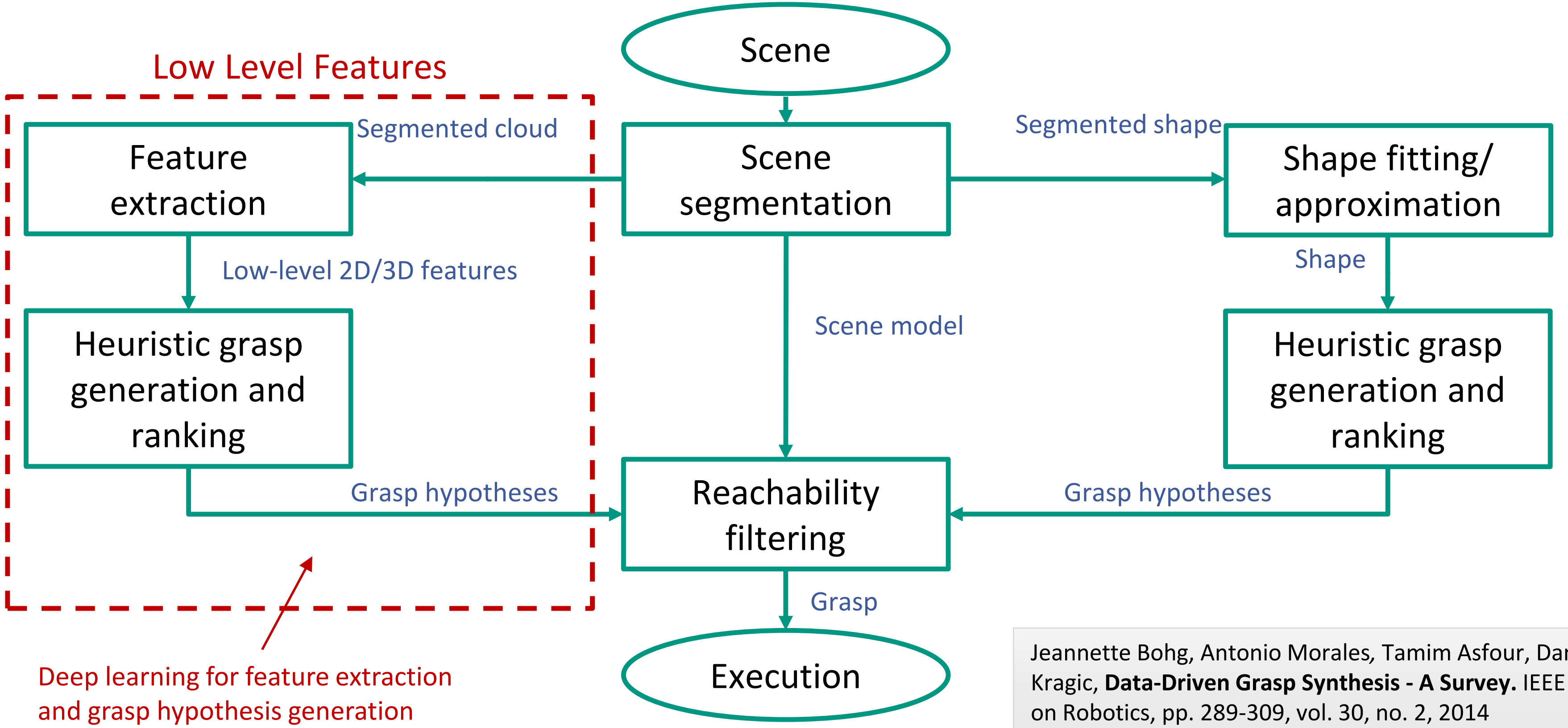


Grasp Synthesis using Primitive Fitting and PCA



Pohl, C., Hitzler, K., Grimm, R., Zea, A., Hanebeck, U. D. and Asfour, T., *Affordance-Based Grasping and Manipulation in Real World Applications*, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), pp. 9569-9576, October, 2020

Grasping Unknown Objects: Flow-Chart



Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, **Data-Driven Grasp Synthesis - A Survey.** IEEE Tran. on Robotics, pp. 289-309, vol. 30, no. 2, 2014

From Low-Level Features to Grasp Hypotheses

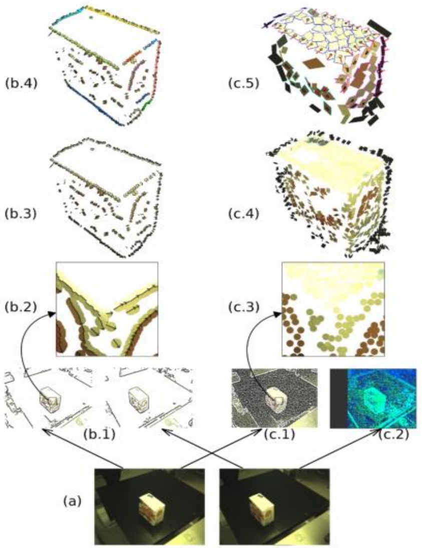
- Step 1: Vision/Image Processing
  - Edge detection
  - Surface detection

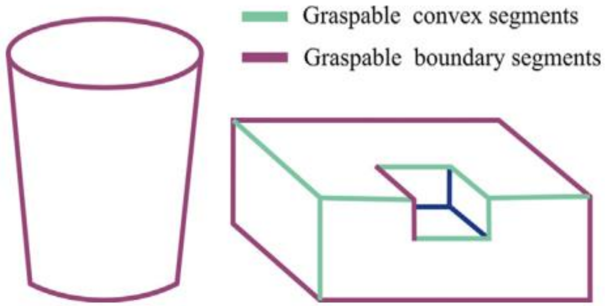
- Step 2: Abstract elements extraction
  - Edge based
  - Surface based

- Step 3: Geometry analysis for grasping
  - Edge based
  - Surface based

From Low-Level Features to Grasp Hypotheses 2/2

- Early Cognitive Vision (ECV) based Elementary Grasping Action (EGA) (Kraft et al. 2009, Popovic et al. 2011)
- Graspable Boundary and Convex Segments (Ala et al. 2015)





Early Cognitive Vision based Elementary Grasping Action (I)

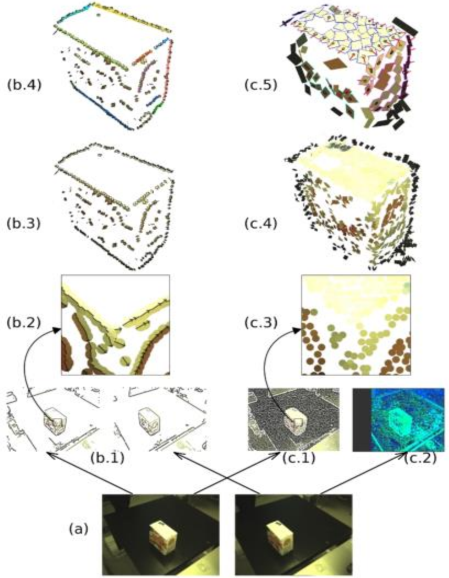
- Hierarchical ECV system (Step 1: Vision/Image Processing)

3D contours

3D line segments

2D line segments

- Proximity
- Collinearity
- Co-circularity
- Similar appearance



3D surflings

3D texlets

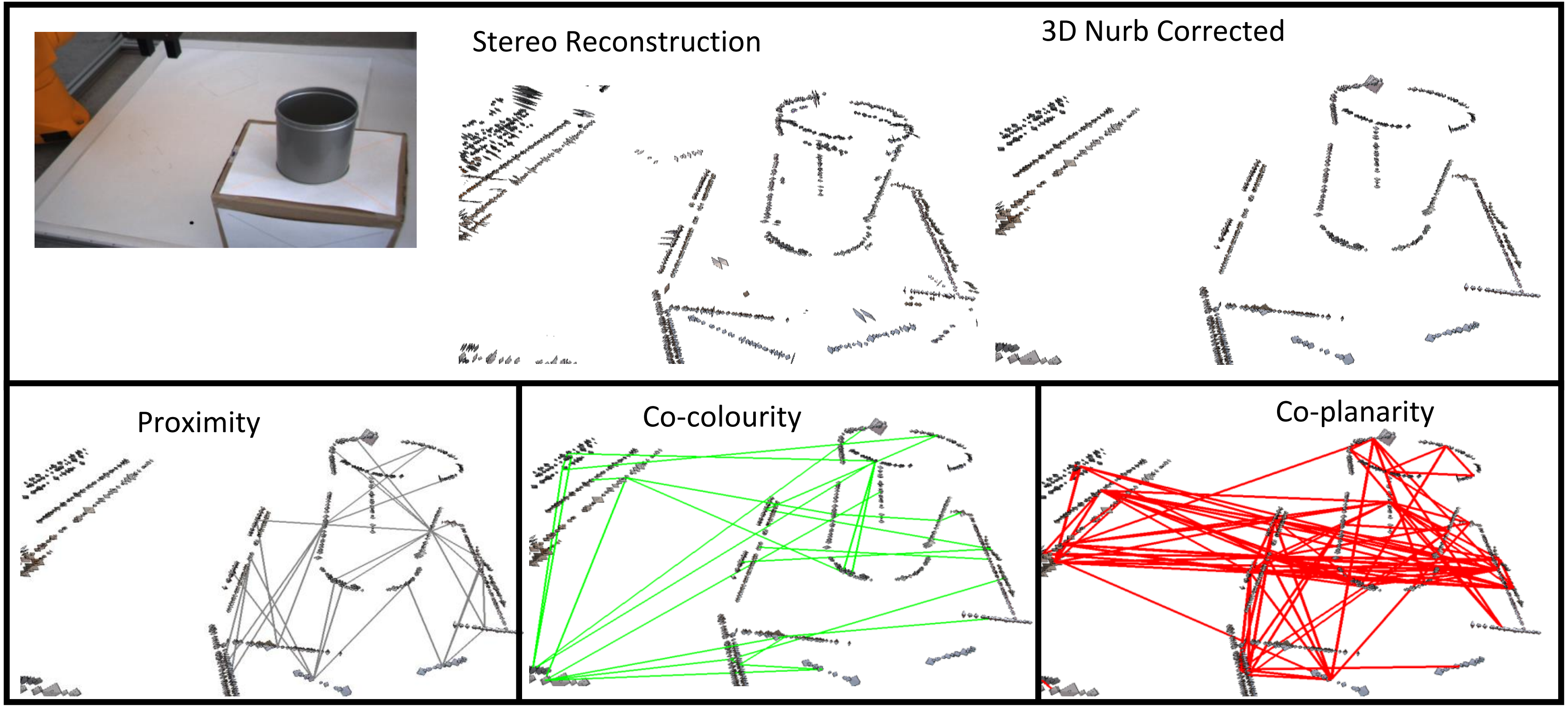
2D texlets

- Color
- Position
- Orientation

Dirk Kraft, Renaud Detry, Nicolas Pugeault, Emre Baseski, Justus Piater, Norbert Krüger, **Learning objects and grasp affordances through autonomous exploration**. International Conference on Computer Vision Systems, pp. 235-244, 2009

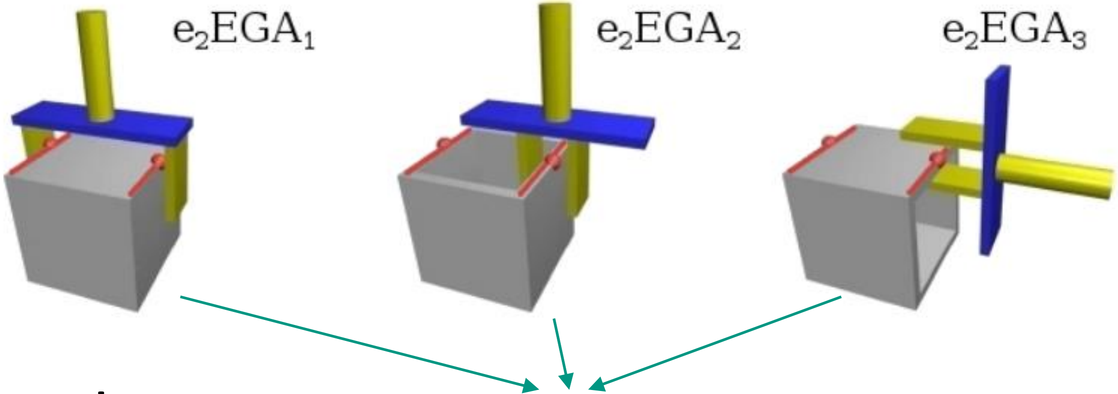
Mila Popović, Dirk Kraft, Leon Bodenhagen, Emre Başeski, Nicolas Pugeault, Danica Kragic, Tamim Asfour, Norbert Krüger, **A strategy for grasping unknown objects based on co-planarity and colour information**. Robotics and Autonomous Systems, pp. 551-565, vol. 58, no. 5, 2010

Early Cognitive Vision based Elementary Grasping Action (II)



Early Cognitive Vision based Elementary Grasping Action (III)

- Edge Elementary Grasping Action (eEGA)
  - Extract abstract contours (Step 2: Abtract elements extraction)
  - Generate edge based grasping actions (Step 3: Geometry analysis for grasping)

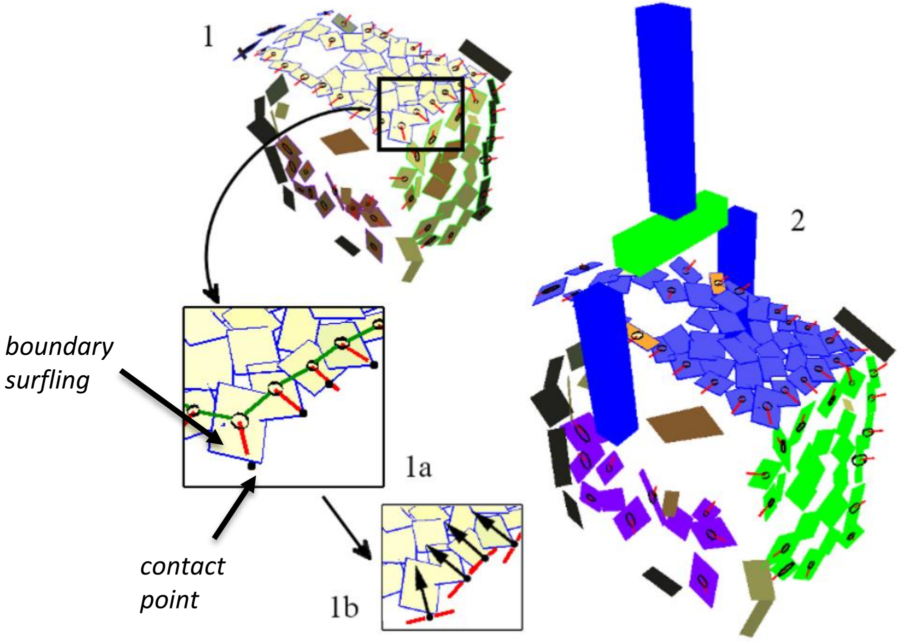


Geometry Analysis

Find a pair of contours with similar properties (co-planarity and co-colority)

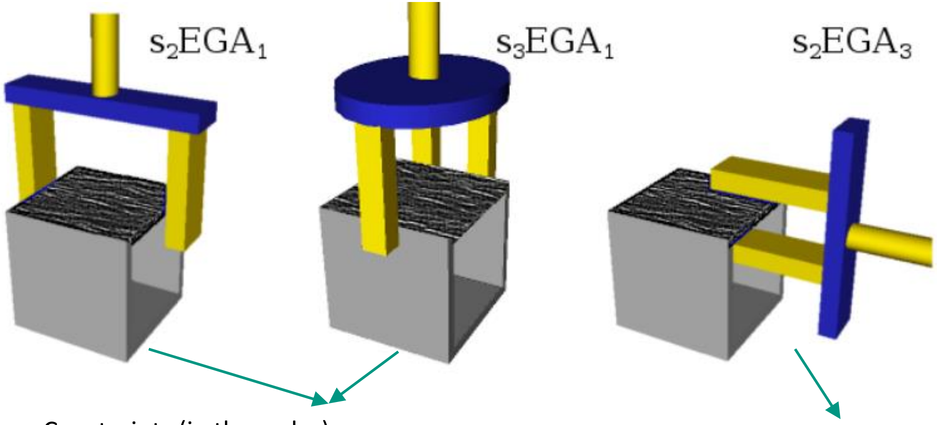
Early Cognitive Vision based Elementary Grasping Action (IV)

- Surface Elementary Grasping Actions (sEGA)
  - Contact points extraction (Step 2: Abtract elements extraction)



Early Cognitive Vision based Elementary Grasping Action (V)

- Surface Elementary Grasping Actions
  - Contact points extraction (Step 2: Abtract elements extraction)
  - Contact points selection (Step 3: Geometry analysis for grasping)



Geometry Analysis

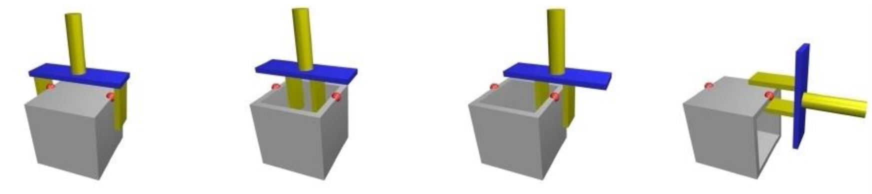
Constraints (in the order):

1. Contact combinations are too far apart;
2. The angle between contact normal and direction of the force (stable grasping);

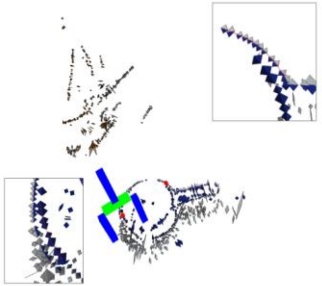
Pinch grasps: any contact points generate a valid grasping attempt

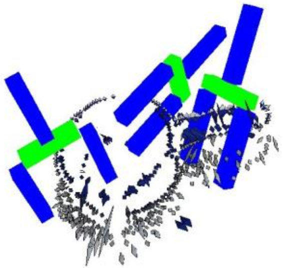
Early Cognitive Vision based Elementary Grasping Action (VI)

- ’Grasping Reflex’ based on Co-planarity

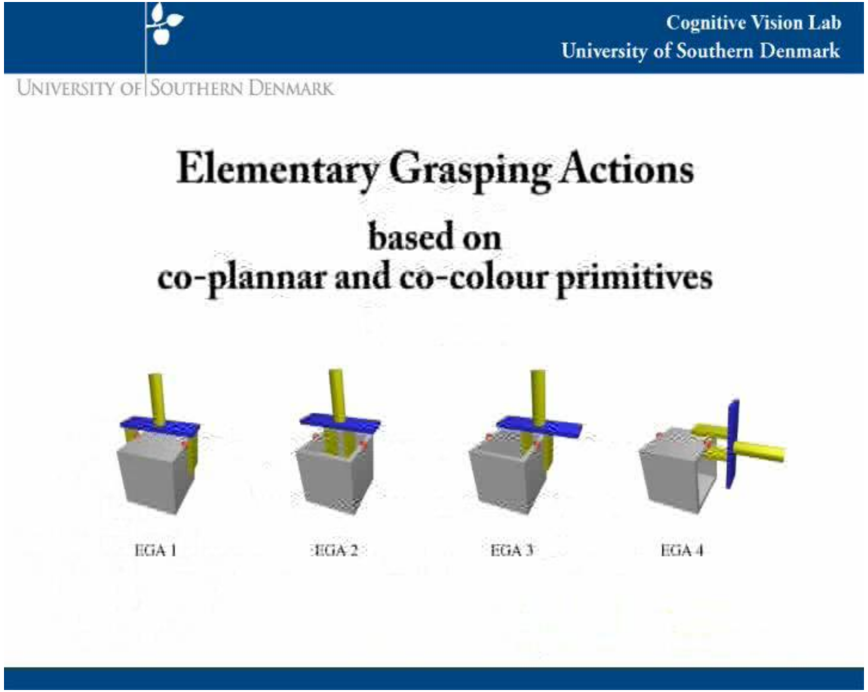


EGA 1 EGA 2 EGA 3 EGA 4



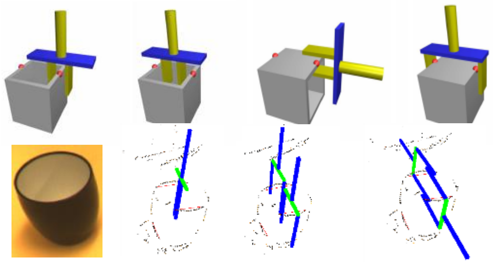


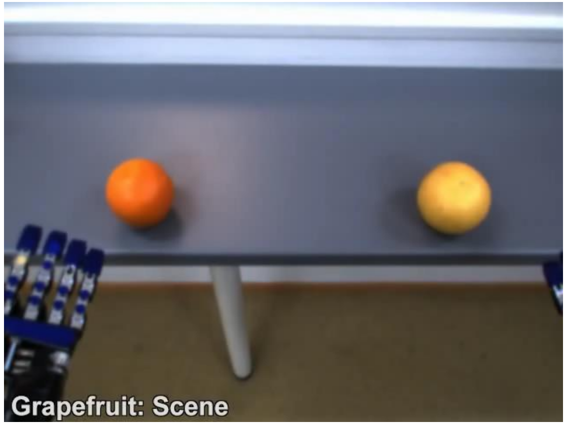
Early Cognitive Vision based Elementary Grasping Action (VII)



Early Cognitive Vision based Elementary Grasping Action (VIII)

- 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 the 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

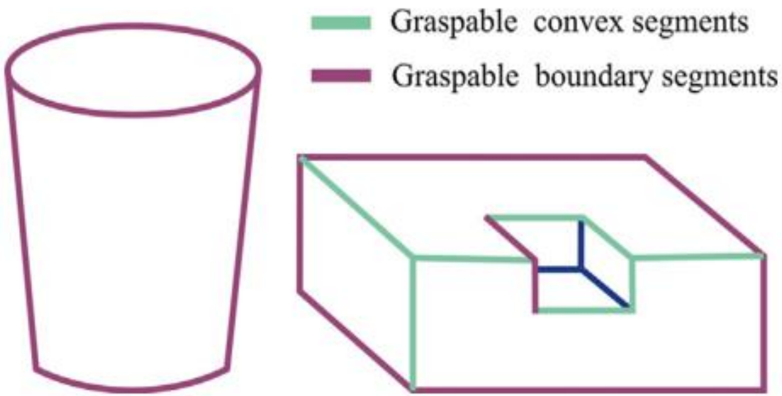




Joint work with Norbert Krüger, Dirk Kraft and Mila Popovic, University of Southern Denmark

Graspable Boundary and Convex Segments (I)

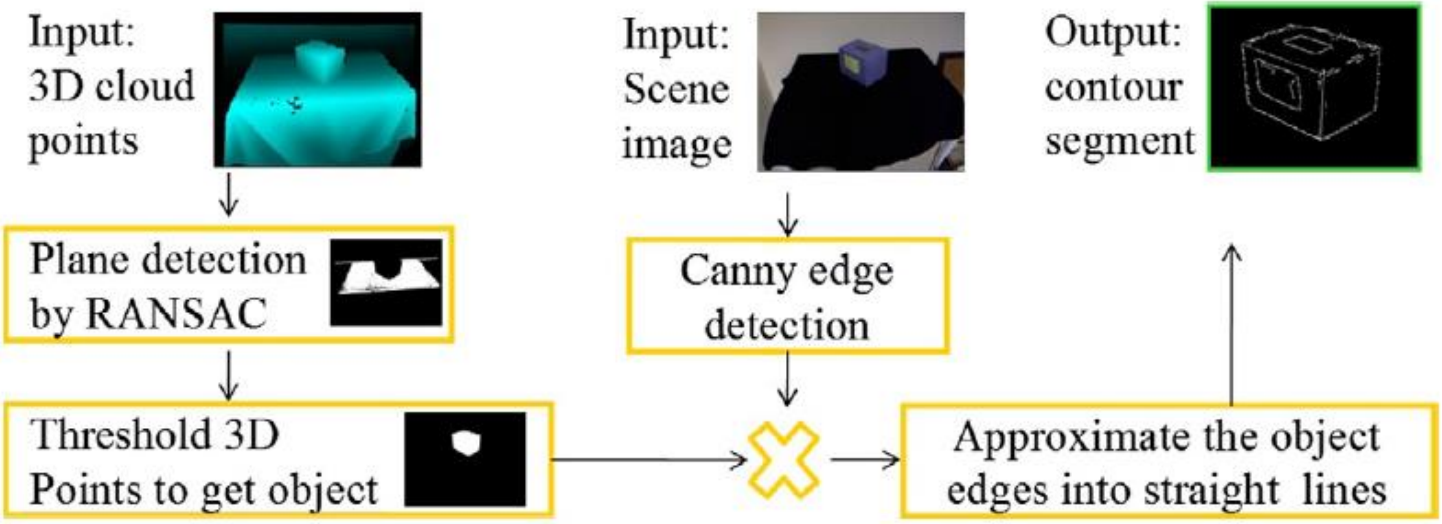
- Grasplet
  - Graspable boundary segment: A segment that corresponds to a 3D spatial discontinuity.
  - Graspable convex segment: A segment along which the angle between the two faces forming the segment is greater than 180 deg.



RajeshKanna Ala, Dong Hwan Kim, Sung Yul Shin, ChangHwan Kim, Sung-Kee Park, **A 3D-grasp synthesis algorithm to grasp unknown objects basedon graspable boundary and convex segments.** Information Sciences, vol. 295, pp. 91-106, 2015

Graspable Boundary and Convex Segments (II)

- Contour segments (Step 1: Vision/Image Processing)

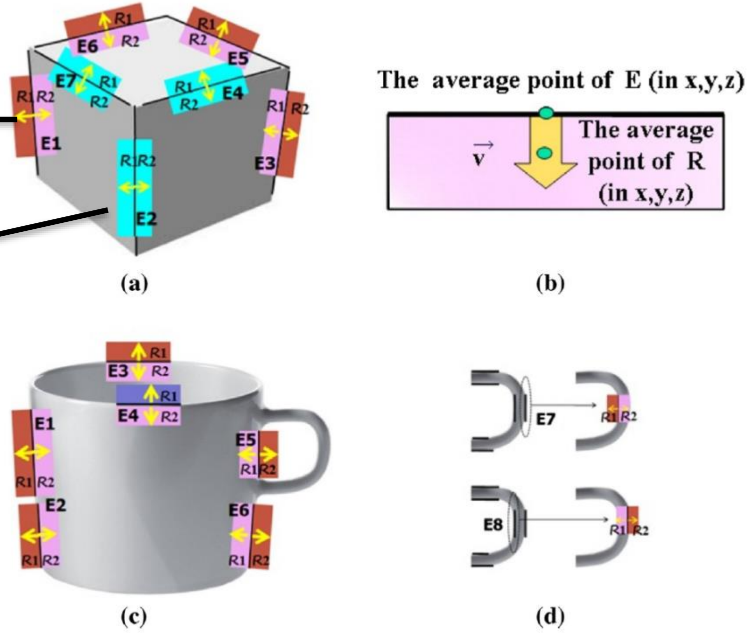


Graspable Boundary and Convex Segments (III)

- Grasplets extraction (Step 2: Abtract elements extraction)

graspable boundary segment

graspable convex segment



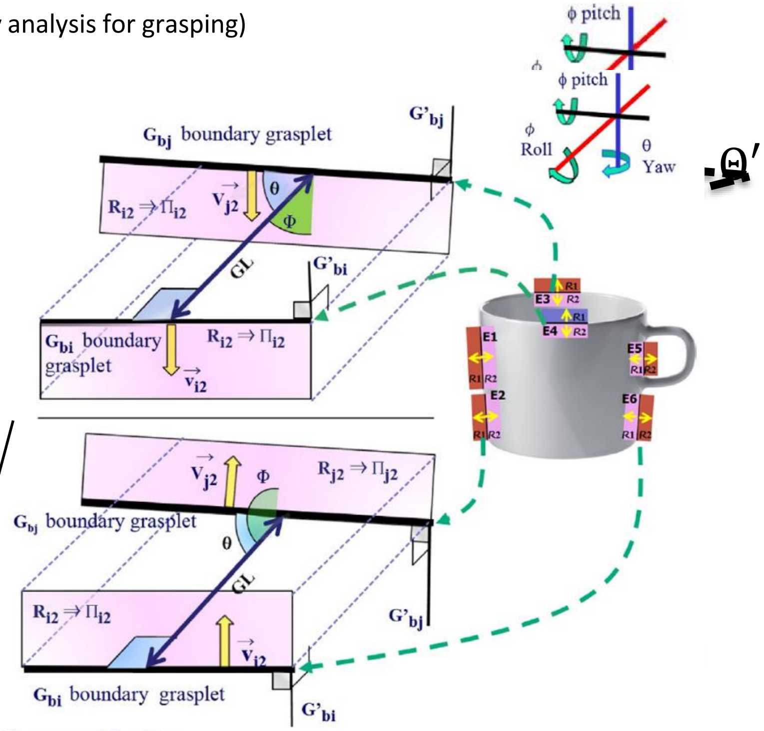
Graspable Boundary and Convex Segments (IV)

- Grasping generation (Step 3: Geometry analysis for grasping)

Steps:

1. Draw line
   - $GL\ s.t.\ GL \perp G_{ni}, GL \perp G_{nj}$
   - $G'_{ni}\ s.t.\ G'_{ni} \perp GL, G'_{ni} \perp G_{ni}$
   - $G'_{nj}\ s.t.\ G'_{nj} \perp GL, G'_{nj} \perp G_{nj}$
2. Calculate angles
   - $\theta' \ \coloneqq\ \angle G_{nj}, GL$
   - $\Theta' \ \coloneqq\ \angle G'_{ni}, G'_{nj}$
   - $\phi' \ \coloneqq\ \angle \Pi_{im}, \Pi_{jm}$
3. Grasping decision

   $\theta' \approx 90^o, \Theta' \approx 0^o, \phi' \approx 180^o$
   - $\vec{V}_{im}$ and $\vec{V}_{jm}$ are inward and in opposite direction => PLANAR grasp
   - $\vec{V}_{im}$ and $\vec{V}_{jm}$ are parallel and in same direction => PARALLEL grasp



Machine Learning Approaches

Deep Learning Approaches to Grasp Synthesis: A Review

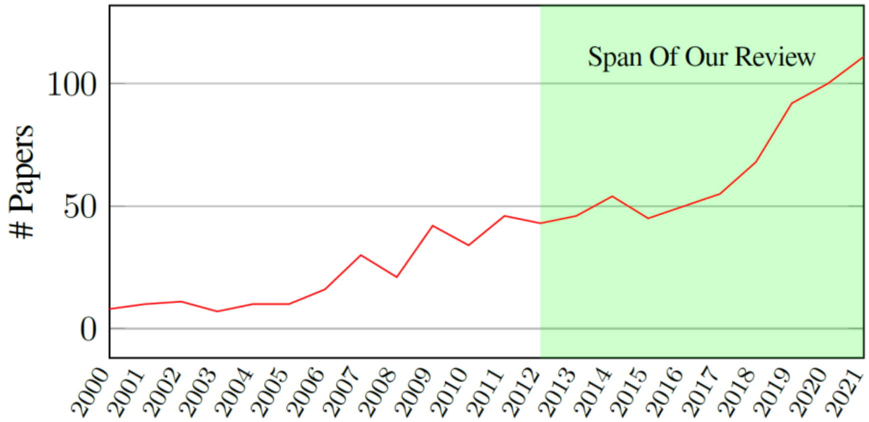


Fig. 4: The number of publications on IEEExplore that includes the keyword "Grasping" in metadata and "6DoF" in the full text is increasing year-by-year. We consider works published after Jan 1, 2012 – when AlexNet [34] was published – in our review.

Rhys Newbury, Morris Gu, Lachlan Chumbley, Arsalan Mousavian, Clemens Eppner, Jürgen Leitner, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, Dieter Fox, Akansel Cosgun. **Deep Learning Approaches to Grasp Synthesis: A Review.** Transactions on Robotics, 2023

Deep Learning Approaches to Grasp Synthesis: A Review

- Core topics in the survey
  - Main Methods
  - Supporting methods
  - Dataset Design
  - Benchmarking

Rhys Newbury, Morris Gu, Lachlan Chumbley, Arsalan Mousavian, Clemens Eppner, Jürgen Leitner, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, Dieter Fox, Akansel Cosgun. **Deep Learning Approaches to Grasp Synthesis: A Review.** Transactions on Robotics, 2023

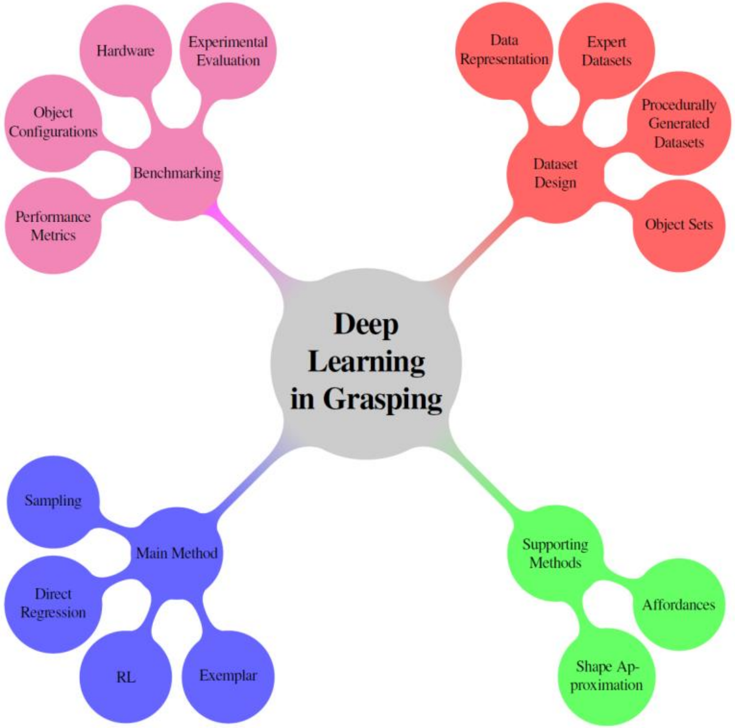


Fig. 5: A visual representation of the core topics covered in this systematic survey.

Training Data for Grasping

- Every learning approach depends on the training data
- What sources of data are available in the case of grasping?

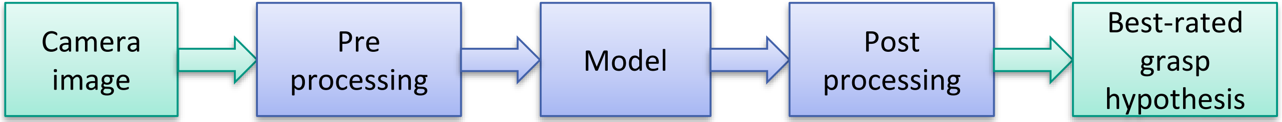
- **Learning by demonstration**
  - Human teacher record grasping data with motion capture and data gloves
- **Training data collection on the target system**
  - Trial and error on the target system
  - Data is collected while the grasps are executed and strategy is refined (reinforcement learning)
- **Training data generation in simulation**
  - Simulate grasps kinematics with grasp metrics
  - Simulate the whole robot/object dynamics with a dynamic simulator
- **Hand-labeled data**

Deep learning approaches for grasping

- **Learning by demonstration**
- **Grasp hypothesis generation and scoring**
  - Generation of datasets in simulation
  - Hand-labeled datasets
  - **Direct regression, discriminative approaches, heat maps**
- **Sim2real**
  - Reinforcement learning
  - Domain randomization
  - Domain adaptation, generative adversarial models
- **Learning on the target system**
  - Reinforcement learning

Grasp hypothesis generation and scoring

- The starting point for the learning is a dataset
- Each entry in the dataset consists of a
  - Camera image (RGB or RGBD) or point cloud
  - Hand pose
  - Hand configuration
  - Tactile information (sometimes)
  - Grasp score
- Grasp hypothesis generation pipeline
  - Pre-processing
  - Model inference
  - Post processing



Regression Approach

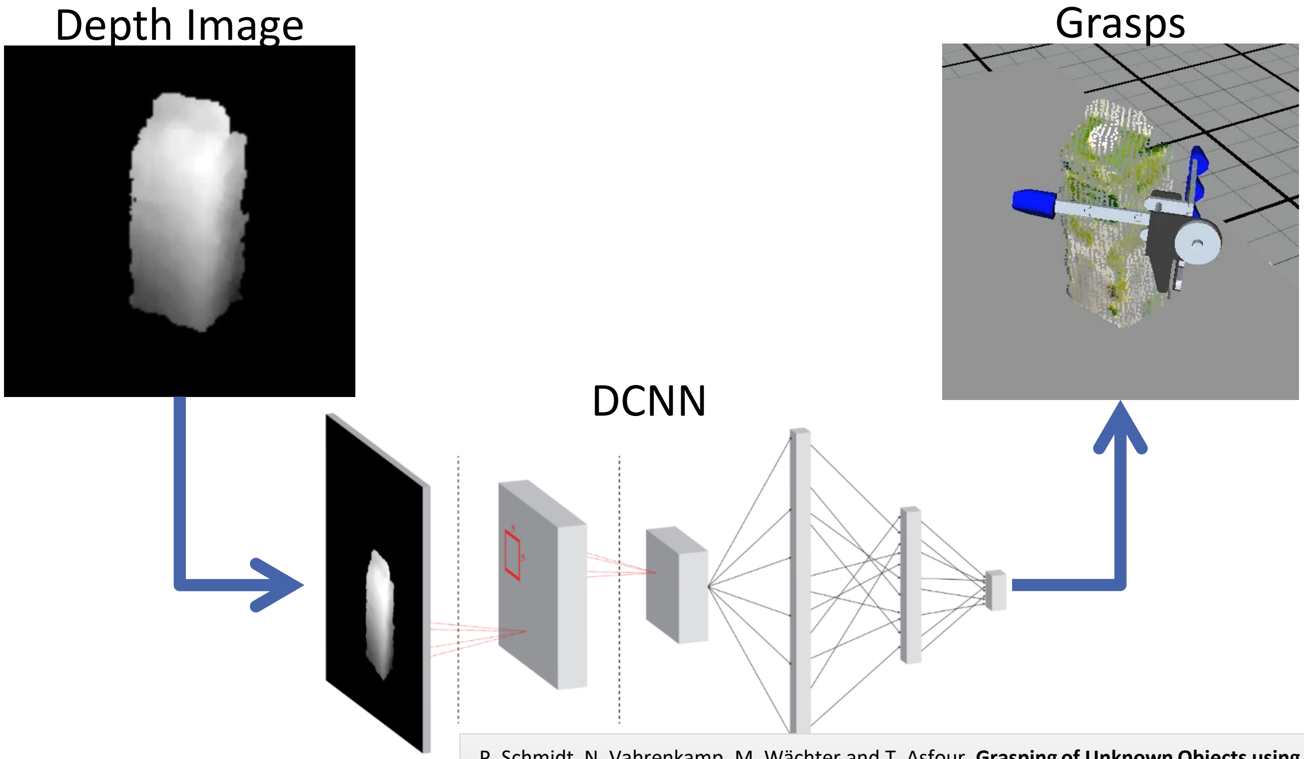
- Regression approaches are straightforward when it comes to deep learning for grasping
- **Idea/Approach:**
  - No pre/post processing
  - Directly feed camera images into the network and predict the best grasp

Camera image → Neural network → Best-rated grasp hypothesis

- Common network architecture
  - Convolutional layers, followed by some fully connected (FC) layers

Camera image → conv → conv → FC → FC → Grasp pose

Regression Approach: Deep Grasping (I)

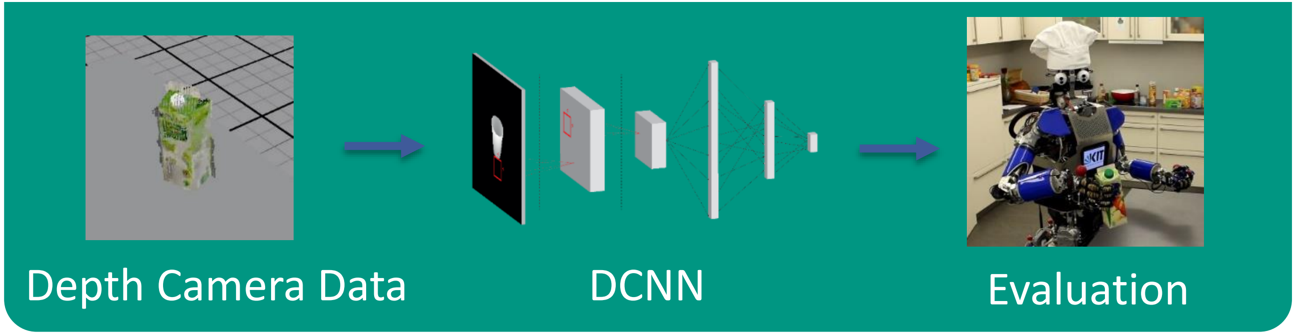


P. Schmidt, N. Vahrenkamp, M. Wächter and T. Asfour, **Grasping of Unknown Objects using Deep Convolutional Neural Networks based on Depth Images**, IEEE International Conference on Robotics and Automation (ICRA), 2018

Regression Approach: Deep Grasping (II)

- Training

- Execution

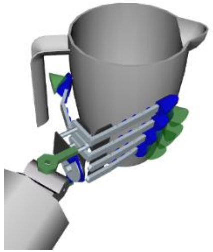


Regression Approach: Deep Grasping (III)

- KIT object models database
- Yale-CMU-Berkeley object and model set

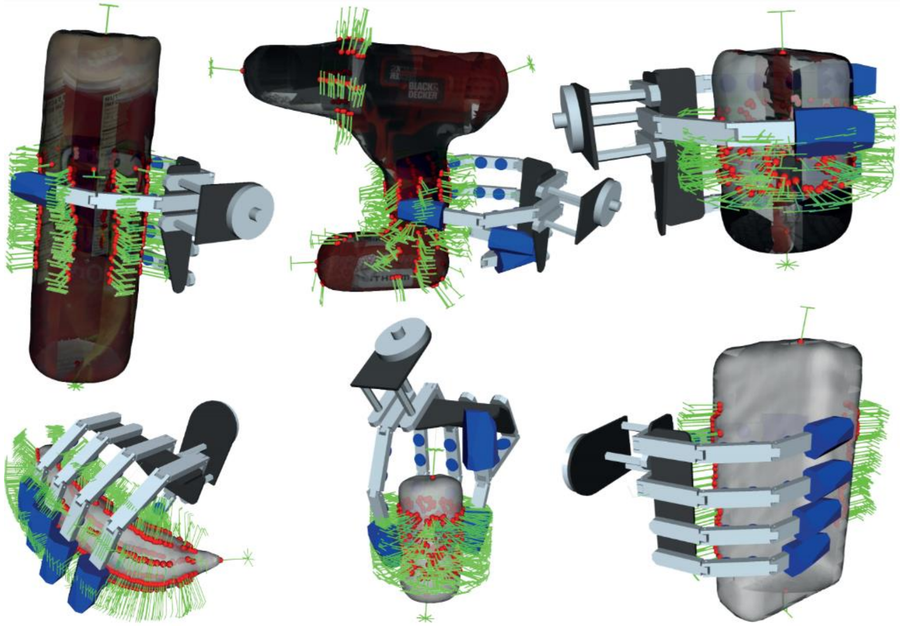
Regression Approach: Deep Grasping (IV)

- Simox Skeleton Grasp Planner



$$\begin{pmatrix} x \\ y \\ z \\ roll \\ pitch \\ yaw \end{pmatrix}$$

- 12 objects
- 250 grasps each

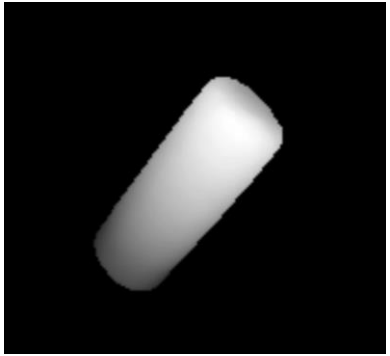


Regression Approach: Deep Grasping (V)

- ArmarX Simulation
- Rendered depth images of the training objects
  - Objects placed in front of camera and rotated randomly
  - Small random offset in distance
- Selection of suitable grasp:
  - Golden grasp Φ (reference grasp; manual)
  - Available grasps Θ_i
  - Normalisers θ and ω
  - Penalty Metric:

$$\Psi_i = \frac{\|\Theta_i - \Phi\|}{\theta} + \frac{axisAngle(\Theta_i, \Phi)}{\omega}$$

  - **For current object pose, determine grasp $\boldsymbol{\Theta} \in \boldsymbol{\Theta}_i$ which is most similar to $\boldsymbol{\Phi}$**



Regression Approach: Deep Grasping (VI)

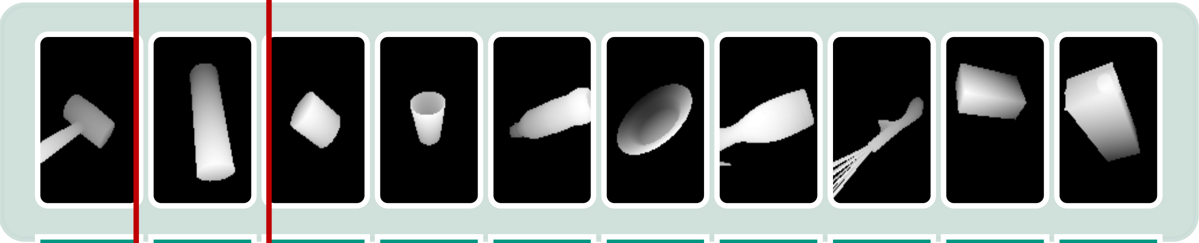
Karlsruher Institut für Technologie

- Training Dataset

12 objects; 5.000 samples per object -> 60.000 samples

~10GB of training data

Depth Image



x	5	3	34	10	5	45	20	10	3	5	…
y	23	-10	90	56	23	23	-40	56	-10	23	
z	512	456	550	434	512	499	550	434	456	512	
r	15°	78°	10°	4°	15°	30°	41°	4°	78°	15°	
p	45°	12°	23°	34°	45°	56°	-10°	34°	12°	45°	
y	11°	35°	56°	110°	11°	21°	30°	110°	35°	11°	

single training sample

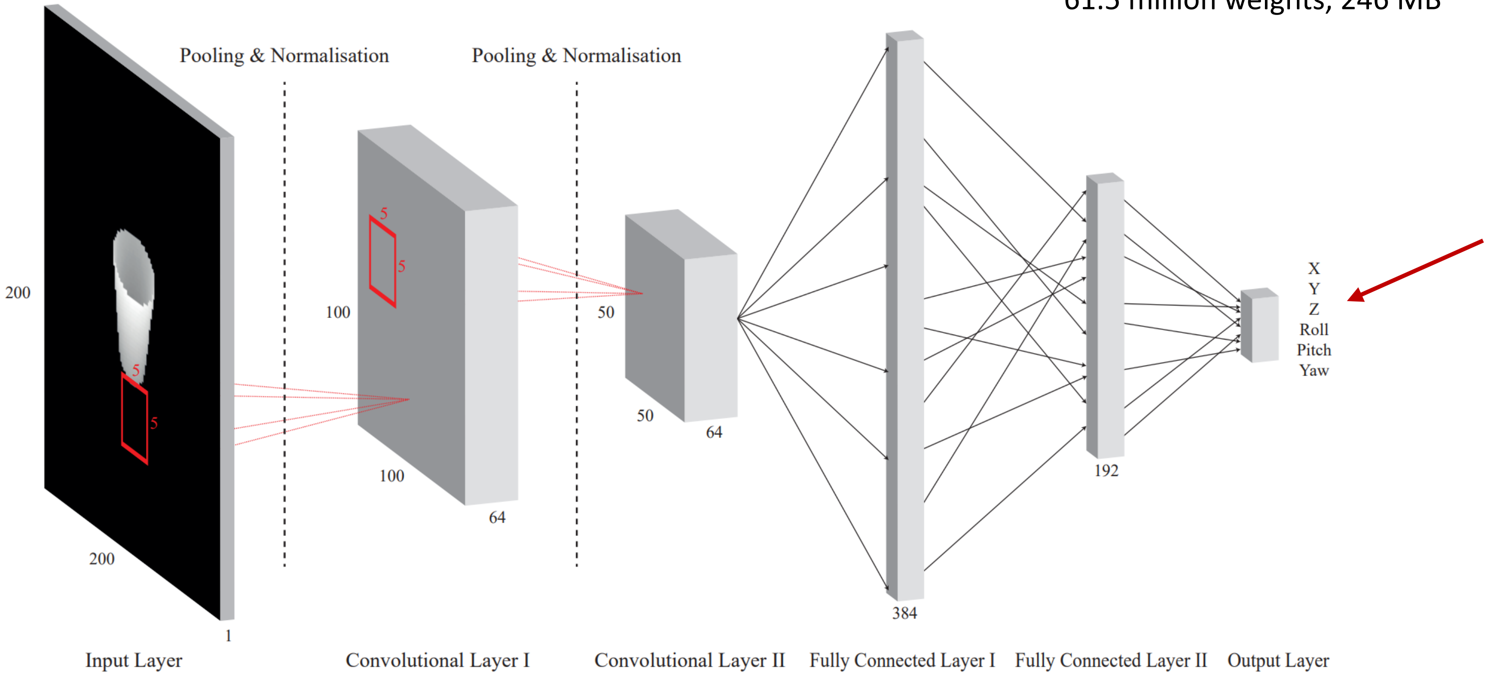
Grasp Configuration (camera transformed)

H2T

Regression Approach: Deep Grasping (VII)

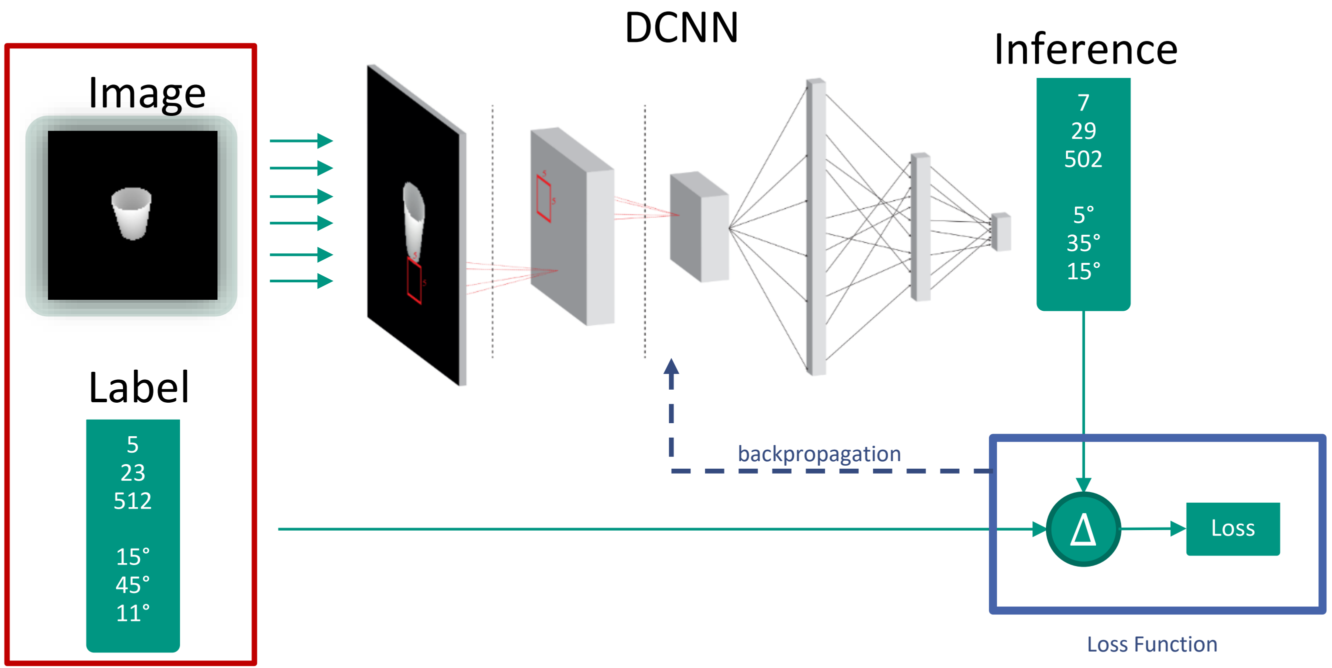
- Architecture

61.5 million weights, 246 MB



Regression Approach: Deep Grasping (VIII)

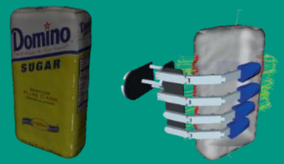
- Training

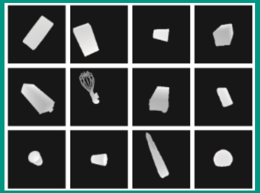


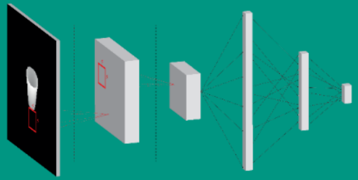
single training sample

Regression Approach: Deep Grasping (IX)

- **Training**

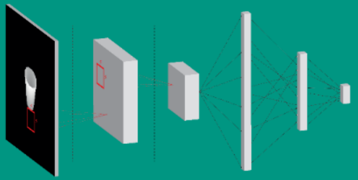






Objects and Grasp Information → Dataset → DCNN

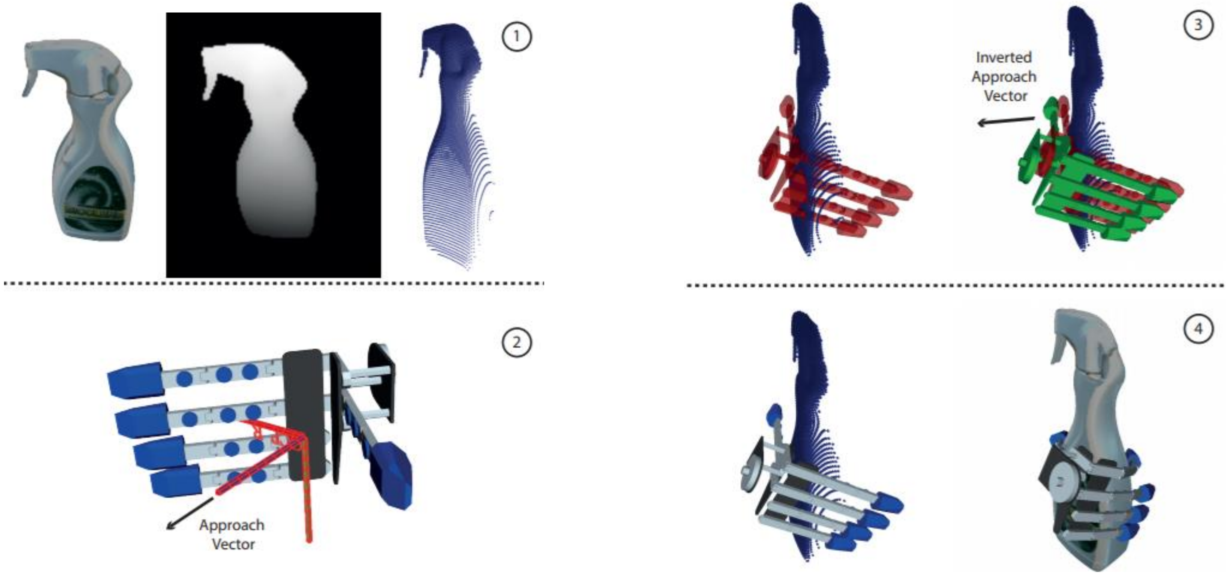
- **Execution**



Depth Camera Data → DCNN → Evaluation

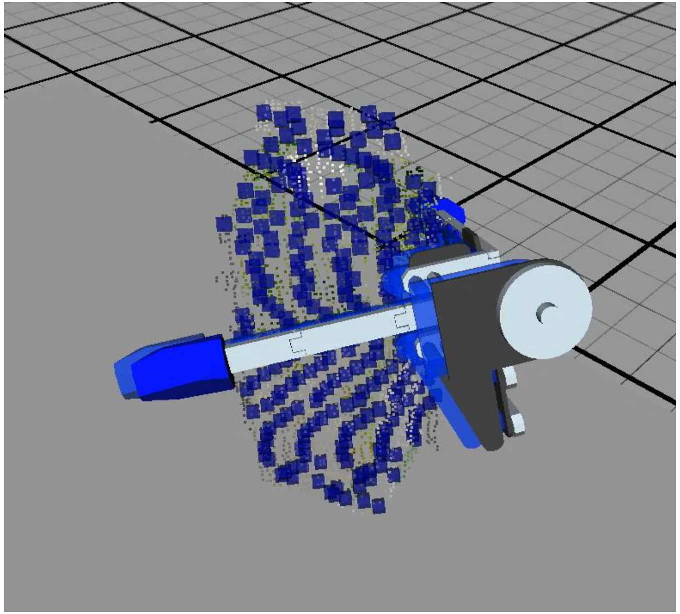
Regression Approach: Deep Grasping (X)

- Post Processing
- Approach Vector Post Processing (AVPP): uses **only** raw data and collsion model of th hand



Regression Approach: Deep Grasping (X)

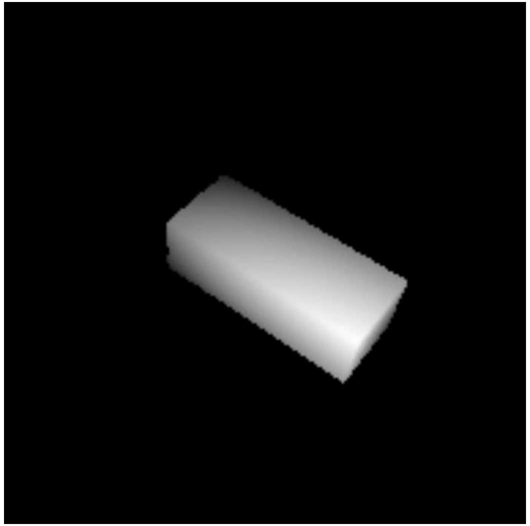
- Post Processing
- Approach Vector Post Processing (AVPP): uses **only** raw data and collsion model of the hand

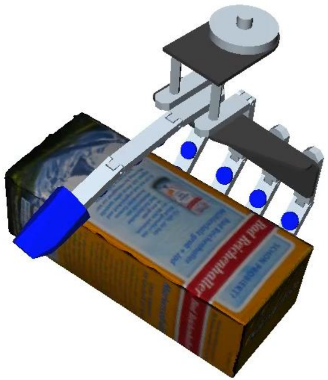


Regression Approach: Deep Grasping (XI)

- Evaluation in simulation: Force Closure Analysis in Simox

Input → Analysis of Inference



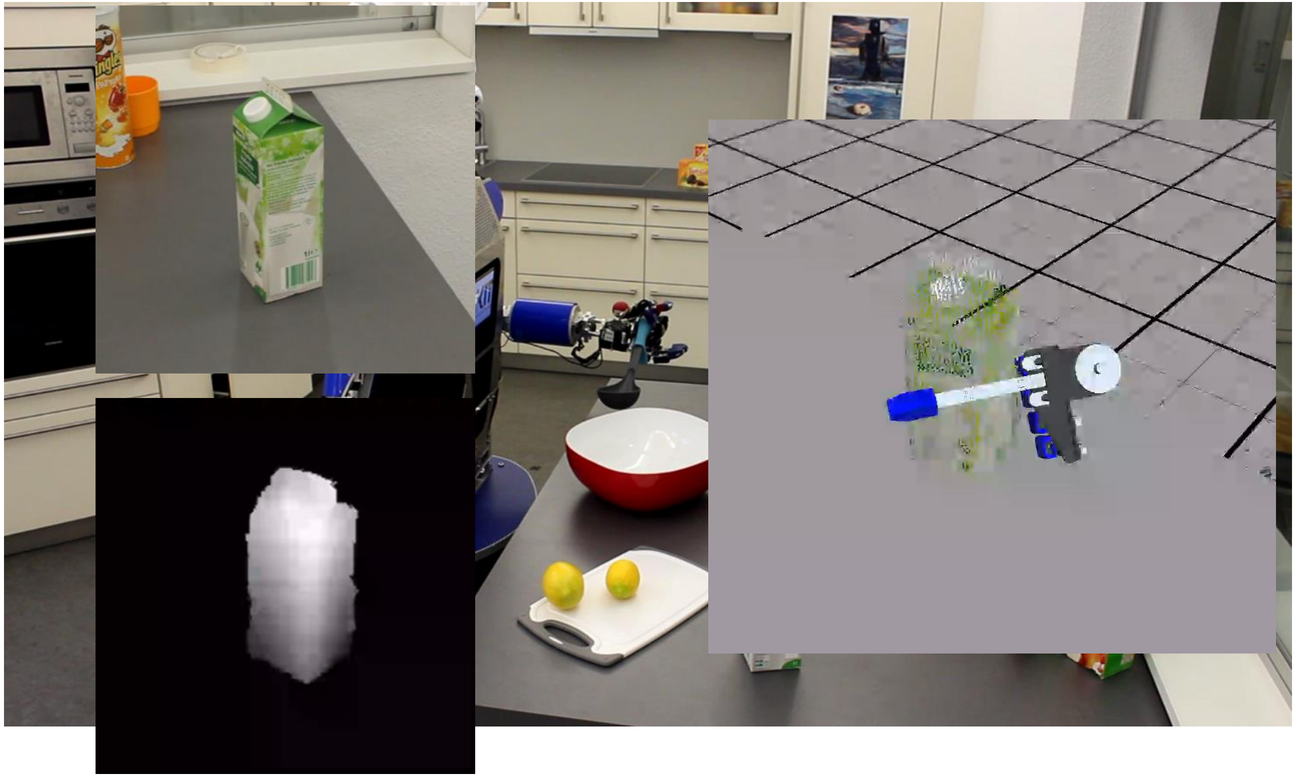


Regression Approach: Deep Grasping (XII)

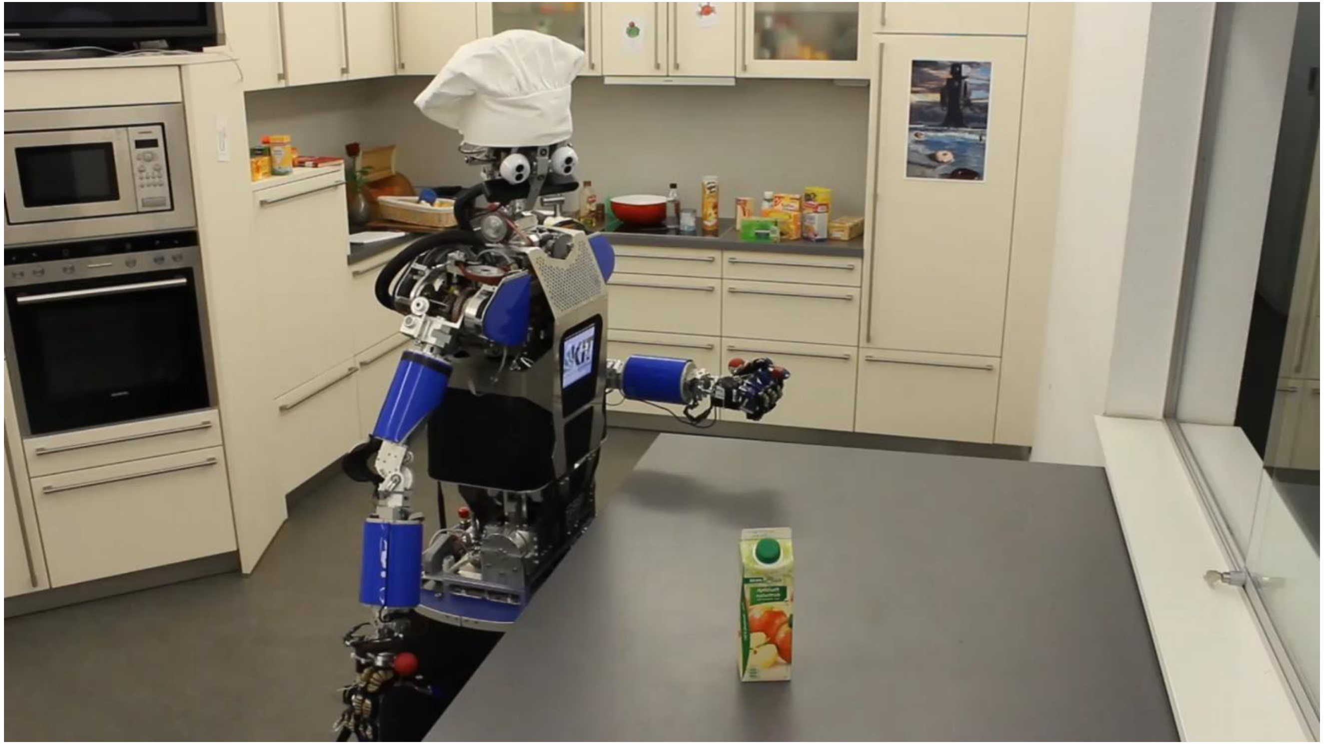
- 256 grasps per object
- Objects were not previously included in training

Object	Force-Closure	AVPP necessary
salt	71,88%	86,72%
oil	70,31%	91,02%
appletea	57,42%	82,81%
softball	100%	49,22%
softcake	36,33%	82,42%
spraybottle	37,5%	73,43%
spam12oz	94,14%	73,05%
tennisball	94,92%	42,58%
bleach	92,58%	85,16%

Regression Approach: Deep Grasping (XIII)

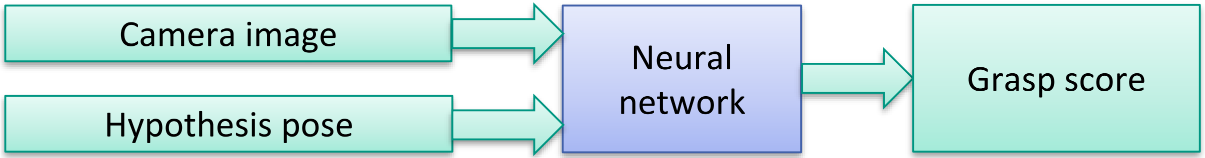


Regression Approach: Deep Grasping (XIV)

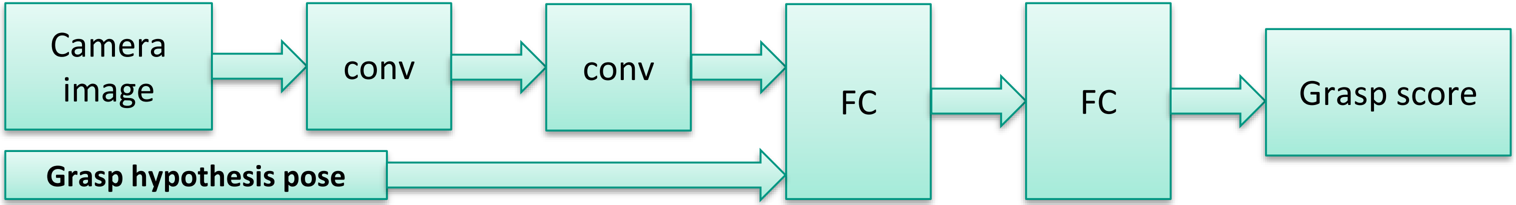


Discriminative Approaches

- Discriminative approaches **learn a score for grasp hypothesis** based on sensor data
- **Idea/Approach:**
  - Neural Network estimates the quality of a grasp based on incomplete information
  - Assumption: Network will learn to internally complete the missing information

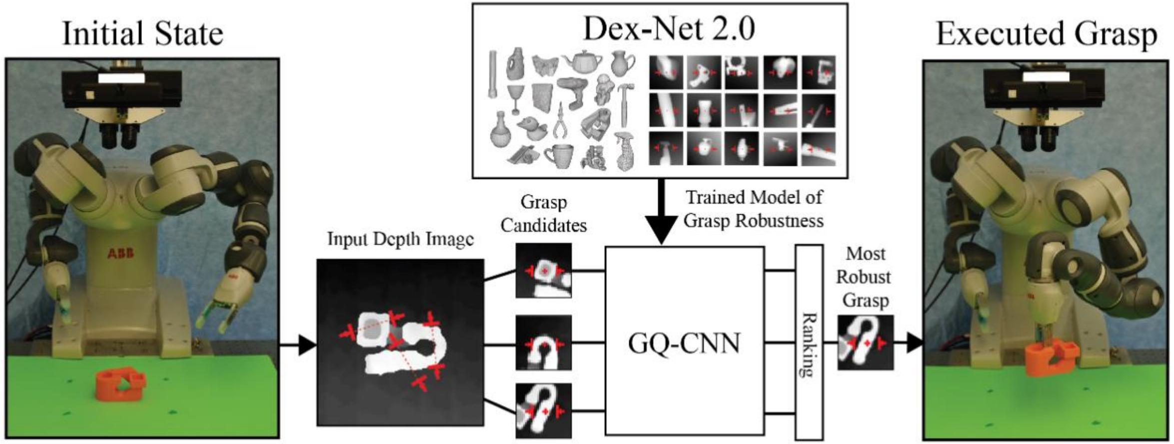


- Common network architecture
  - Convolutional layers, followed by fully connected (FC) layers



Discriminative Approach: Dex-Net 2.0 (I)

- Generate grasp hypothesis/candidates
- Score candidates with grasp quality CNN
- Select best-rated grasp candidate for execution



Dex-Net 2.0: Deep Learning to Plan Robust Grasps with Synthetic Point Clouds and Analytic Grasp Metrics, Mahler et al., ICRA 2015

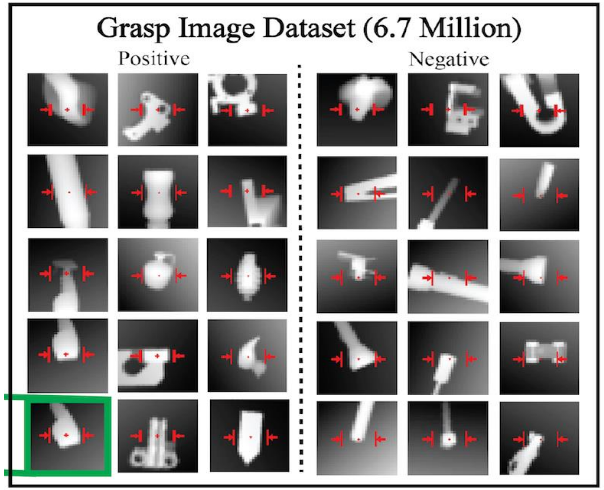
Discriminative Approach: Dex-Net 2.0 (II)

- How to generate grasp candidates?
- Here: Gripper-specific approach

> *"Our grasp candidate model p(u|x) is a uniform distribution over pairs of antipodal contact points on the object surface that form a grasp axis parallel to the table plane"*
> Mahler et al., 2015

- Good grasp candidate generation is problem-specific
- Mostly approached by hand crafted classical algorithms

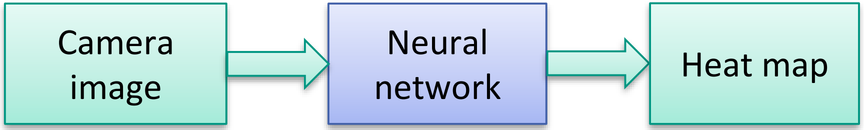
Training data



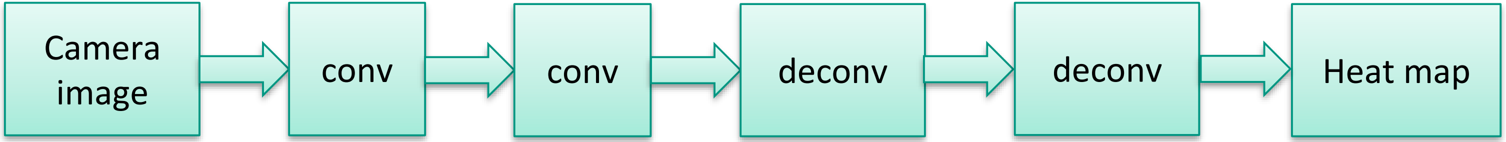
➔ Training data has to contain **positive** and **negative** training samples

Heat Map Approaches

- Heat map based approaches map images to images
- **Idea/Approach:**
  - Rate the grasp quality for **each pixel** in the input image
  - Use image to image techniques from computer vision
  - Select pixel with highest predicted grasp score for execution

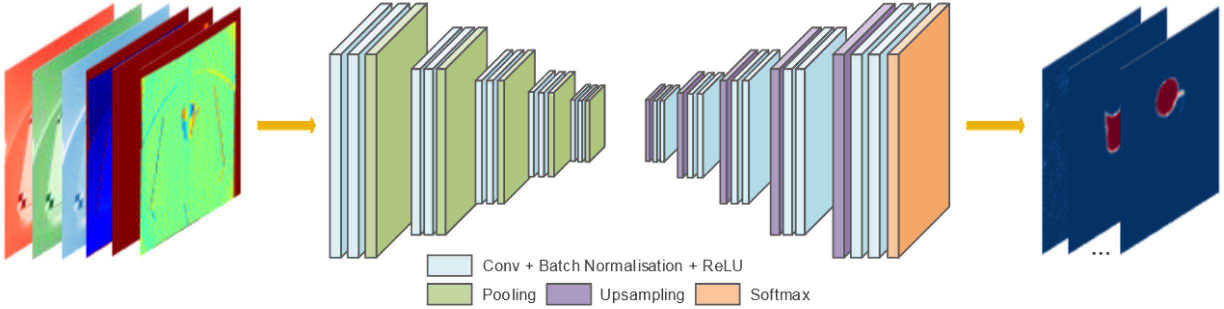


- Common network architecture
  - Convolutional layers, followed by deconvolutional layers



Heat Map Approach: Example (I)

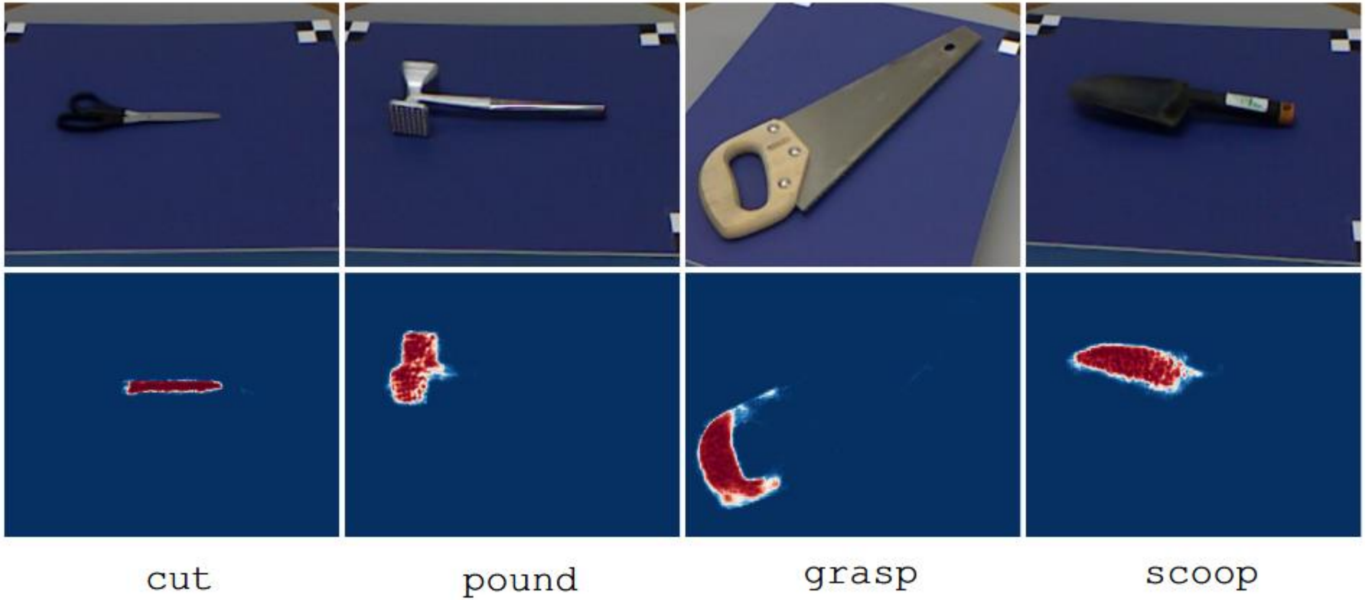
- Input data is represented as multiple modalities from RGB-D image
  - Original RGB image, depth image, ground truth affordance
  - HHA encoding: **H**orizontal disparity, **H**eight above ground, **A**ngle of surface normal with gravity
- The CNN makes use of an encoder-decoder architecture and produces a *k*-channel image of probabilities, where *k* is the number of affordance classes



Anh Nguyen, Dimitrios Kanoulas, Darwin G. Caldwell, and Nikos G. Tsagarakis,
Detecting object affordances with Convolutional Neural Networks, IROS 2016

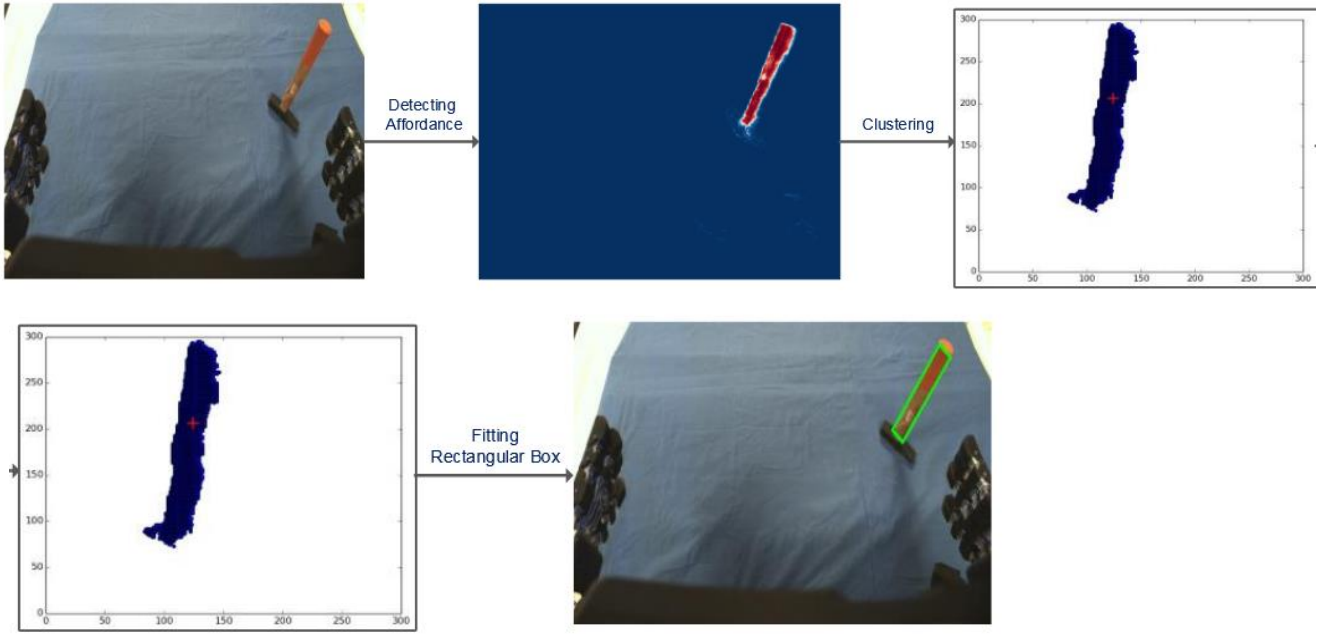
Heat Map Approach: Example (II)

- Affordance prediction results of the CNN



Heat Map Approach: Example (III)

- All points of the detected affordances are clustered and a grasp is represented as a rectangular box



Comparison

Direct Regression

+ Simple structure, no post processing

- Averaging over all grasps

Discriminative

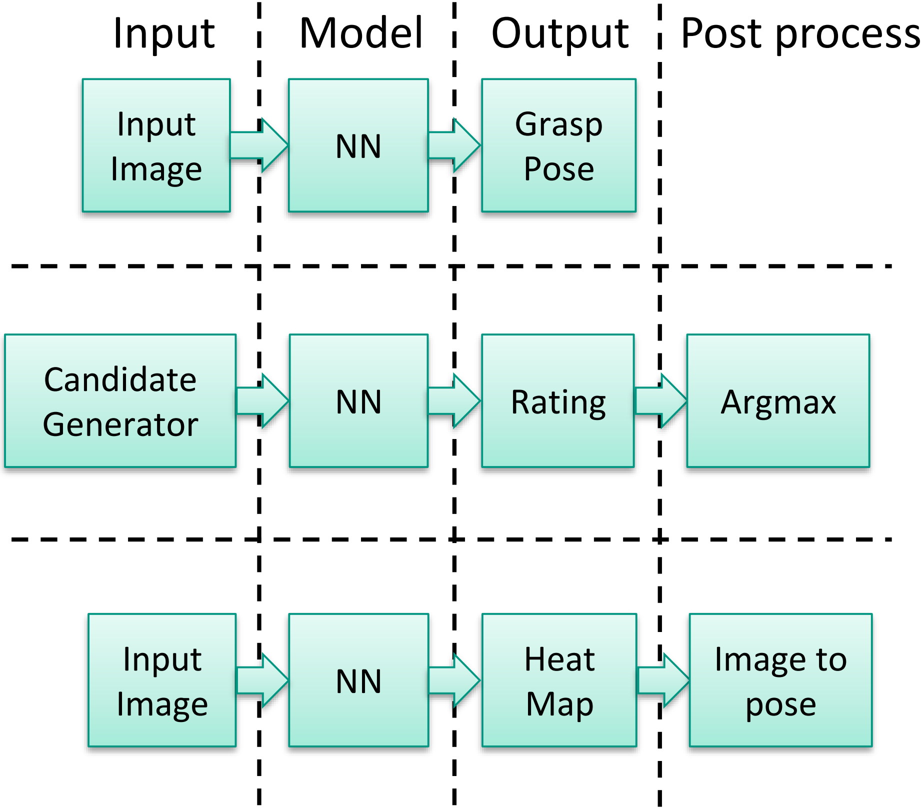
+ Multiple grasps per image

- Candidate generator is problem specific

Heat Map

+ Multiple grasps per image

- Post processing: From image to 6D pose



Review Papers on Grasping

Karlsruher Institut für Technologie

- Antonio Bicchi, Vijay Kumar, **Robotic grasping and contact: A review.** International Conference on Robotics and Automation, ICRA 2000
- Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic. **Data-Driven Grasp Synthesis - A Survey.** IEEE Transactions on Robotics, pp. 289-309, vol. 30, no. 2, 2014
- Rhys Newbury, Morris Gu, Lachlan Chumbley, Arsalan Mousavian, Clemens Eppner, Jürgen Leitner, Jeannette Bohg, Antonio Morales, Tamim Asfour, Danica Kragic, Dieter Fox, Akansel Cosgun. **Deep Learning Approaches to Grasp Synthesis: A Review.** https://doi.org/10.48550/arXiv.2207.02556
(accepted to IEEE Transactions on Robotics in April 2023)

The End

… still a lot to do in robotic grasping!