Interaction and collaboration

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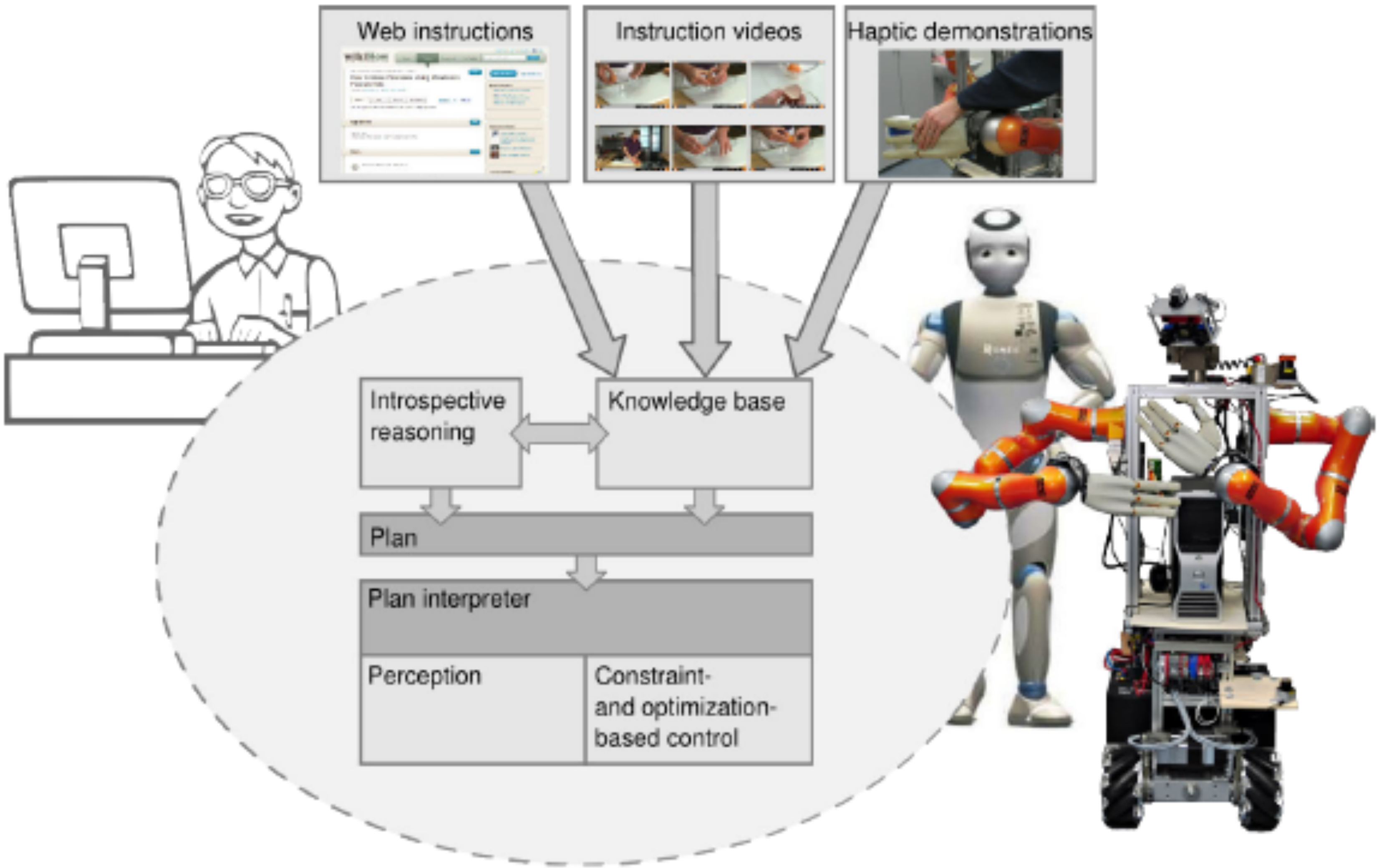
Object interaction important skill

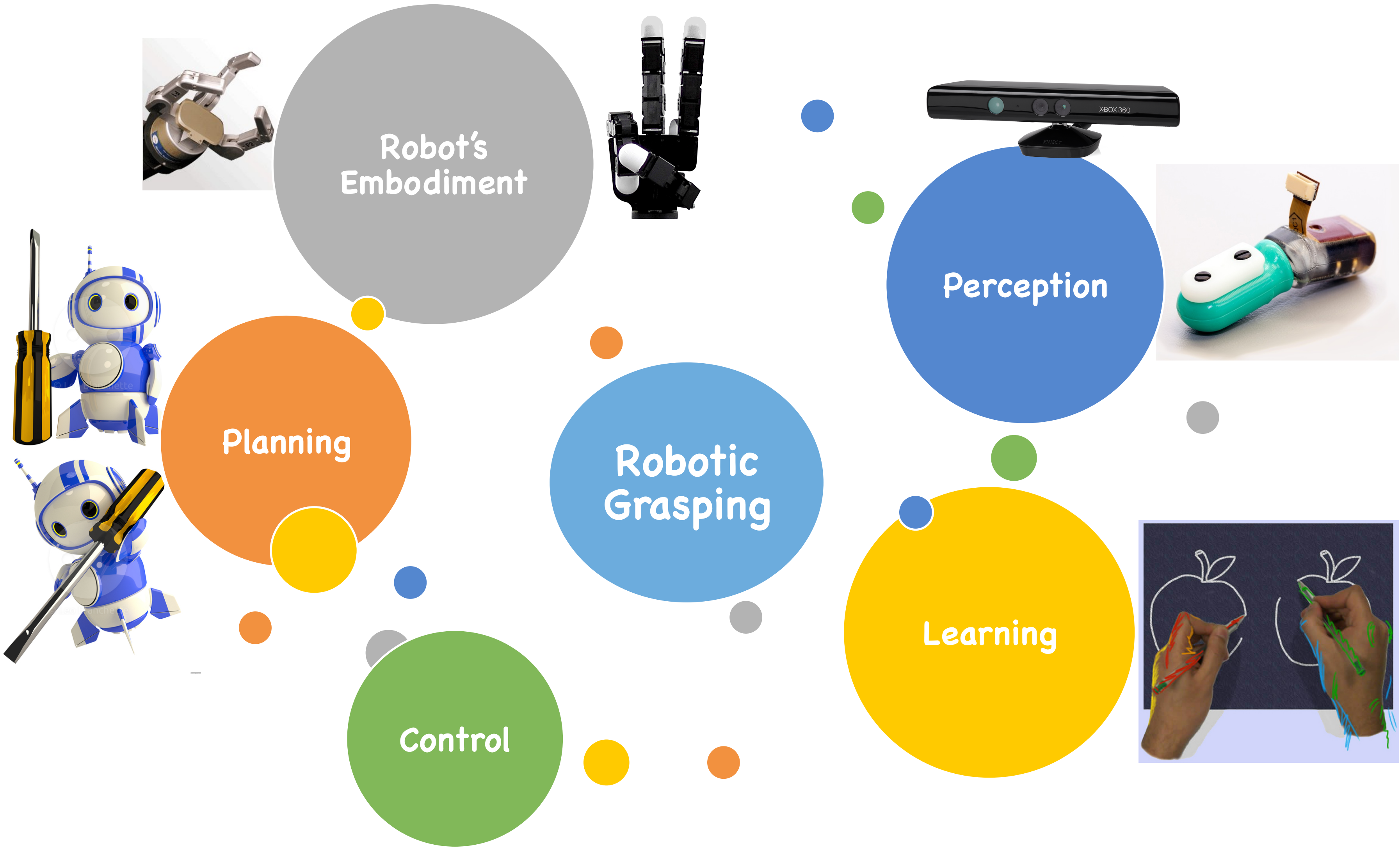
Amazon picking challenge

The challenge combines object recognition, pose recognition, grasp planning, compliant manipulation, motion planning, task planning, task execution, and error detection and recovery. The robots are scored by how many items are picked in a fixed amount of time …….

RoboHow.cog (FP7, 2012-16)



Grasping


Robot's Embodiment
Perception
Planning
Robotic Grasping
Learning
Control
XBOX 360

Taxonomy

Power Grasp

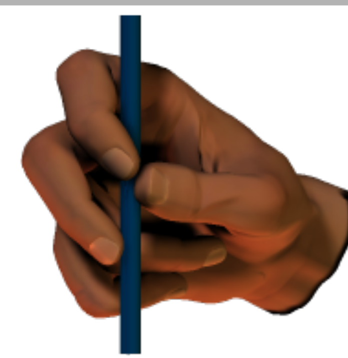
- Stable
- Large contacts
- Enveloping
- Holding

Grasp Classification

Napier 1956

Precision Grasp

- Dexterous
- Exact contacts
- Precise Planning
- In-hand Manipulation



Taxonomy

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Grasp Classification

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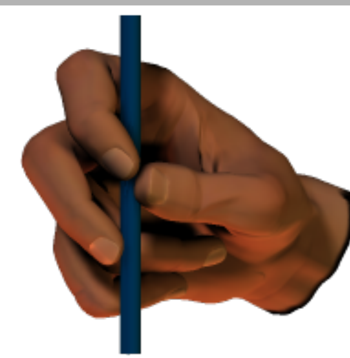
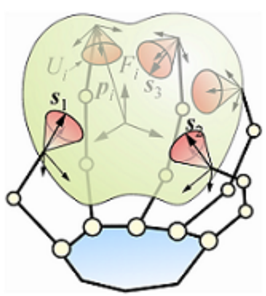
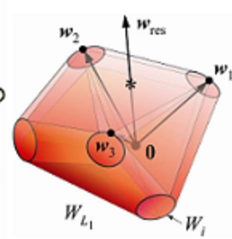


Grasp synthesis

- **Analytic**
  - Force Closure
  - Task Wrench
  - Manipulability
  - Reachability
  - ……

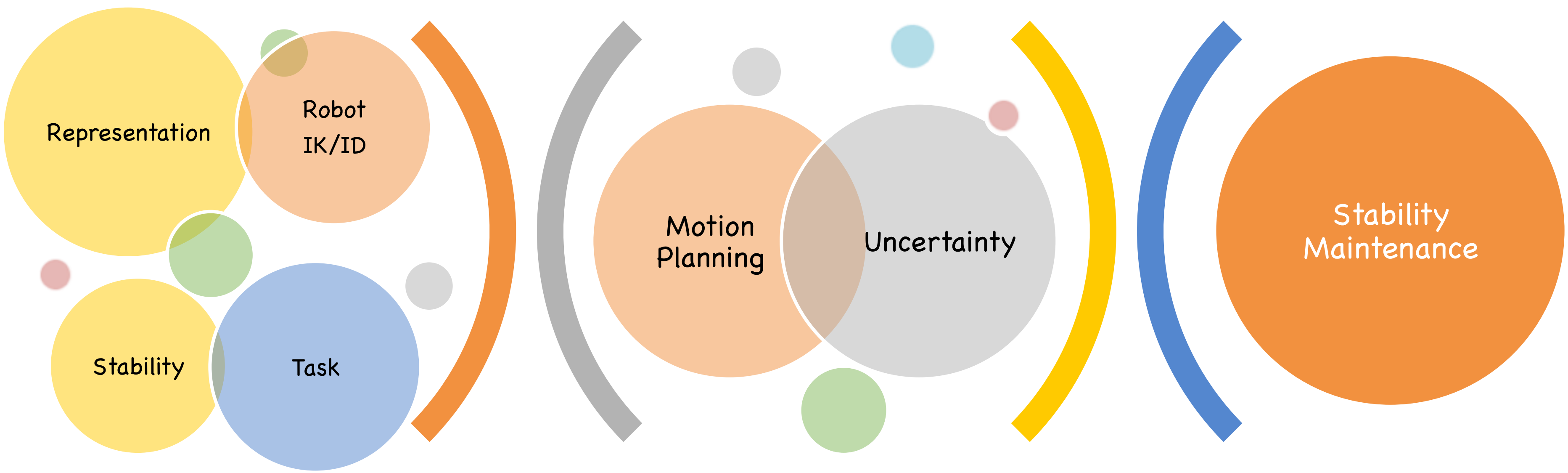




- **Data-Driven**
  - – Learning
  - – Shape Approximation
  - – Feature Extraction
  - – Heuristics
  - – ……

“Data driven grasp synthesis – a survey”; Bohg et al, IEEE TRO, 2014

Problem unrolled



Pre-Grasping

[Ferrari et. al. 1992]
[Bicchi et. al. 2000]
[Borst et. al. 2003]
[Saut et. al. 2012]
[Hjelm et. al. 2014]

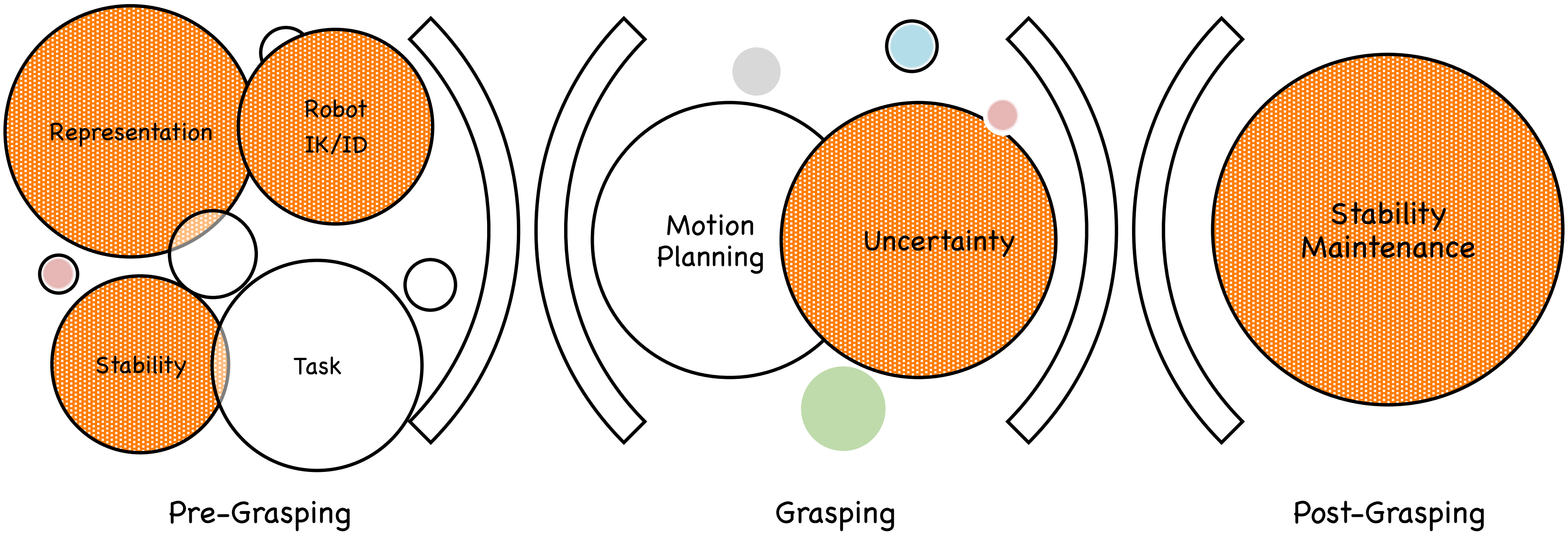
Grasping

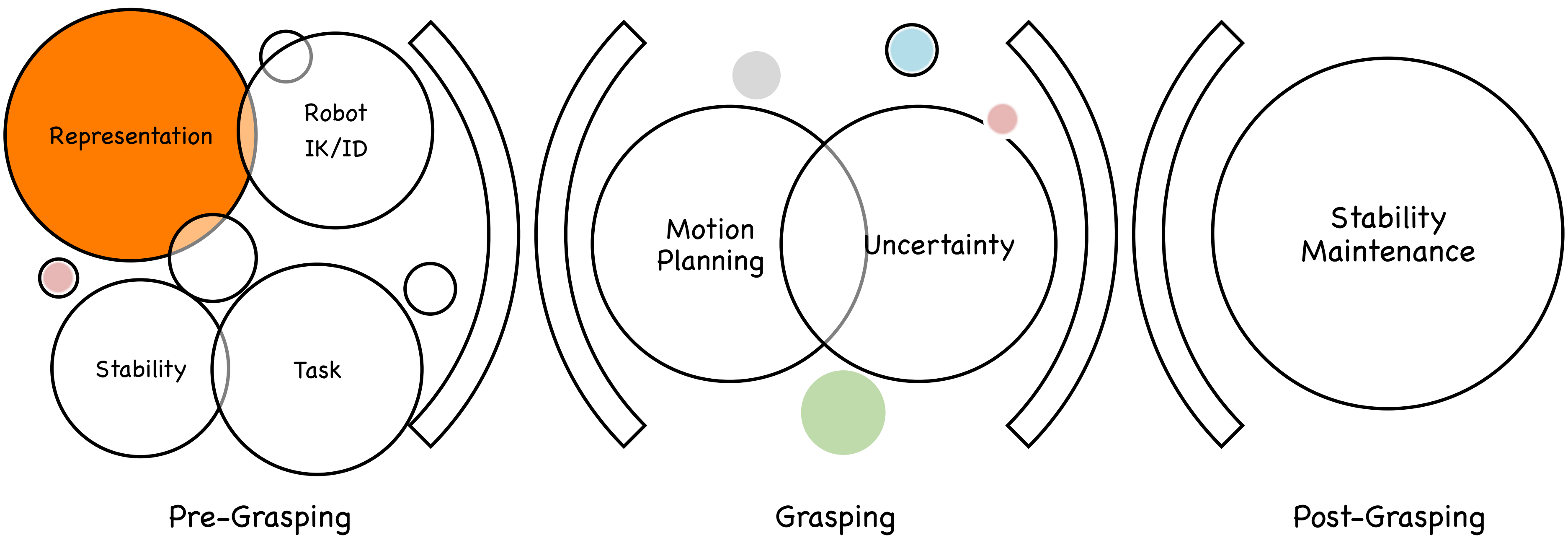
[Tahara et. al. 2010]
[Diankov et. al. 2010]
[Koval et. al. 2014]
[Li et. al. 2014]

Post-Grasping

[Yoshikawa et. al. 2010]
[Bekiroglu et. al. 2011]
[Hyttinen et. al. 2003]
[Li et. al. 2014]

Our focus

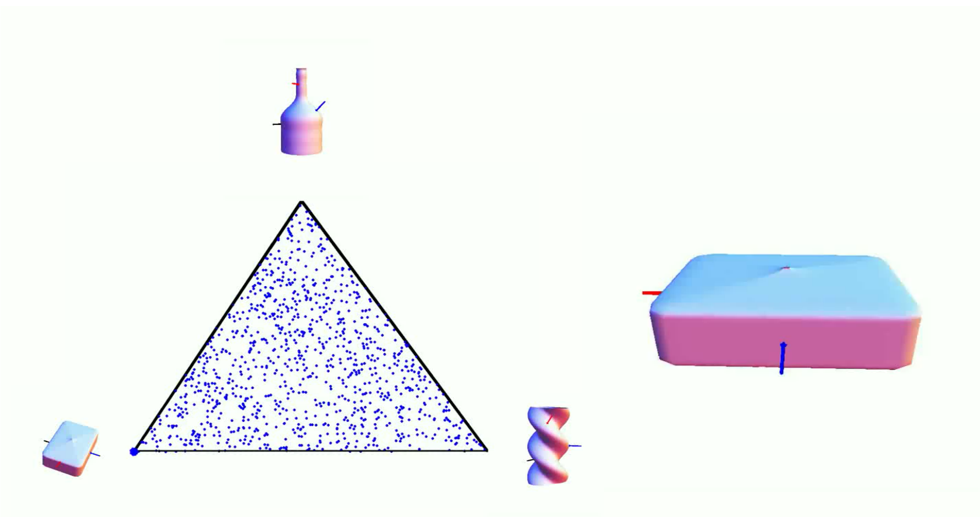

Representation
Robot IK/ID
Stability
Task
Motion Planning
Uncertainty
Stability Maintenance
Pre-Grasping
Grasping
Post-Grasping



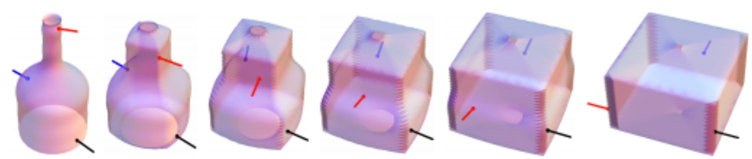
- Integrated space of grasps and shapes

Grasp Moduli Spaces

- Why integrated space of grasps and shapes?
  - Formalize nearby grasp/shape configurations
  - Transfer grasps between similar shapes



We can continuously move between configurations.



F. T. Pokorny, K. Hang, and D. Kragic, “Grasp moduli spaces,” in Robotics: Science and Systems 2013.

Grasp Moduli Spaces

- Most real world objects can be locally approximated by smooth surfaces in $\mathbb{R}^3$.

- A large subset of these surfaces can furthermore be specified by **cylindrical coordinates**:

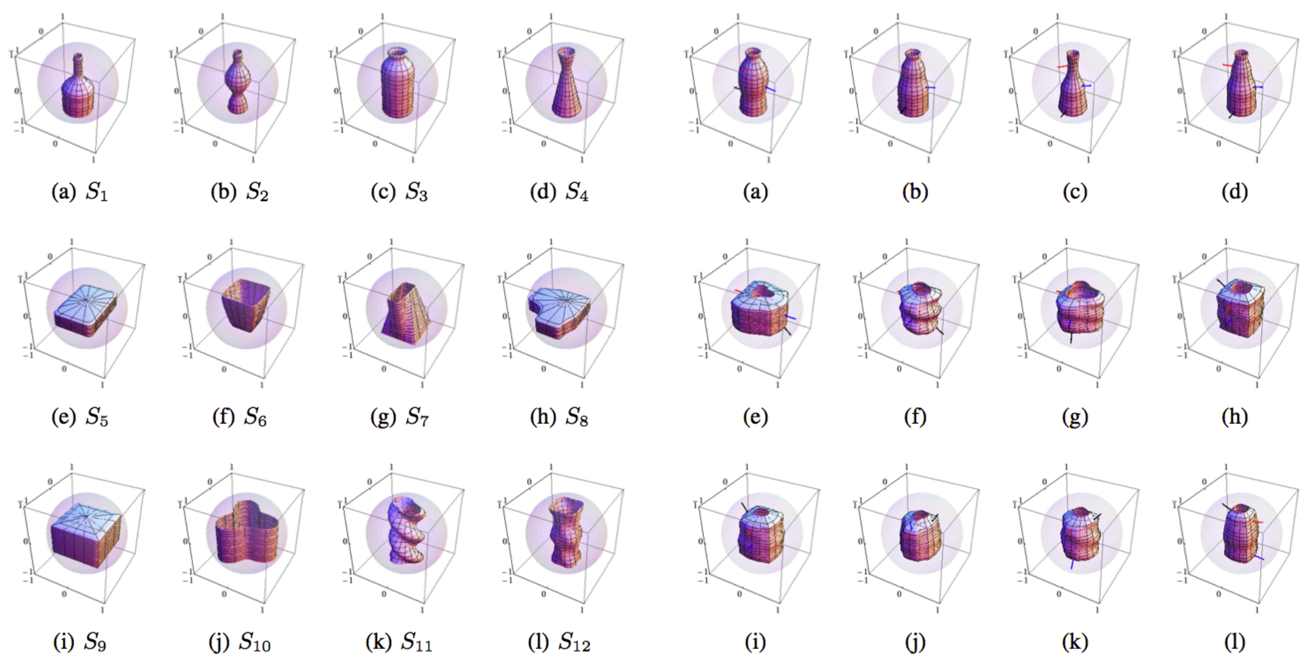
$$S_{f,a,b} = \{(f(u,\theta)\cos\theta, f(u,\theta)\sin\theta, (1-u)a + ub) : u \in [0,1], \theta \in \mathbb{S}^1\}$$

- We call the set of these surfaces with cylindrical coordinates $\mathcal{M}^{cyl}$.

F. T. Pokorny, K. Hang, and D. Kragic, "Grasp moduli spaces," in Robotics: Science and Systems 2013.

Grasp Moduli Spaces

- Convex Set (linearly deformable):



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F. T. Pokorny, K. Hang, and D. Kragic, “Grasp moduli spaces,” in Robotics: Science and Systems 2013.

Grasp Moduli Spaces

- **Definition**:

The ***Grasp Moduli Space*** for surfaces with cylindrical coordinates and grasps with m contact points is given by:

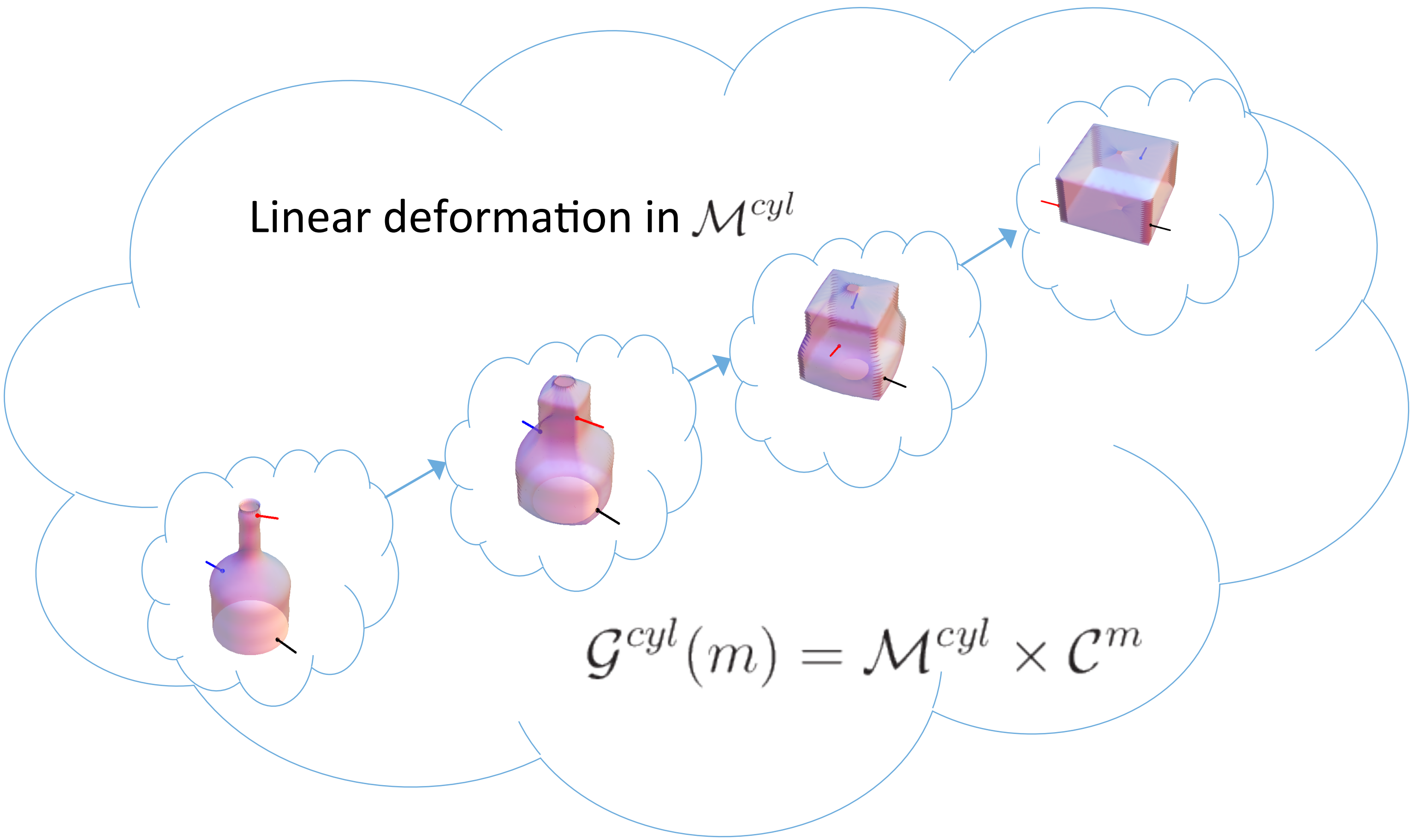
$$\mathcal{G}^{cyl}(m) = \mathcal{M}^{cyl} \times \mathcal{C}^{m}$$

where

$$\mathrm{C}^{m} = [0, 1]^{m} \times (\mathbb{S}^{1})^{m}$$

F. T. Pokorny, K. Hang, and D. Kragic, "Grasp moduli spaces," in Robotics: Science and Systems 2013.

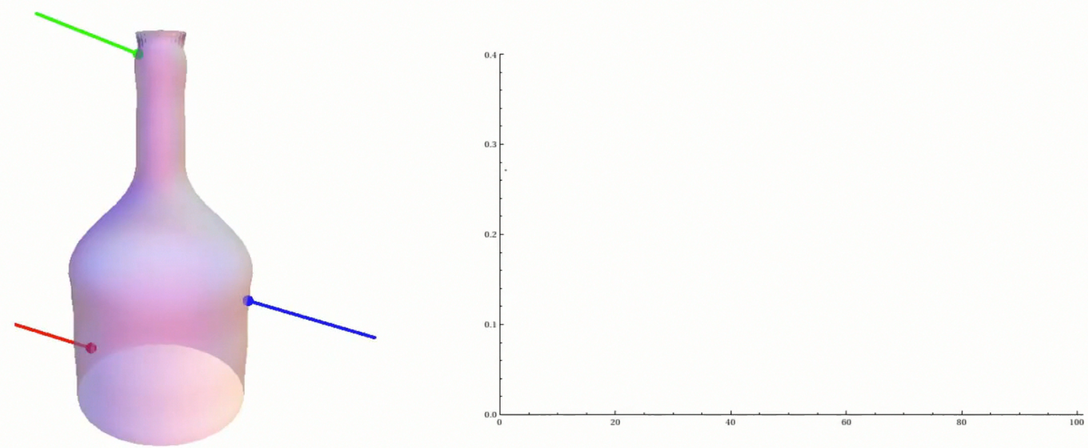
Grasp Moduli Spaces



F. T. Pokorny, K. Hang, and D. Kragic, "Grasp moduli spaces," in Robotics: Science and Systems 2013.

Grasp Moduli Spaces

- Grasp can then be transferred **between grasp-shape configurations** in the Grasp Moduli Space:



Surface is deforming while grasp configuration is fixed

Grasp is becoming unstable

Naive grasp transfer

F. T. Pokorny, K. Hang, and D. Kragic, "Grasp moduli spaces," in Robotics: Science and Systems 2013.

Grasp Moduli Spaces

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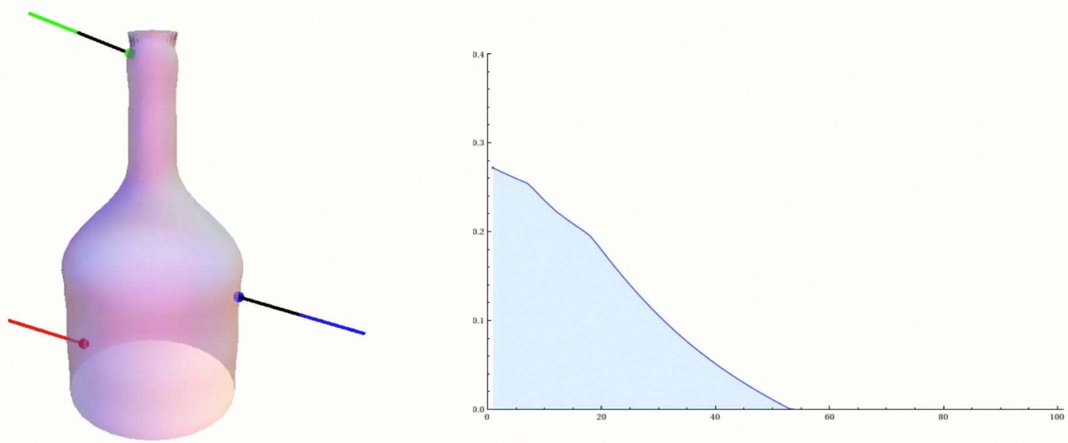
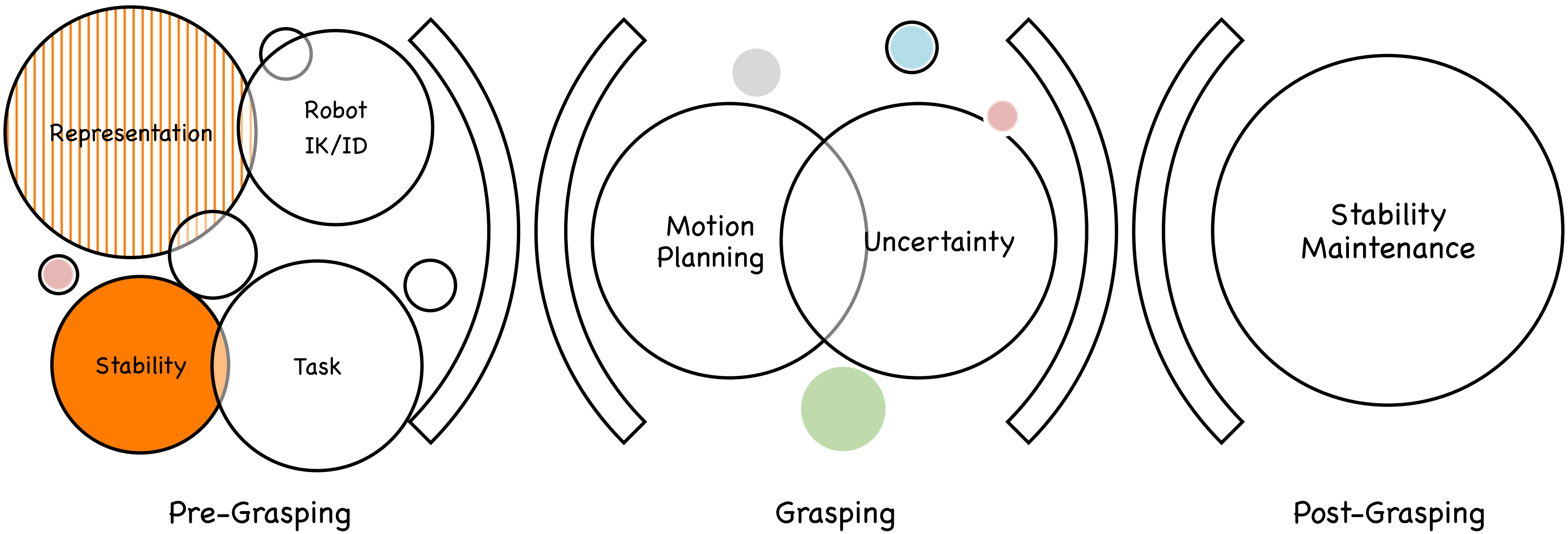


Grasp transferred with gradient descent (colored) as compared to naive transfer (black)

Grasp remains stable (red)

Grasp transfer with gradient descent

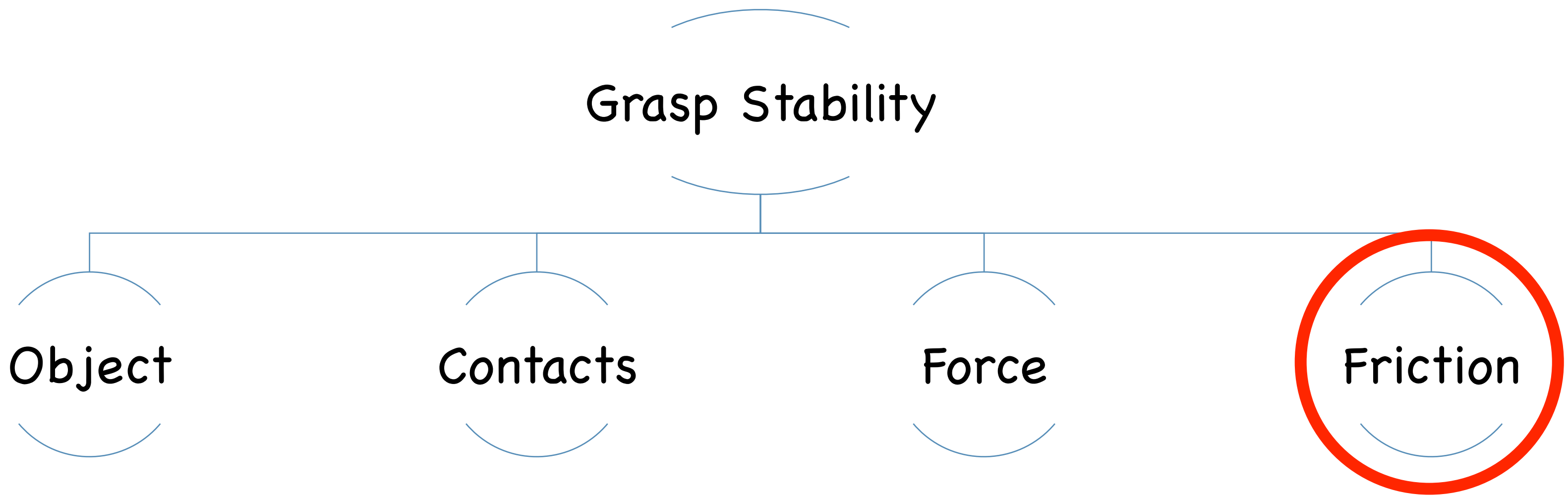
F. T. Pokorny, K. Hang, and D. Kragic, "Grasp moduli spaces," in Robotics: Science and Systems 2013.



- Stability measure

Grasp stability

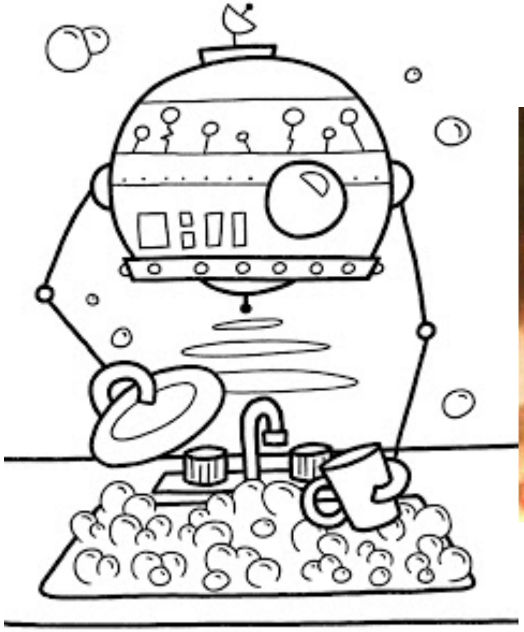
- Force closure analysis [Ferrari et al. 1992]

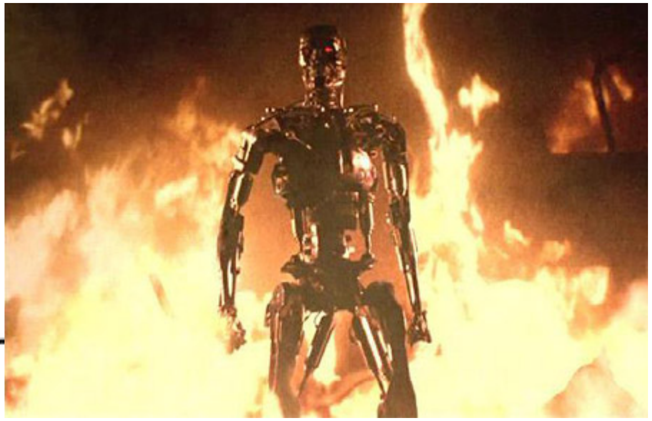


- Is it always easy to estimate the friction coefficient?

K. Hang, F.T. Pokorny, and D. Kragic, “Friction coefficients and grasp synthesis,” in IEEE/RSJ IROS, 2013.

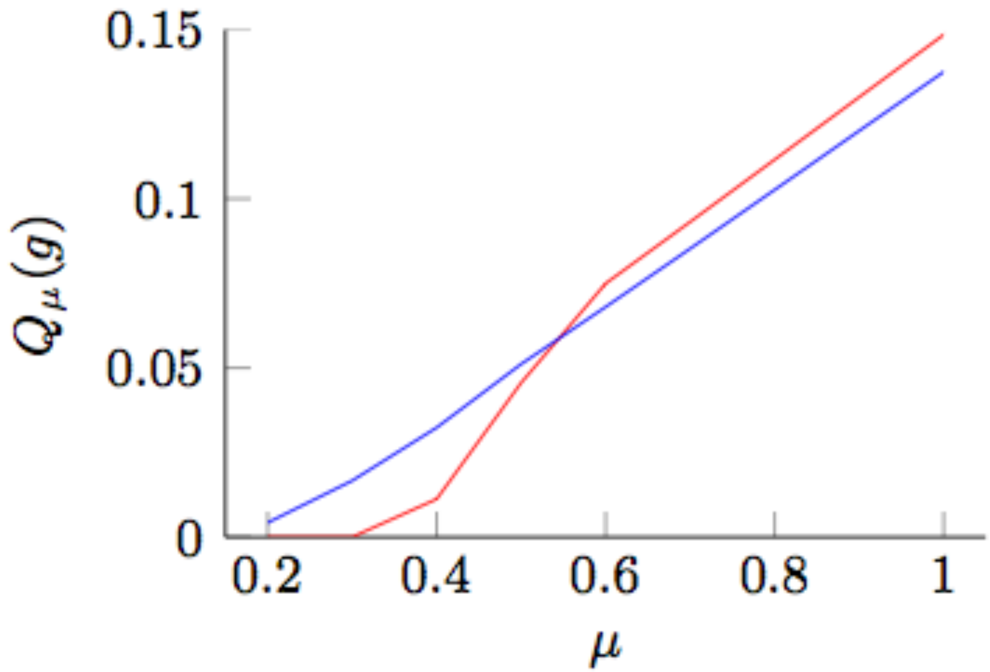
Uncertain estimation of friction

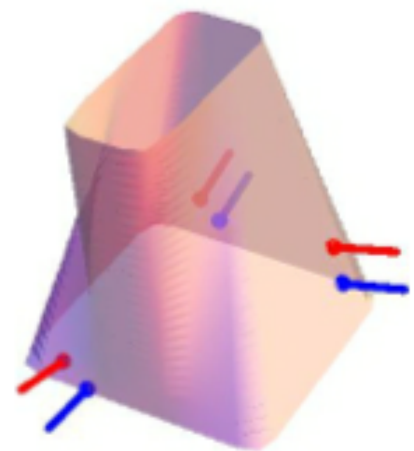




K. Hang, F.T. Pokorny, and D. Kragic, "Friction coefficients and grasp synthesis," in IEEE/RSJ IROS, 2013.

Uncertain Estimation of Friction





- Reduction Rate [Y. Zheng et al. 2005]
- Independent Contact Regions [Ma´ximo A. Roa et al. 2011]

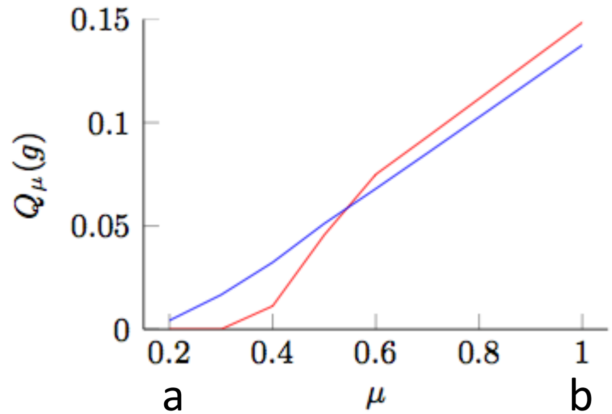
K. Hang, F.T. Pokorny, and D. Kragic, “Friction coefficients and grasp synthesis,” in IEEE/RSJ IROS, 2013.

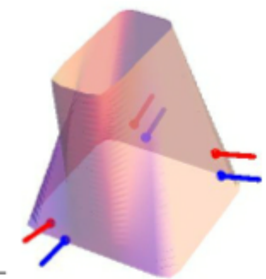
Friction Sensitivity

- ***Definition***:

$$S^n_{a,b}(g) = \frac{1}{n-m}\sum_{i=m}^{n-1} k_i$$

  - n: number of friction intervals
  - m: number of 0 quality intervals
  - k_i: Slope of the i-th interval





- Quantifying a grasp's sensitivity to friction changes
- ***Scoring Function:***

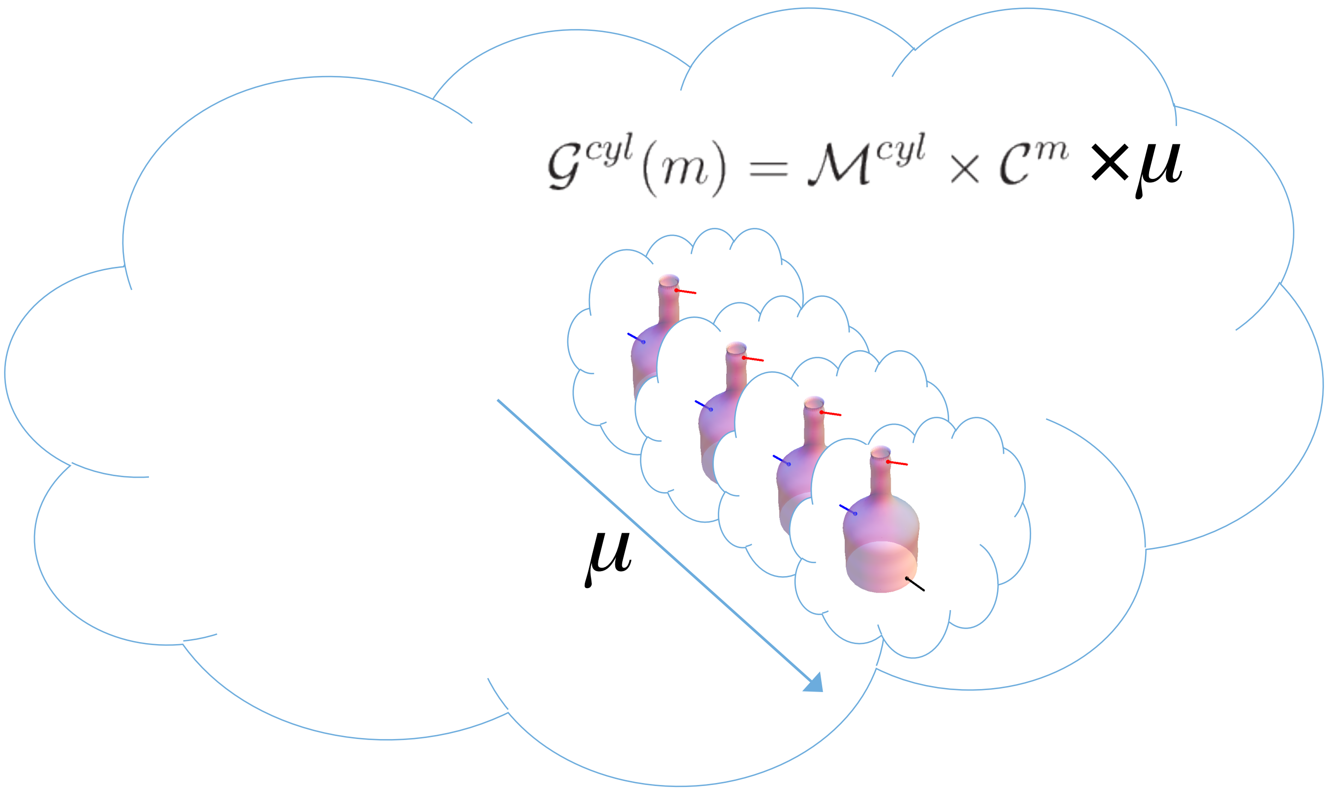
$$\Phi^n_{a,b,\mu}(g) = \frac{Q_\mu(g)}{S^n_{a,b}(g)}$$

K. Hang, F.T. Pokorny, and D. Kragic, "Friction coefficients and grasp synthesis," in IEEE/RSJ IROS, 2013.

Grasp Moduli Spaces

- One more dimension in the GMS:

$$\mathcal{G}^{cyl}(m) = \mathcal{M}^{cyl} \times \mathcal{C}^{m} \times \mu$$



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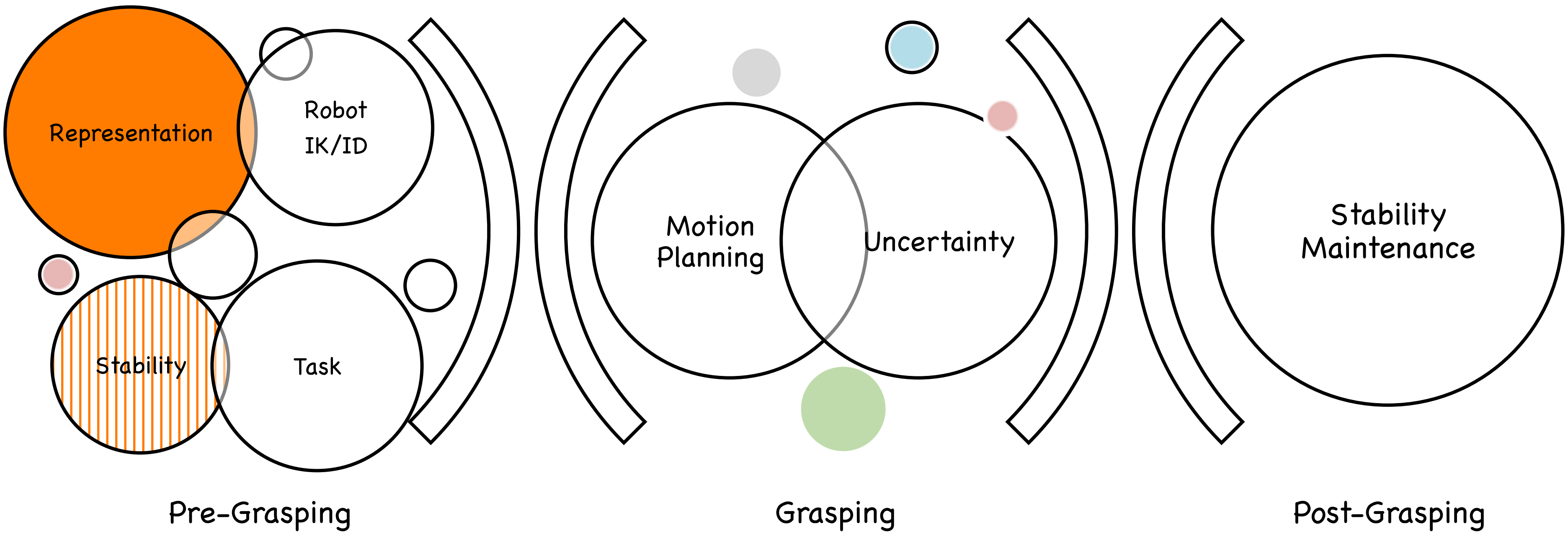
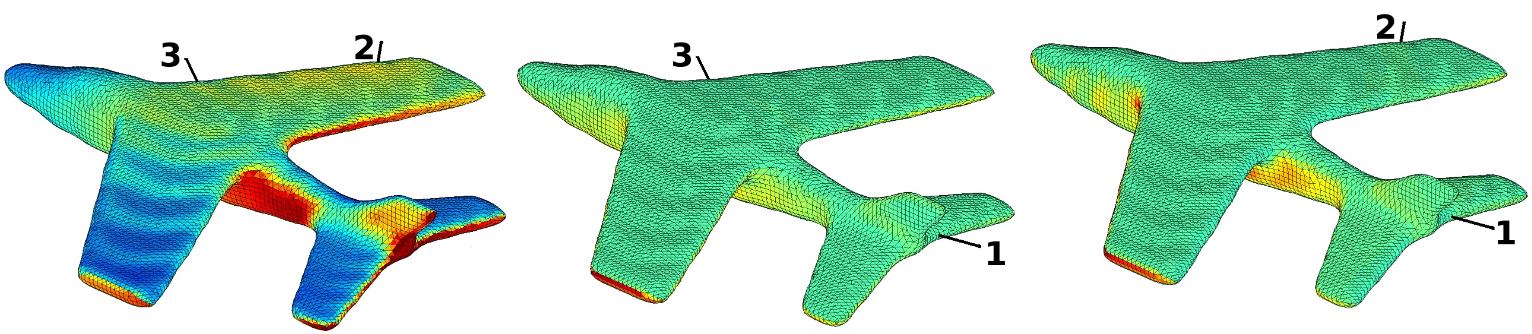


- Representation for Arbitrary shapes

Arbitrary Mesh

- Finding contacts on simple surfaces is a relatively easy problem.

- It becomes more difficult for complex shapes

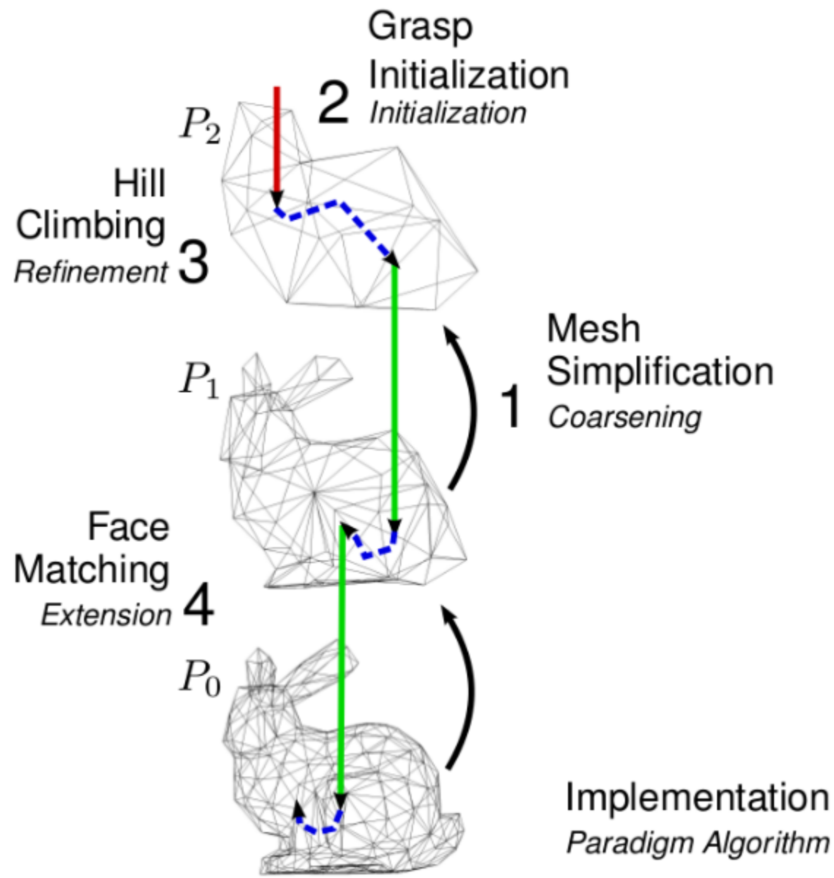


K. Hang, J.A. Stork, F.T. Pokorny, and D. Kragic, "Combinatorial Optimization for Hierarchical Contact-level Grasping" in IEEE ICRA, 2014.

Multilevel Refinement of Contact-level Grasping

- Combinatorial optimization
- Multilevel Refinement [Walshaw 2004]

- 4 Steps:
  - 1) Abstraction
  - 2) Initialization
  - 3) Solution refinement
  - 4) Extension
- 3) and 4) are iterated until a good solution is found.



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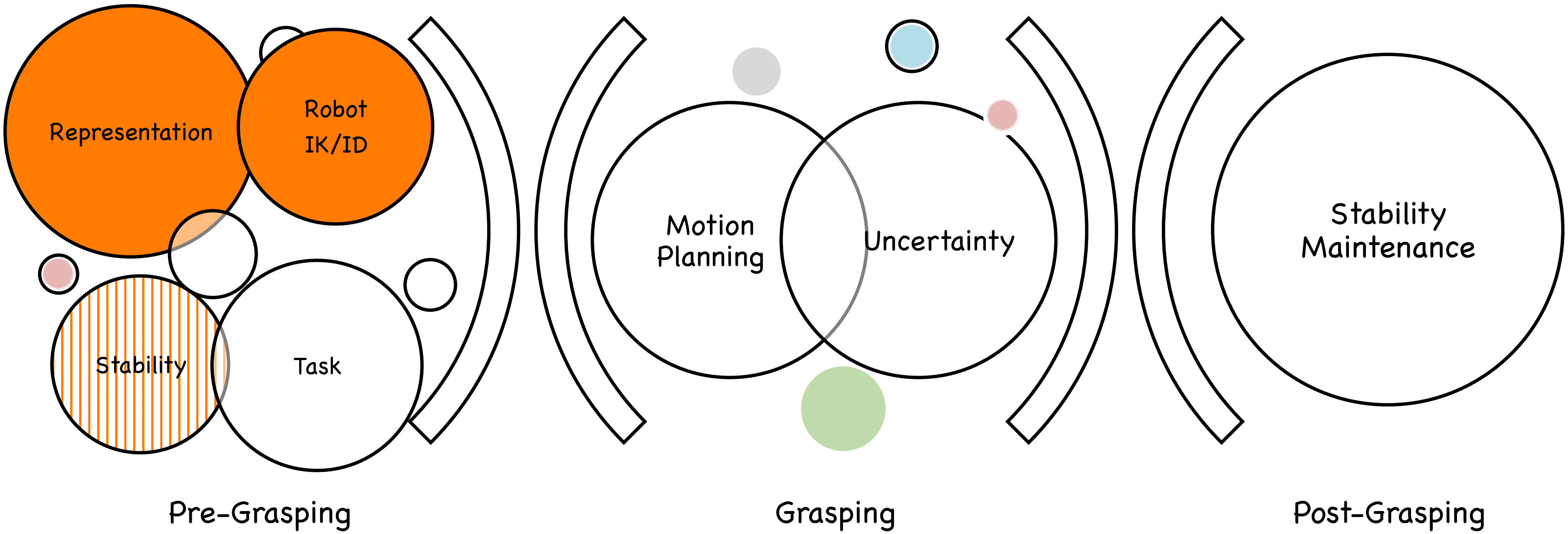
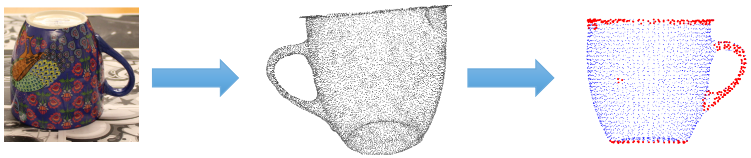
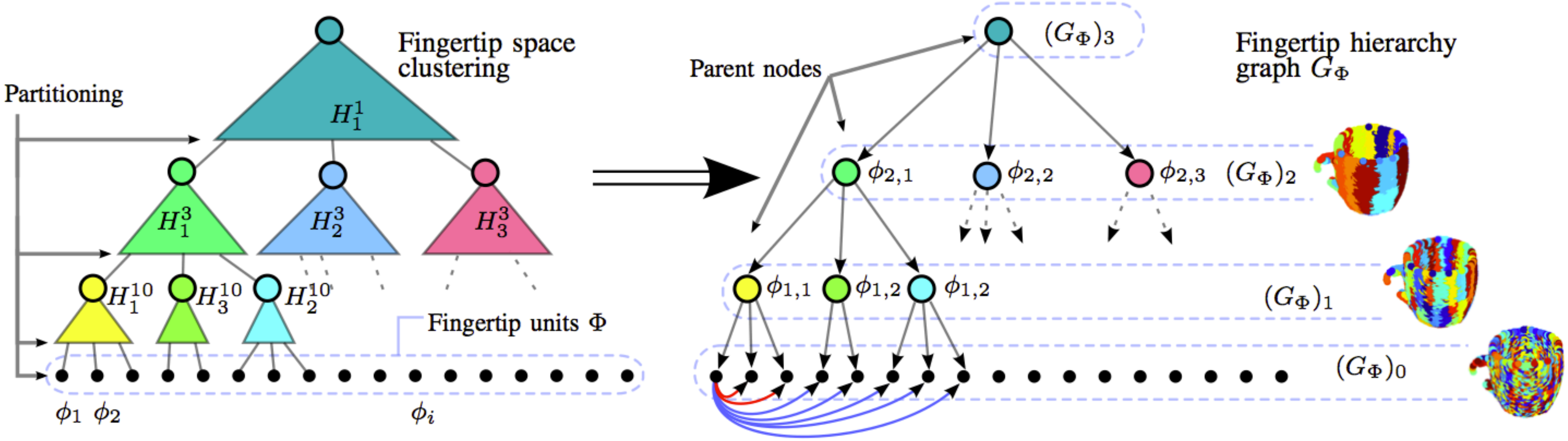


- Point clouds & Hand Reachability

Hierarchical Fingertip Space



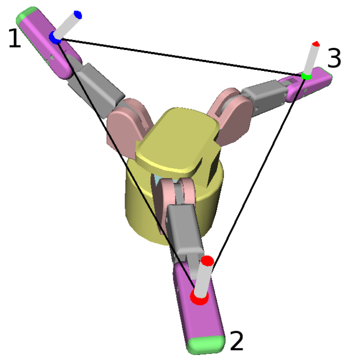


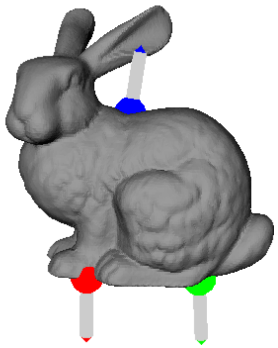
- A space of potential contacts
- A hierarchy of abstracted problems
- A graph for the search space with solutions and connectivity

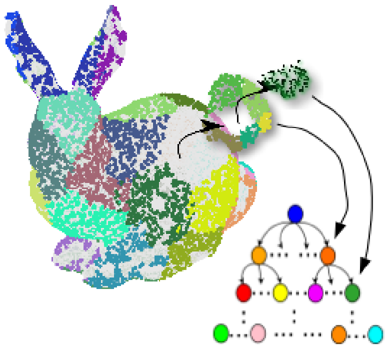
K. Hang, J.A. Stork, F.T. Pokorny, and D. Kragic, "Combinatorial Optimization for Hierarchical Contact-level Grasping" in IEEE ICRA, 2014.

Robot's Hand Reachability

- Whether the desired contacts can be achieved by robot's hand.
  - Non-binary: If not reachable, how far is it from reachable?







  - Affine invariant encoding of hand configurations, omit 6 DoF.
  - Kd-tree for encoding space: ***discrete non-parametric approximation of reachability manifold***, with a residual function (kernel).
  - Any number of fingertips can be encoded, e.g., 3 fingertips – triangle, 4 fingertips – tetrahedron.

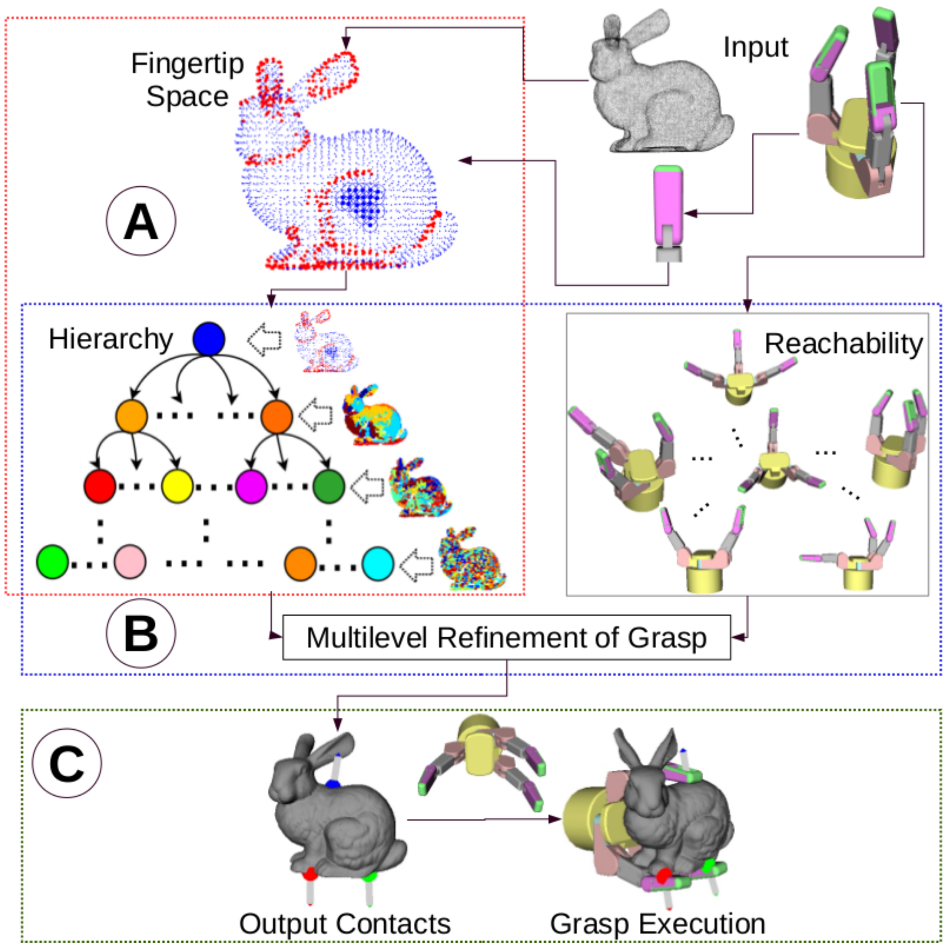
K. Hang, J.A. Stork, F.T. Pokorny, and D. Kragic, "Combinatorial Optimization for Hierarchical Contact-level Grasping" in IEEE ICRA, 2014.

Framework

- Objective function:

$$\theta(C_g) = Q(C_g) + \alpha R(C_g)$$

- Stable & Reachable



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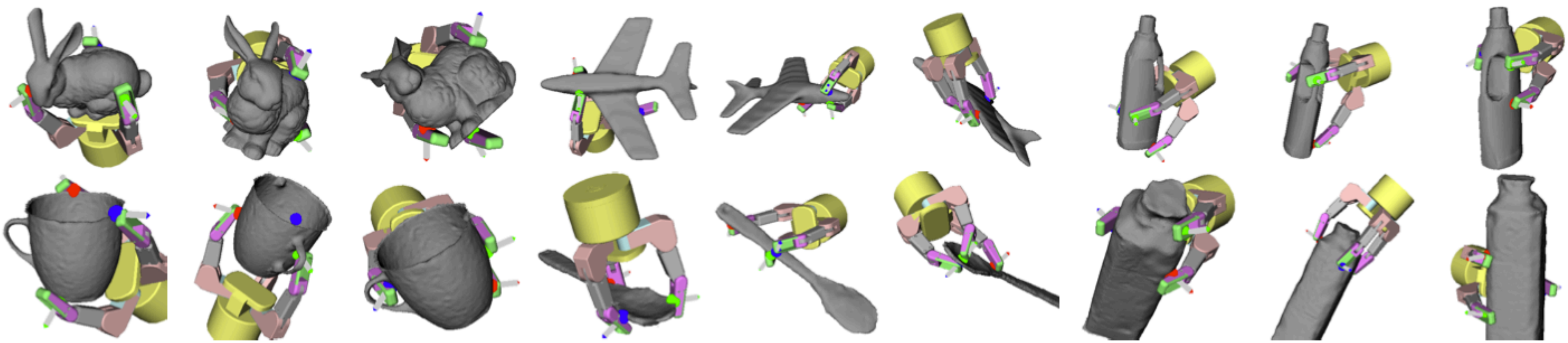
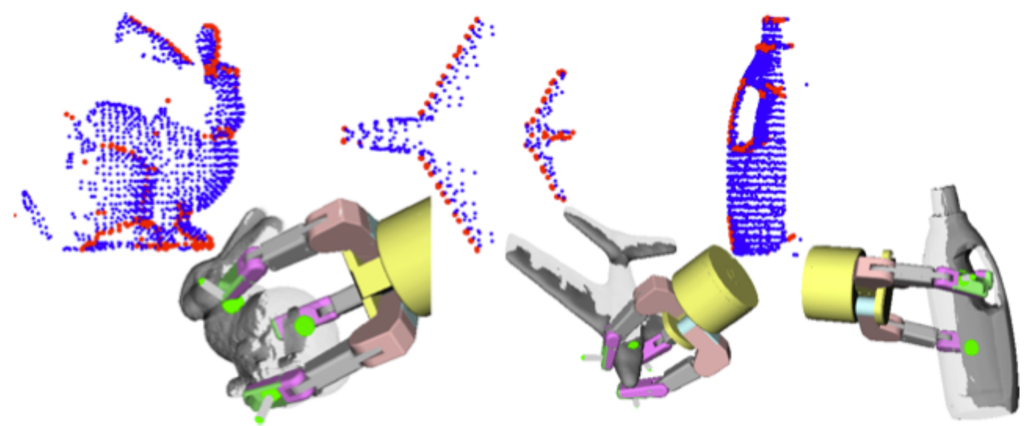
Examples



- Contacts are synthesized at ***visible*** locations only.



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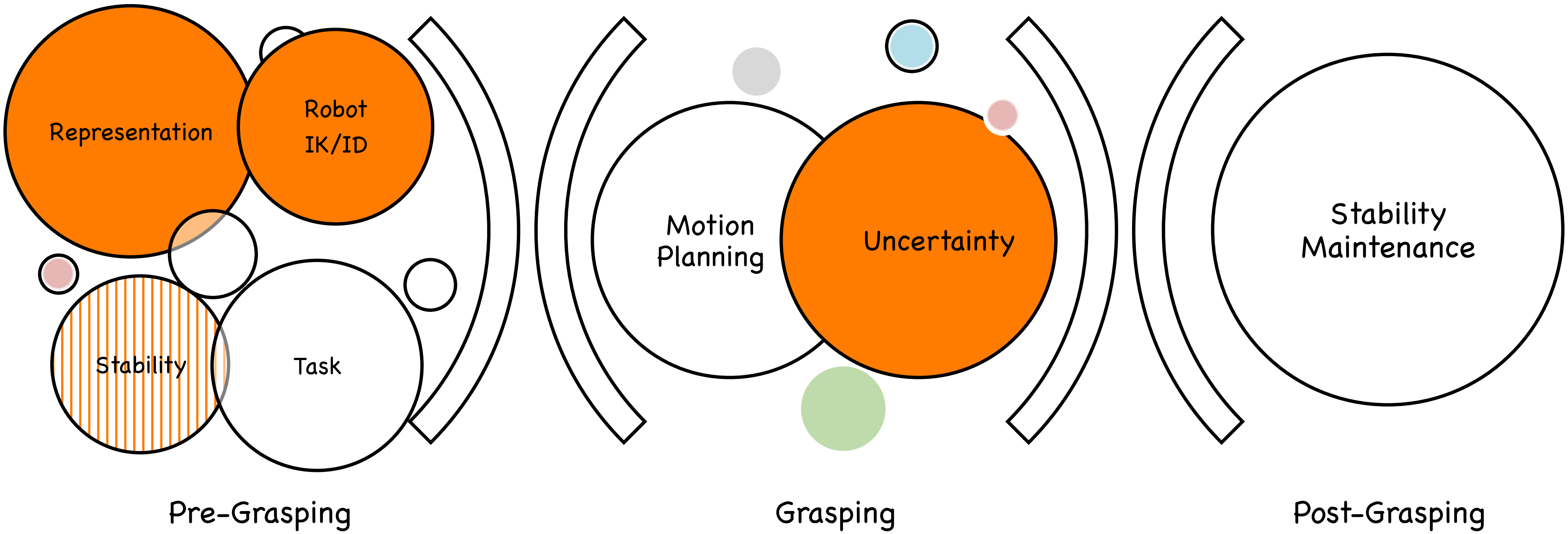
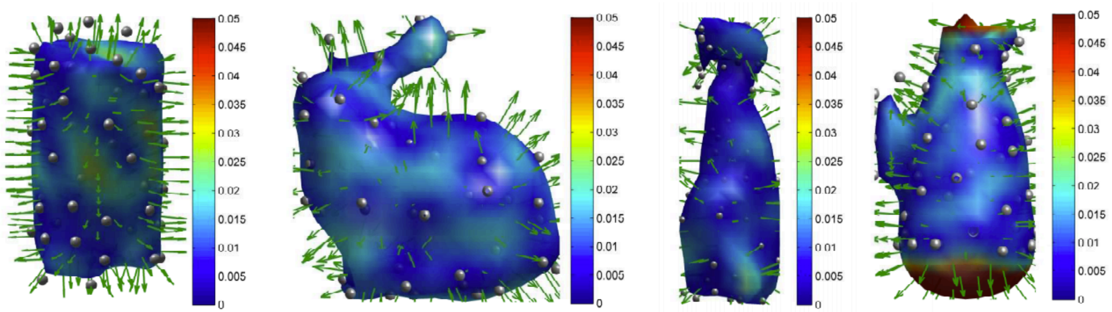


- <u>Incomplete</u> Object Model & Hand Reachability

Object Modeling

- Complete point clouds

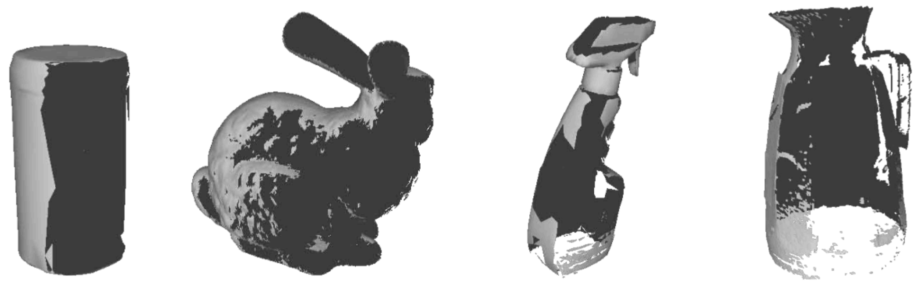
- GP with thin plate spline kernel



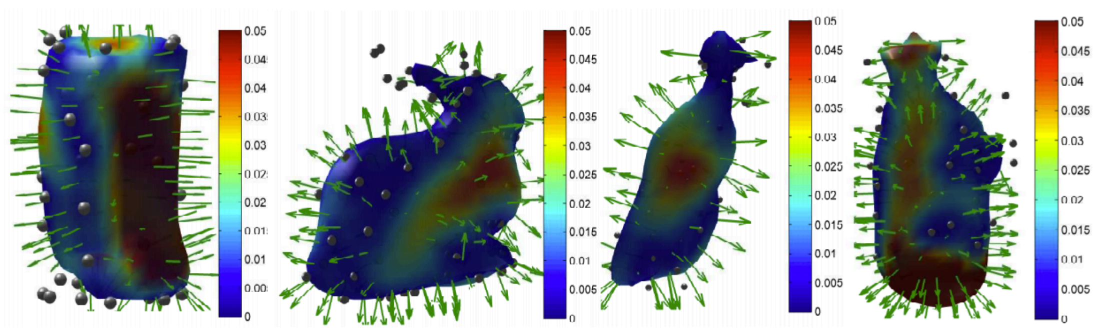
(e) (f) (g) (h)

Object Modeling

- Obtaining complete point cloud is not always feasible



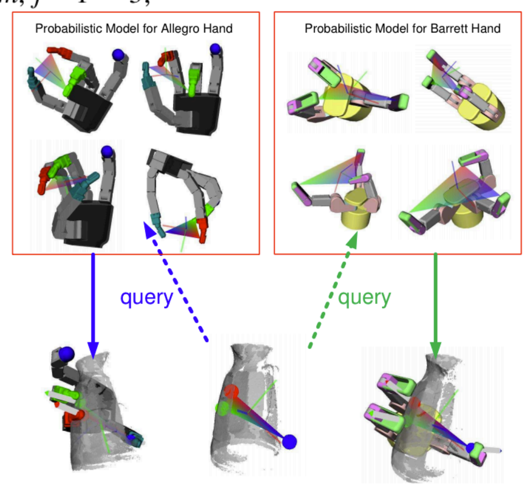
- Shapes and uncertainties are parameterized



K. Hang, J.A. Stork, F.T. Pokorny, and D. Kragic, “Combinatorial Optimization for Hierarchical Contact-level Grasping” in IEEE ICRA, 2014.

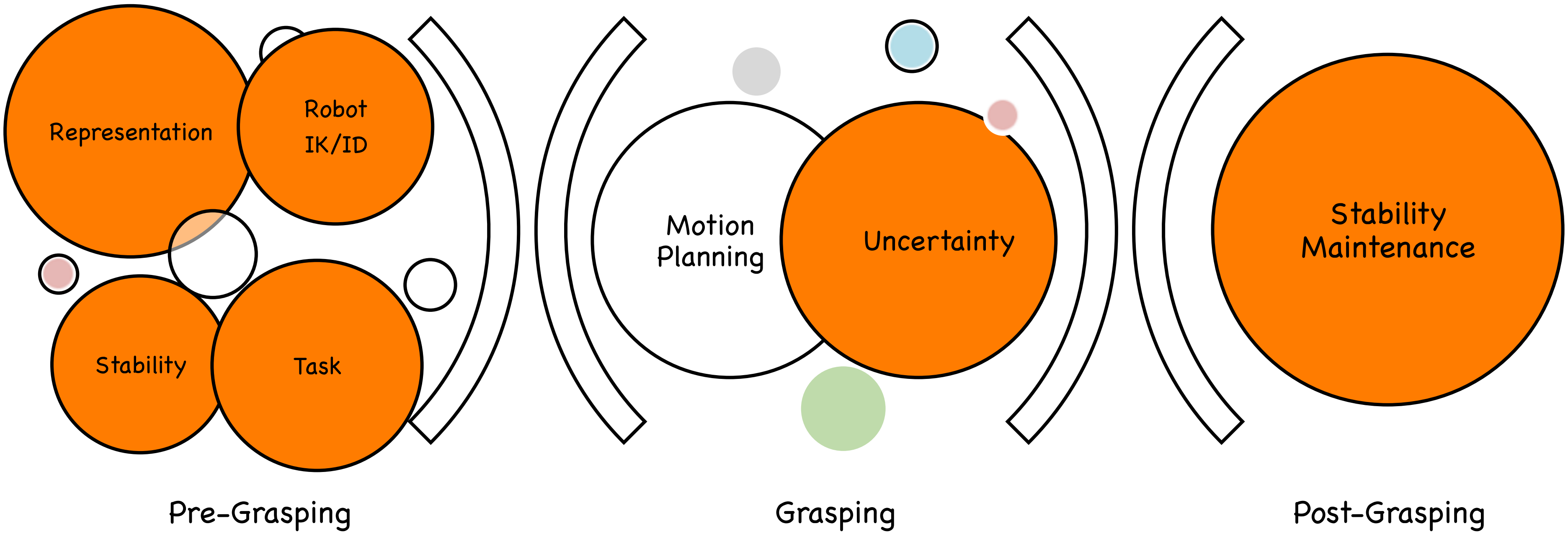
Grasp Synthesis

- Contacts Optimization
  - Position constraint: $f_d(\mathbf{p}^i) = 0, \quad i = 1, 2, 3;$
  - Normal constraint: $\mathbf{n}^i = f_\omega(\mathbf{p}^i), \quad i = 1, 2, 3;$
  - Uncertainty constraint: $f_{cov}(\mathbf{p}_i) < S_{\text{thresh}}, \quad i = 1, 2, 3;$
  - Stability constraint (FC): $\exists \phi^i_j \in \mathbb{R}, \phi^i_j > 0, \sum_{i,j} \phi^i_j = 1, i = 1 \cdots m, j = 1 \cdots 3;$



- Hand Configuration Prediction:
  - GMM for learning a joint distribution of hand configurations and contacts
  - Enable cross-hand grasp transfer

K. Hang, J.A. Stork, F.T. Pokorny, and D. Kragic, "Combinatorial Optimization for Hierarchical Contact-level Grasping" in IEEE ICRA, 2014.



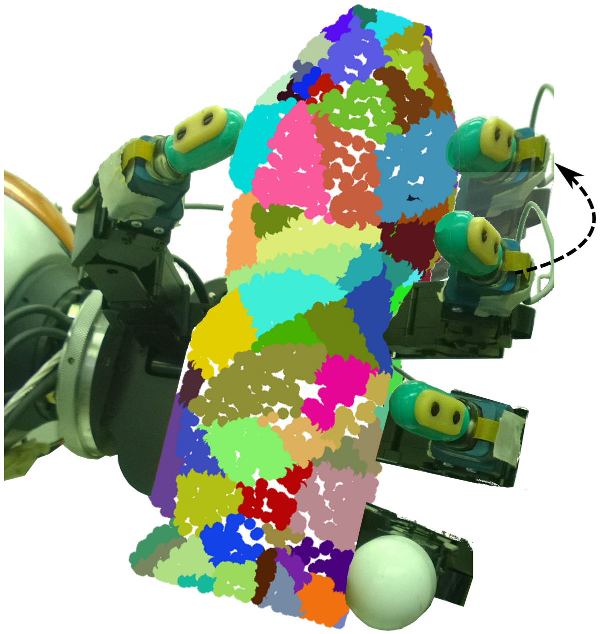
- **<u>Stability Maintenance</u>**

A Unified Framework

- Pre-grasping
  - Stable
  - Adaptable

- Grasping
  - Realize contacts
  - Flexibility to errors/uncertainty

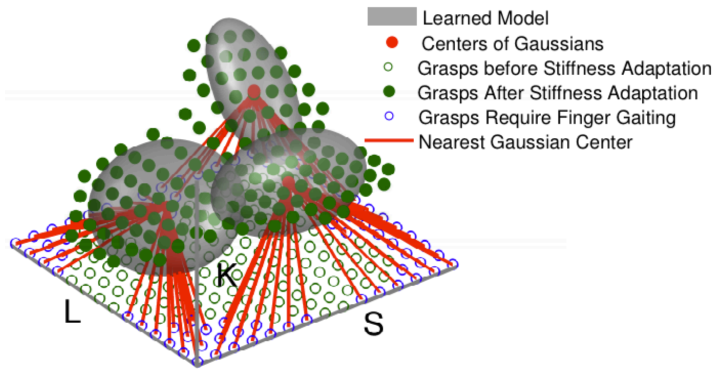
- Post-grasping
  - Force adaptation
  - Fingertip gaiting

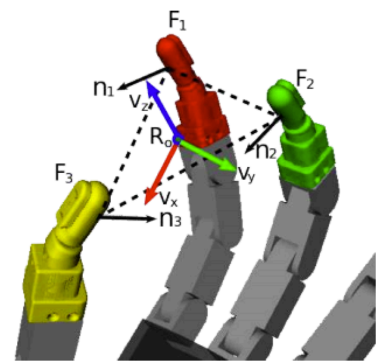


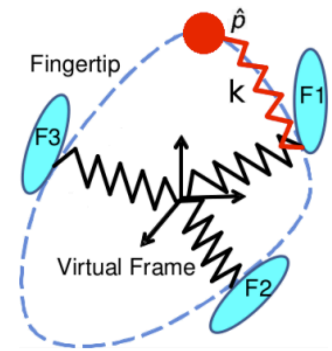
K. Hang, M. Li, J. A. Stork, Y. Bekiroglu, F. T. Pokorny, A. Billard, D. Kragic, "Hierarchical Fingertip Space: A Unified Framework for Grasp Planning and In-Hand Grasp Adaptation ", IEEE T-RO, 2016

Post-grasping

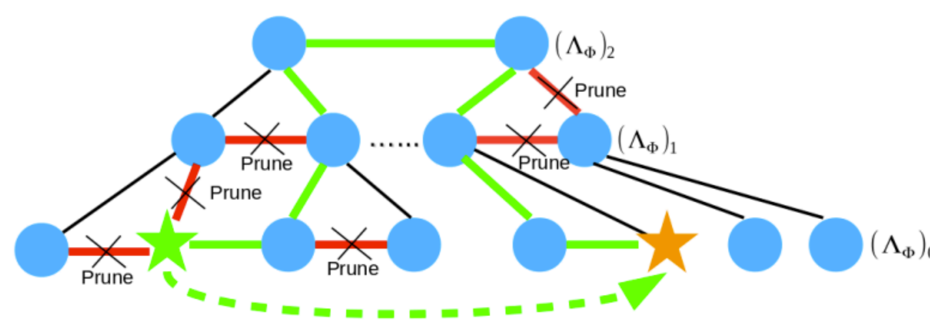
- Learning a joint distribution in a Virtual Frame (impedance control):
  - Tactile readings (Feedback)
  - Rest length (Relative positioning)
  - Grasp stiffness (Force)





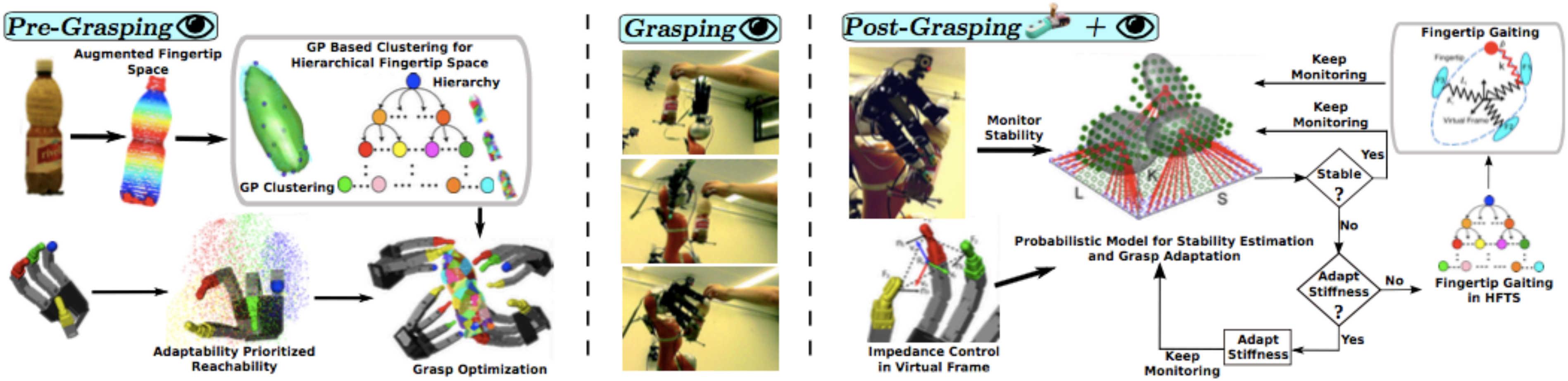


- Fingertip gaiting in HFTS
  - Flood fill
  - One fingertip per time



K. Hang, M. Li, J. A. Stork, Y. Bekiroglu, F. T. Pokorny, A. Billard, D. Kragic, “Hierarchical Fingertip Space: A Unified Framework for Grasp Planning and In-Hand Grasp Adaptation ”, IEEE T-RO, 2016

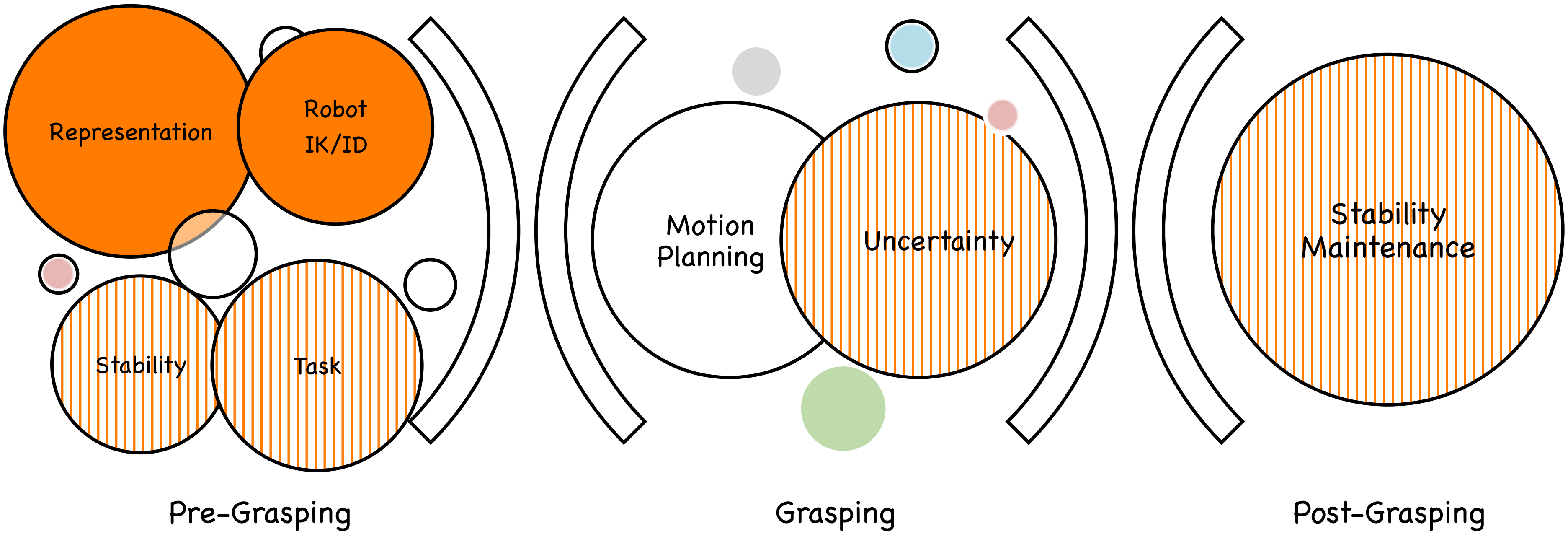
In-hand grasp adaptation



Combinatorial optimization for hierarchical contact-level grasping, *K. Hang, J. A. Stork, F. T. Pokorny, D. Kragic,* IEEE ICRA, 2014

Learning of grasp adaptation through experience and tactile sensing, M. Li, Y. Bekiroglu, D. Kragic, A. Billard, IEEE/RSJ IROS, 2014

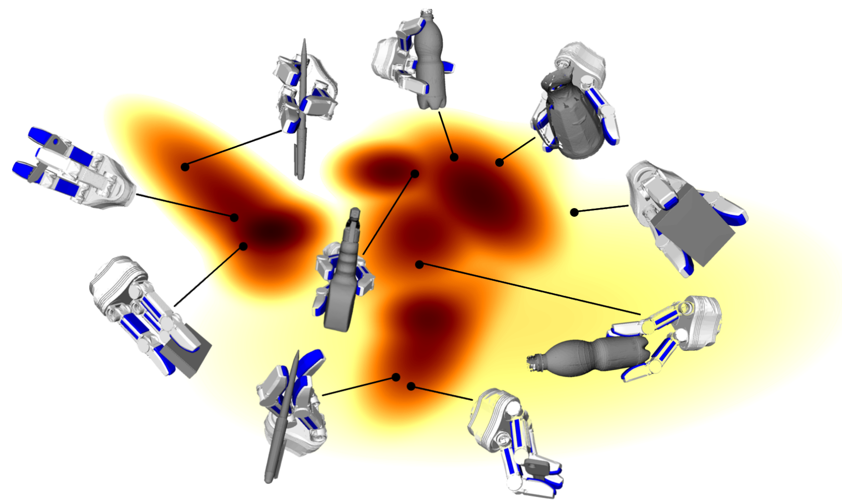
Hierarchical fingertip space for multi-fingered precision grasping, K. Hang, J. Stork, D. Kragic, IEEE/RSJ IROS 2014, 2014



- More accurate and compact kinematic learning

Grasping Manifold

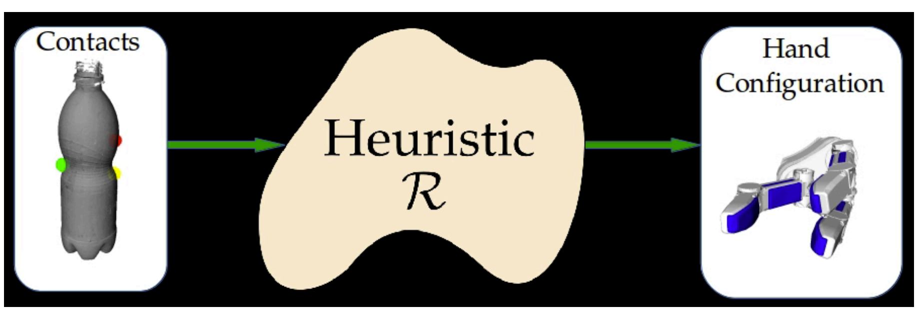
- Sampling based heuristic is an efficient method:
  - Redundant configuration space
  - Efficiency requirement
  - Gradient information



- Grasping Manifold

$$\mathcal{X} = \{\Theta \in \mathcal{C}_{free} | \exists \gamma \in \mathcal{G} : C(\gamma) = C(F(\Theta))\}$$

- Robot Specific Grasp Manifold

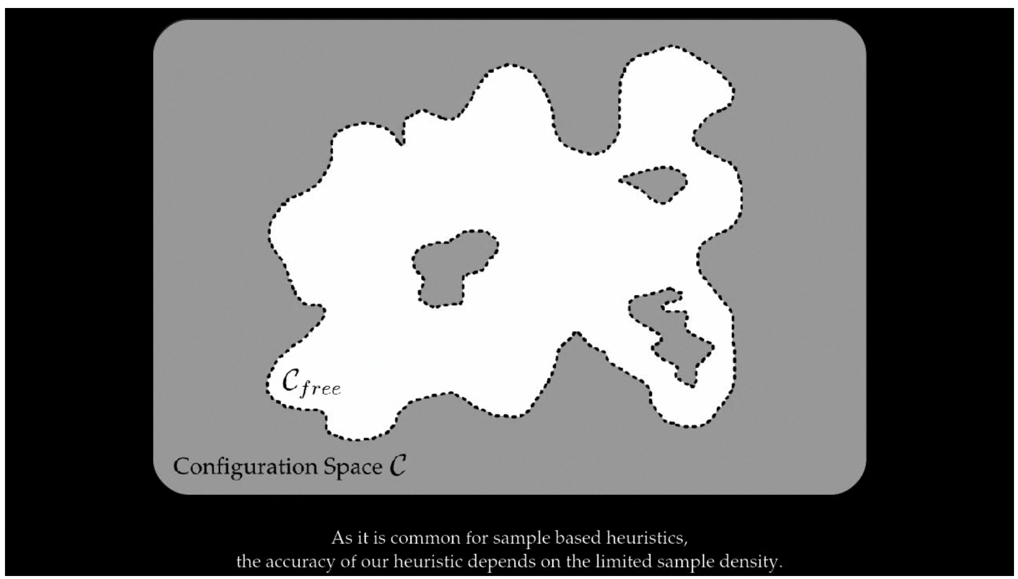


K. Hang, J. Haustein, M. Li, C. Smith, A. Billard, D. Kragic, “On the Evolution of Fingertip Grasping Manifolds”, IEEE ICRA 2016

Evolution

- Grasp relevant hand configurations are difficult to determine without experience.

- Different robots have different manifolds:
    - Task
    - Environment

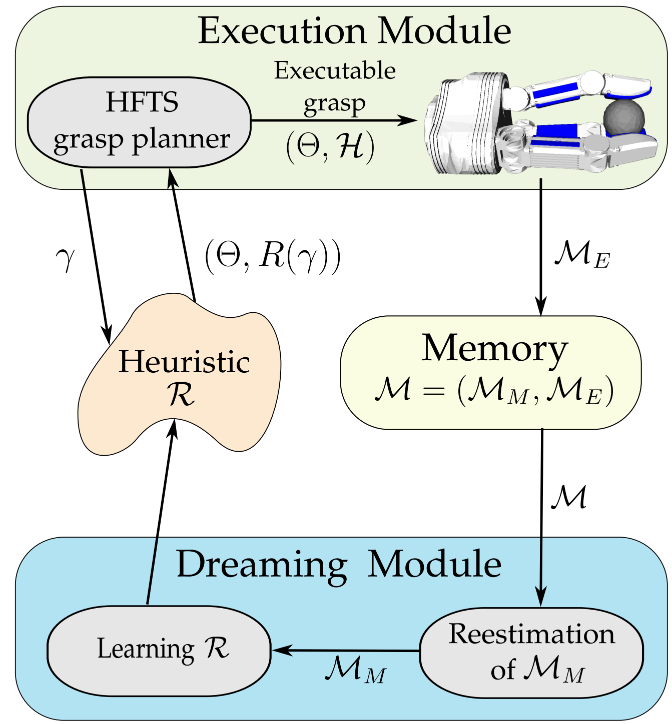


K. Hang, J. Haustein, M. Li, C. Smith, A. Billard, D. Kragic, "On the Evolution of Fingertip Grasping Manifolds", IEEE ICRA 2016

RobDREAM project

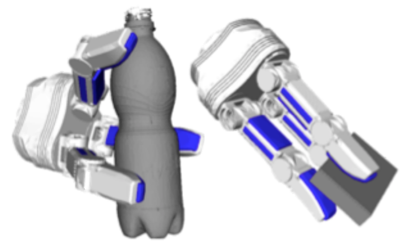
- Execution + Memory + Heuristic + Dreaming
- Feed good experience back to memory
- Evolve the grasping manifold
  - Implicitly suppress irrelevant subspaces
- Regression forest for heuristic:
  - Probabilistic output
  - Efficient for online query

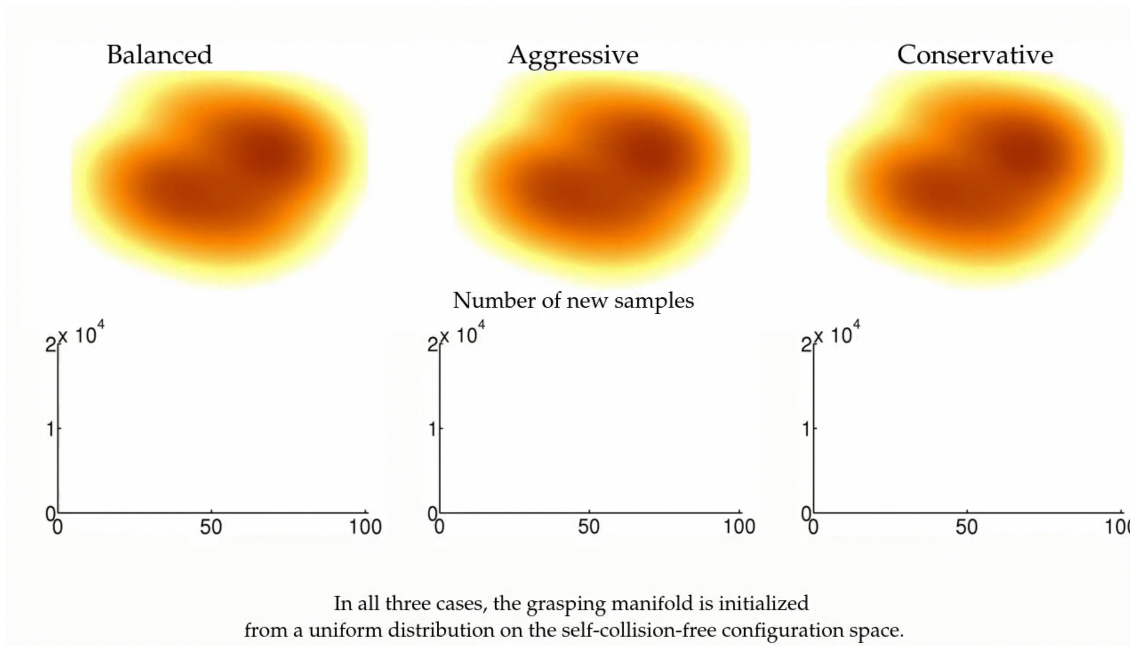
$$\mathcal{R} : \gamma \mapsto (\Theta_\gamma, R(\gamma))$$



K. Hang, J. Haustein, M. Li, C. Smith, A. Billard, D. Kragic, "On the Evolution of Fingertip Grasping Manifolds", IEEE ICRA 2016

Evolution

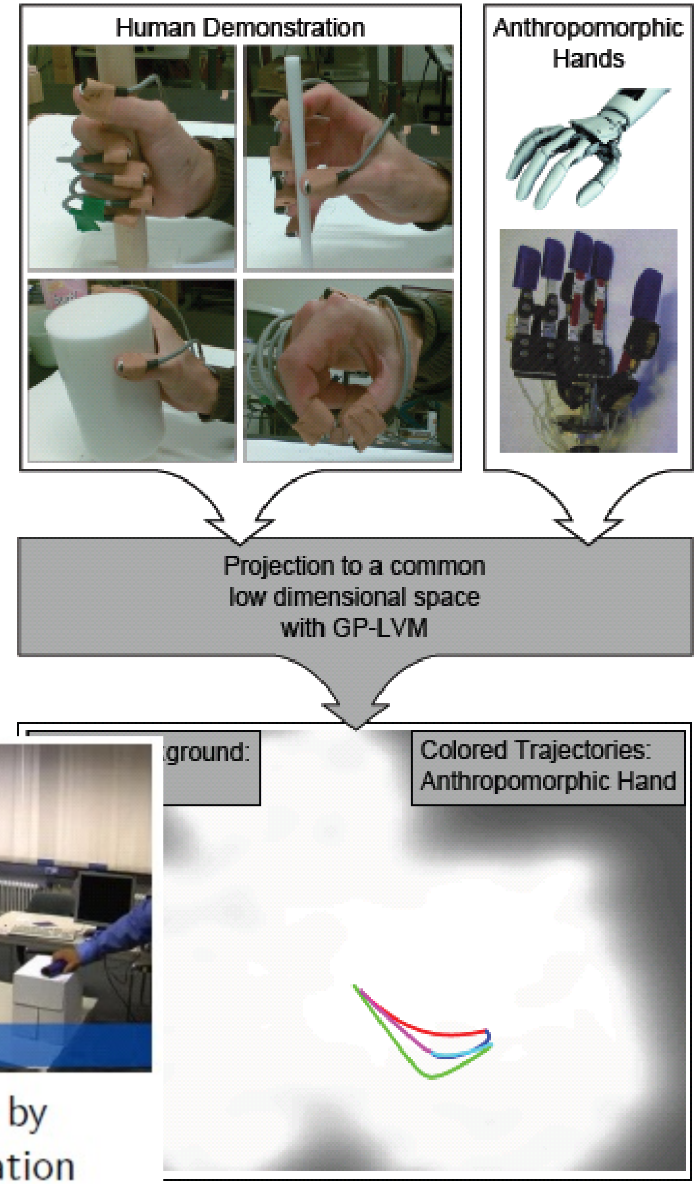




K. Hang, J. Haustein, M. Li, C. Smith, A. Billard, D. Kragic, "On the Evolution of Fingertip Grasping Manifolds", IEEE ICRA 2016

ERC Grant: Flexible object manipulation through statistical learning and topological representations

- How can one (human/robot) interact with the world if the hands have less/more/longer/shorter/ no fingers?
- How can we control *simple* hands to achieve complex behavior?
- Integrates statistics, machine learning, computer vision, mechanical engineering, robotics
- Exploitation and evaluation for prostheses, industrial and service markets



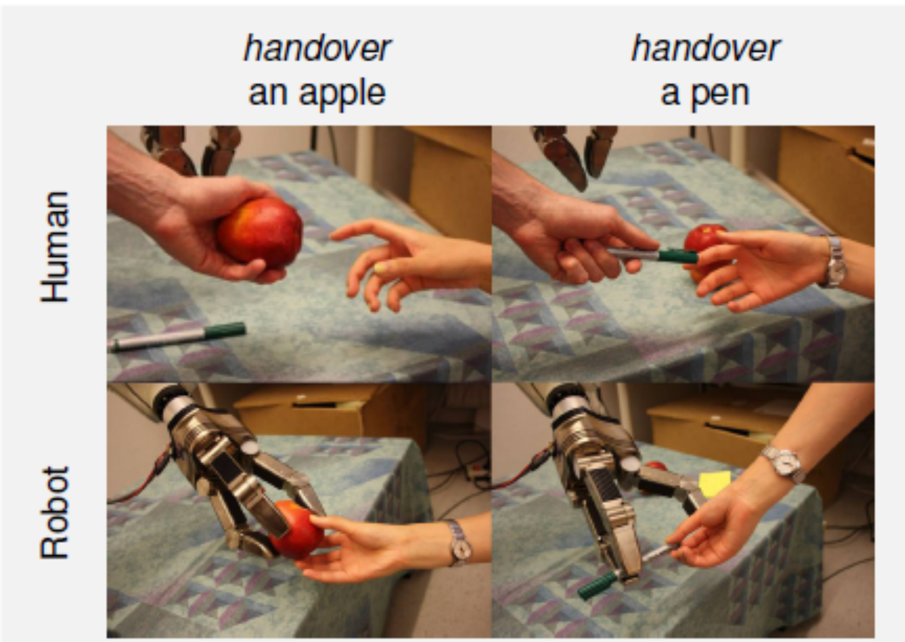
Prosthesis Design

Teleoperation/ Gaming

Learning by Demonstration

What is a good grasp?

If the task is:



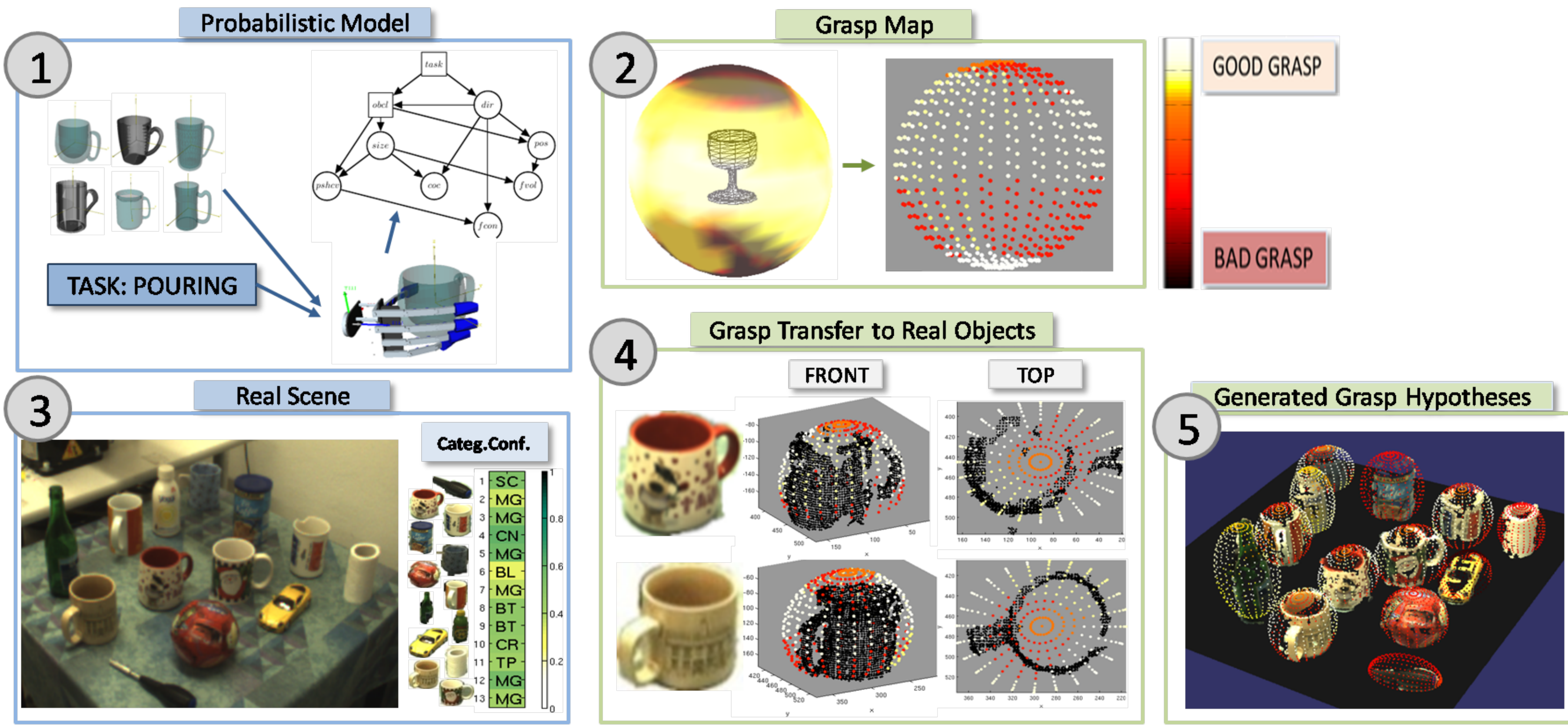
Problems:

1) How does a post-grasp action (or task) constrain which object to use, and how to grasp it? Greeno (1994)
2) How to transfer this task knowledge across different embodiments? Alissandrakis *et al.* (2007)
3) What can be the role of human teacher in task constraint learning? Calinon and Billard (2007)

"Robot, bring me something to drink!"

ACTION OBJECT TASK

- Representation links information about: action + object + task
  to **transfer task-specific grasps from a known to a novel object**



Approach

- A semi-supervised method for encoding task-related grasps. Mixed BN encodes relation between tasks, objects and actions.
- The approach used to solve
  - Action recognition
  - Task based planning
  - Grasp stability assessment

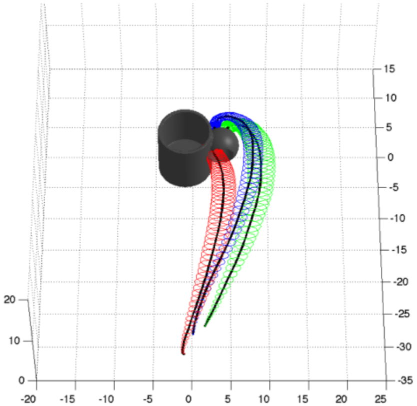
  in an integrated framework

Embodiment-Specific Representation of Robot Grasping using Graphical Models and Latent-Space Discretization, D. Song, CH Ek, K. Huebner, D. Kragic, *IEEE IROS* 2011

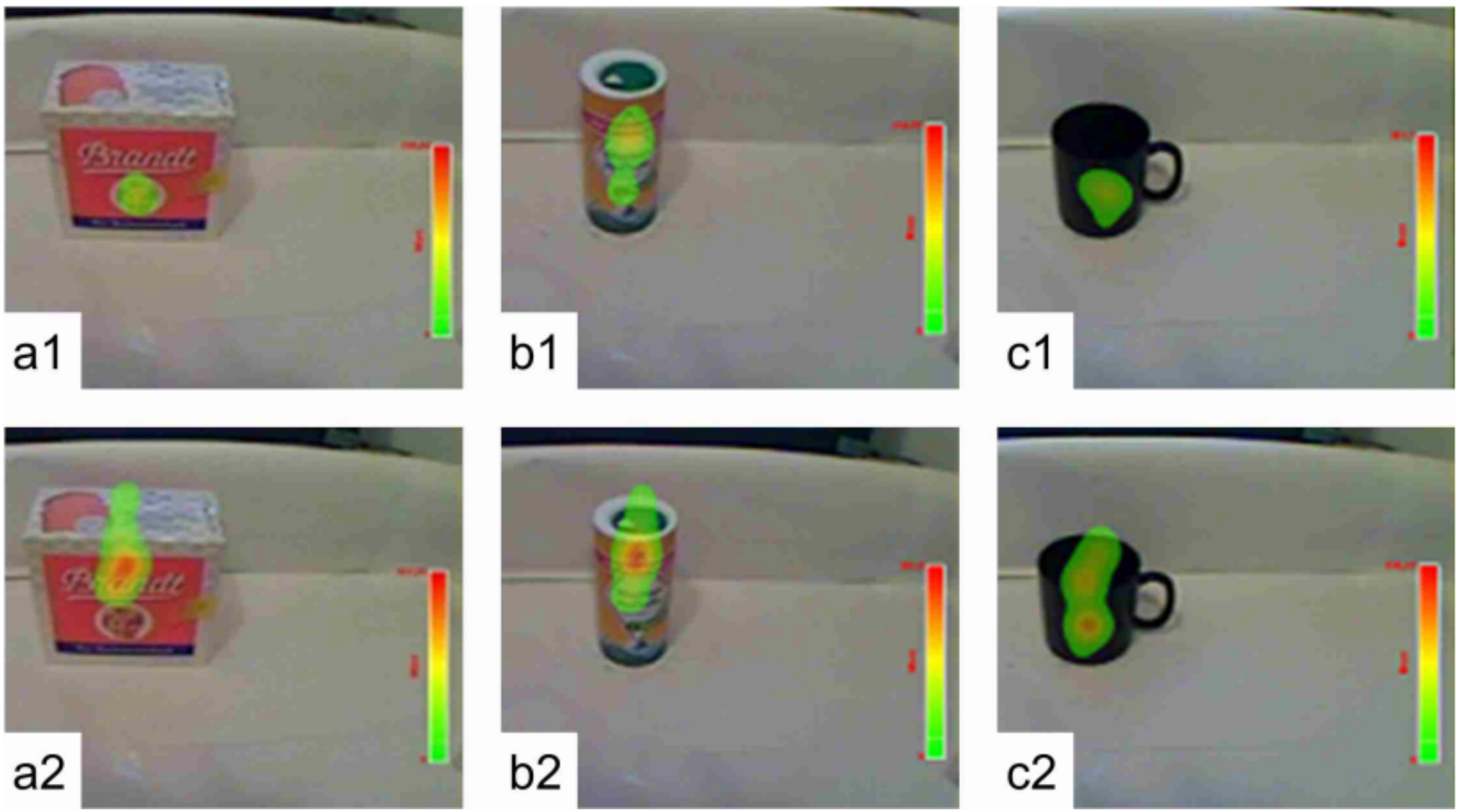
From Object Categories to Grasp Transfer Using Probabilistic Reasoning, M. Madry, D. Song, D. Kragic, *IEEE ICRA* 2012

<u>Task-based robot grasp planning using probabilistic inference,</u> D. Song, C.H. Ek, K. Huebner, D. Kragic, IEEE Transactions on Robotics, 31(3), pp.546-561, June, 2015

Eye fixations during grasping



H. Deubel et al: www.grasp-project.eu

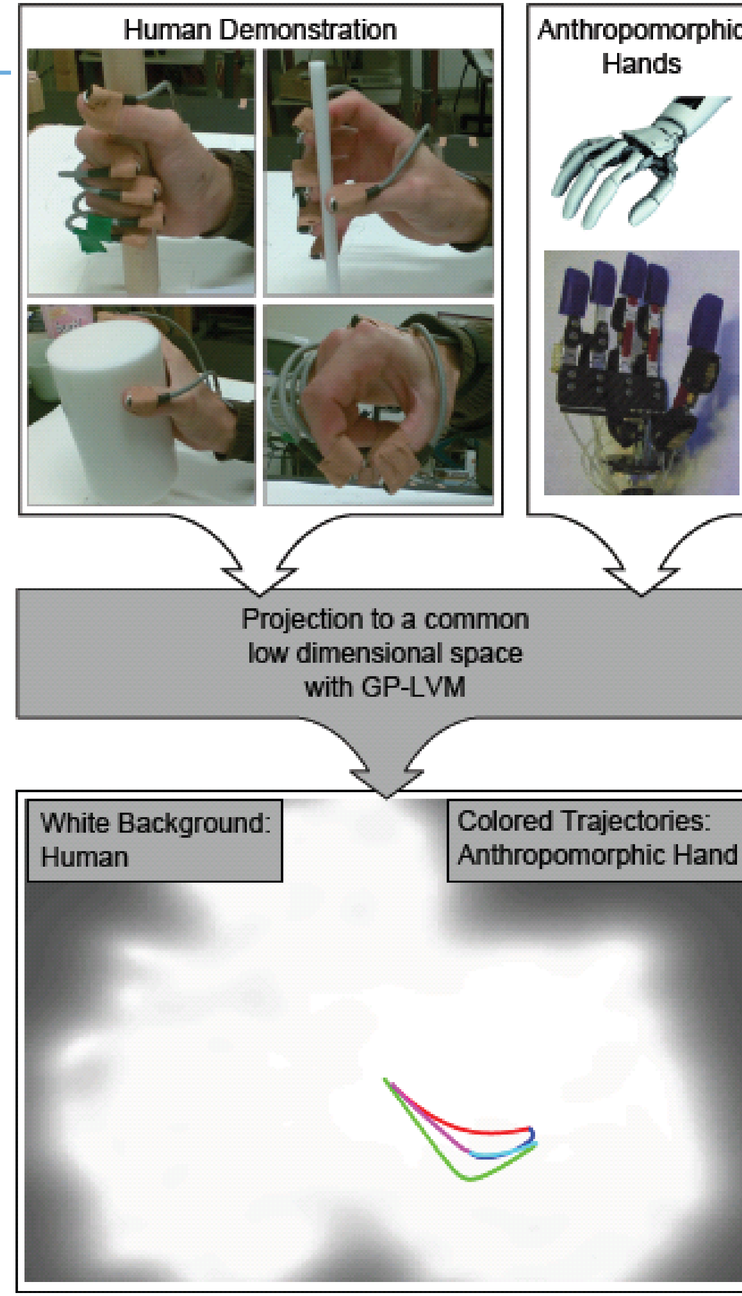


Motivation

- How can one (human/robot) interact with the world if the hands have less/more/longer/shorter/no fingers?
- How can we control *simple* hands to achieve complex behavior?

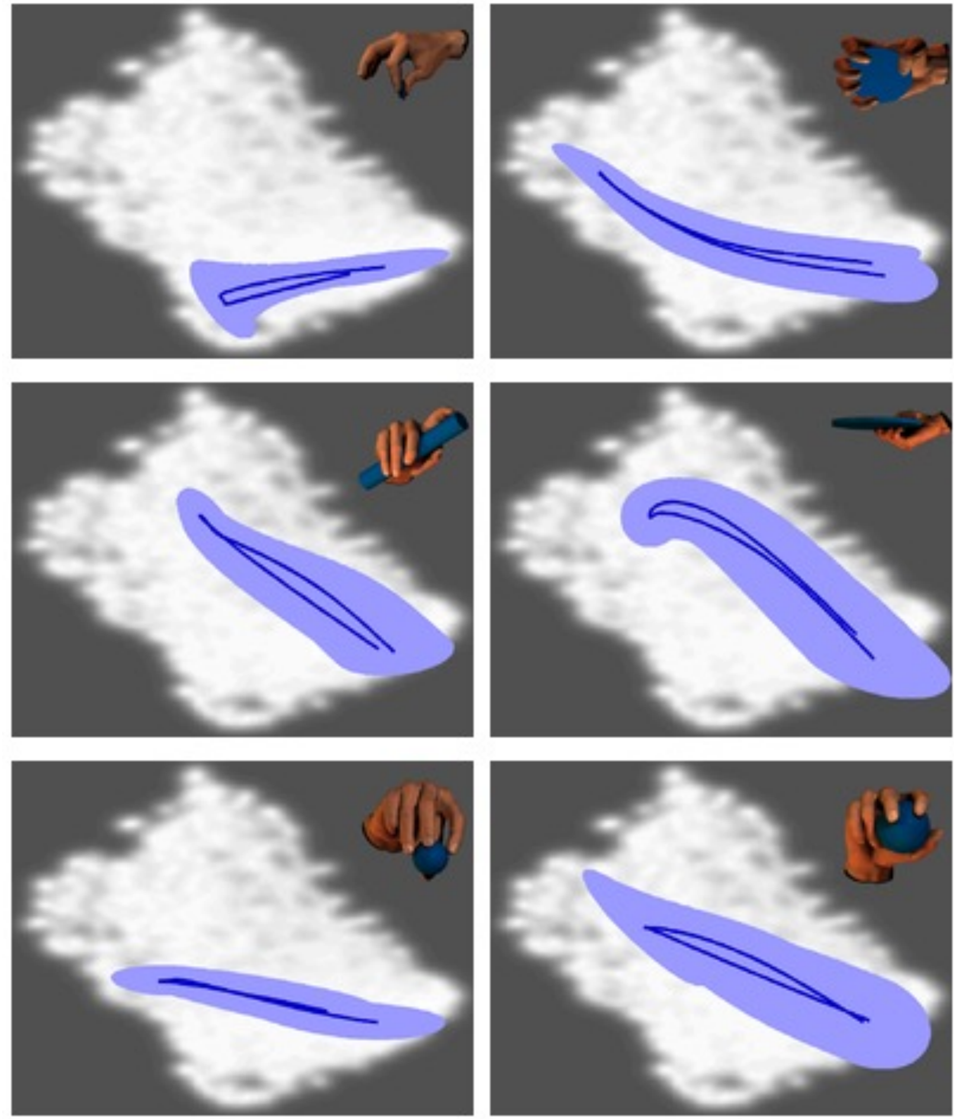
$$R^n \Longrightarrow SE_1(3) \times SE_2(3) \times \cdots \times SE_k(3)$$

- *"How complex or simple a structure is depends upon the way we describe it. Most of the complex structures found in the world are enormously redundant, and we can use this redundancy to simplify their description. But … we must find the **right representation**."* (H.A. Simon, The Sciences of the Artificial)

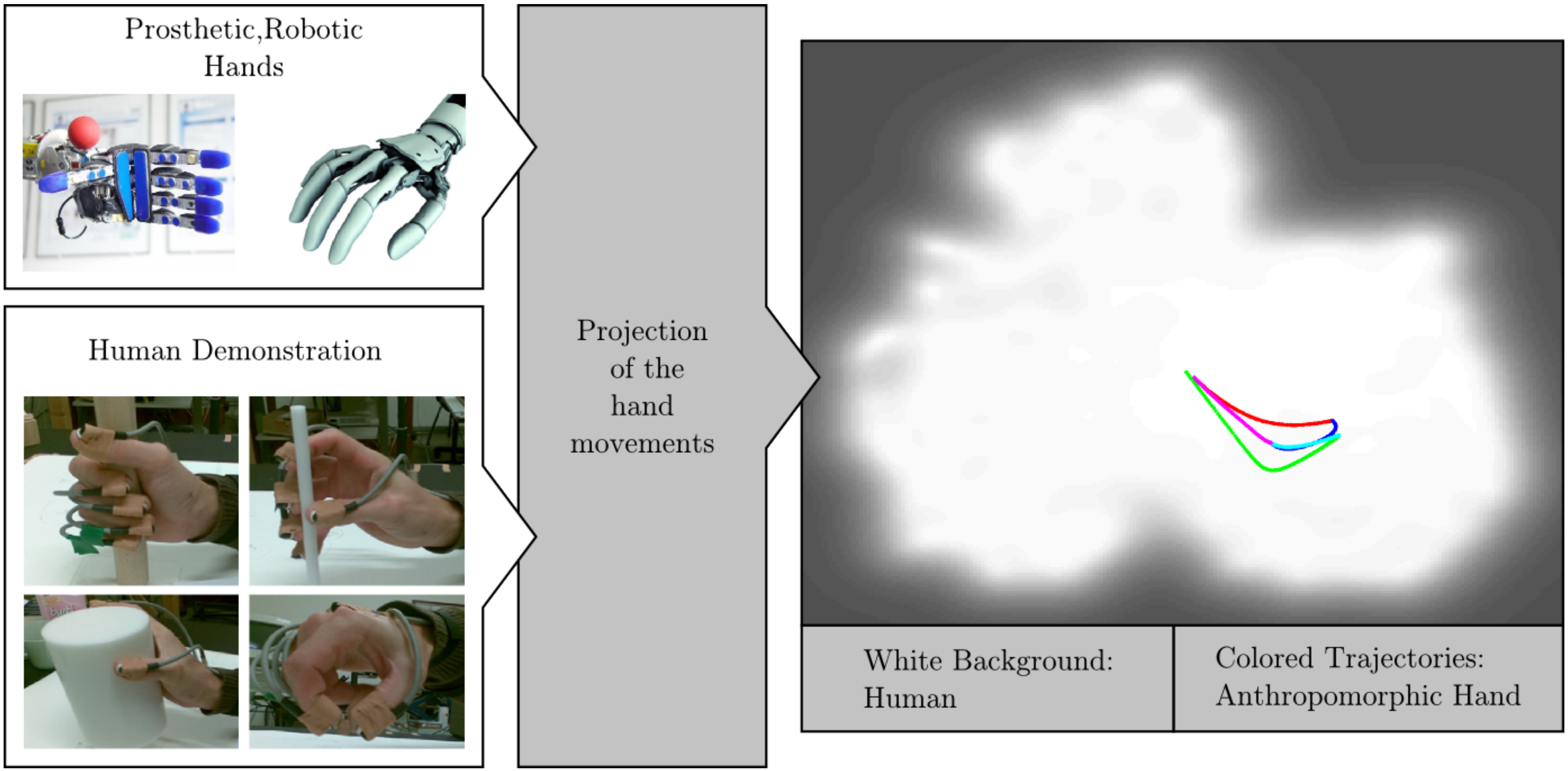


Understanding human grasping

- Human hand postures have high dimensionality
- Actual motion lies on low-dimensional nonlinear manifold
- Find good low-dimensional representation
  - Get new insights about the manifold
  - Simplify control of robotic hands



System Overview

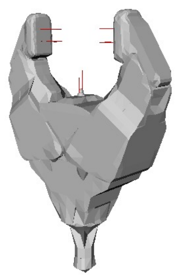


T. Feix et al. A metric for comparing the anthropomorphic motion capability of artificial hands, *IEEE Transactions on Robotics, 2012*

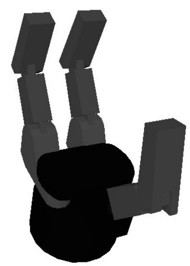
Why is this important?

Prosthesis
OttoBock

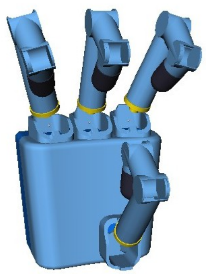
PR-2
Willow Garage



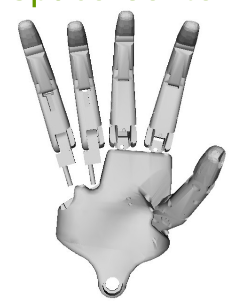
Barrett
Barrett Technologies



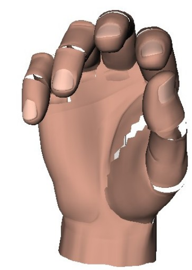
DLR I
German Aero-space Center



Robonaut I
NASA Johnson Space Center



Human



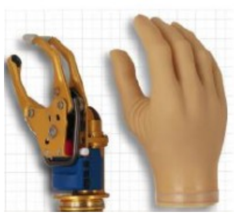
anthropomorphism, versatility →

← simplicity, ease-of-use

M. Ciocarlie

Why is this important?

Prosthesis
OttoBock



PR-
Will
Gara

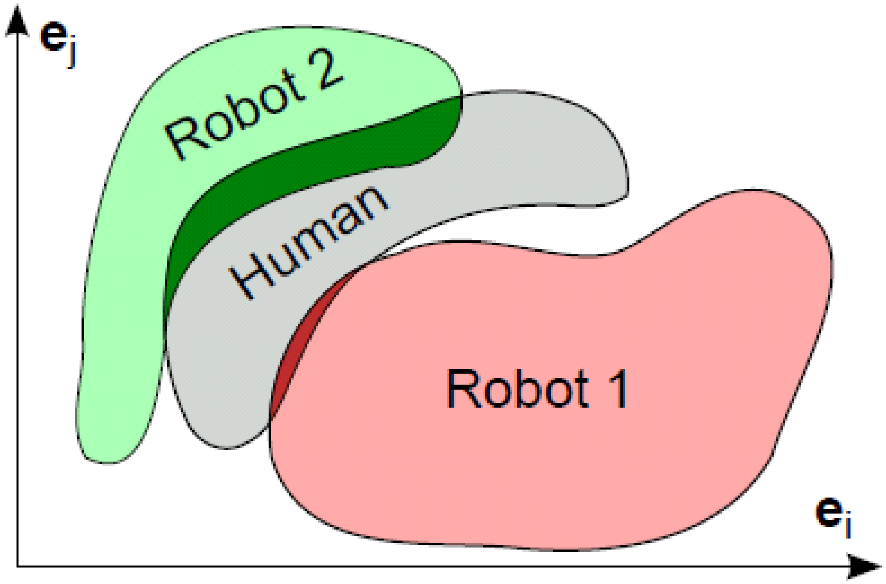
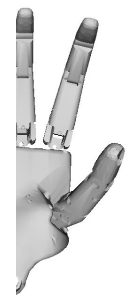
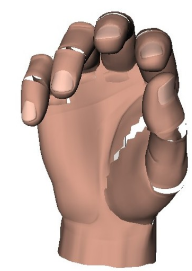


Fig. 2. In the 30 dimensional fingertip space **Y** each hand can reach a certain volume. The human hand is used as the golden standard and artificial hands should be well aligned with the human hand.

aut I
ohnson
Center



Human

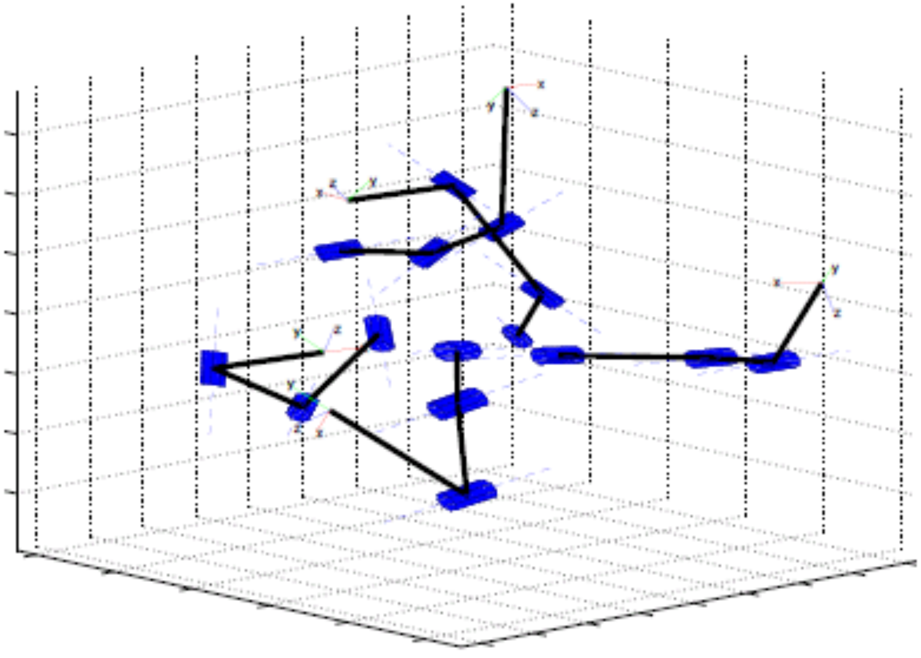


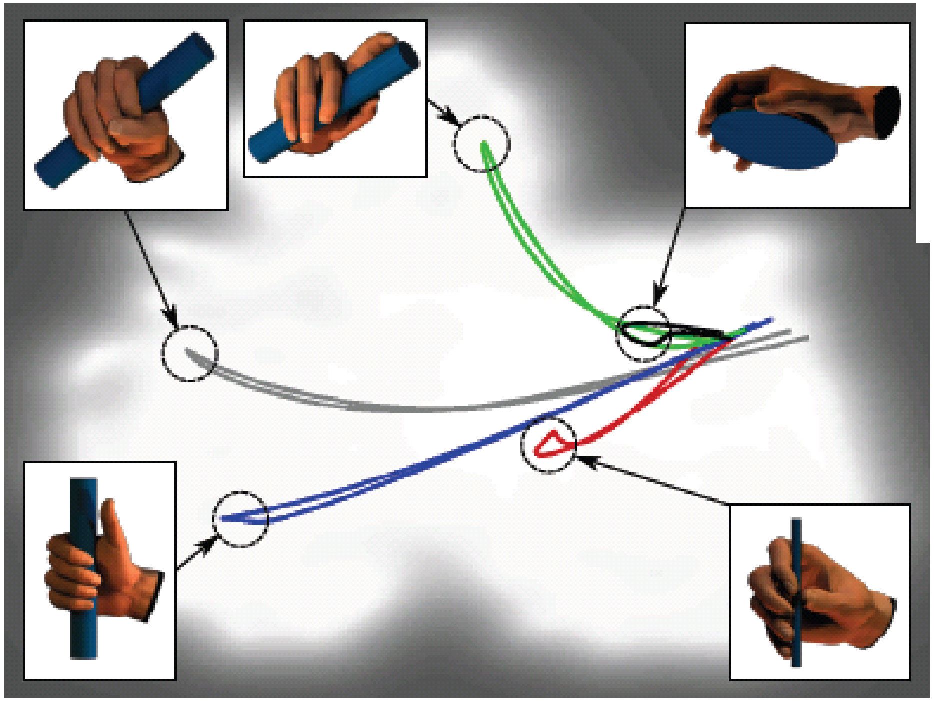
anthropomorphism, versatility →

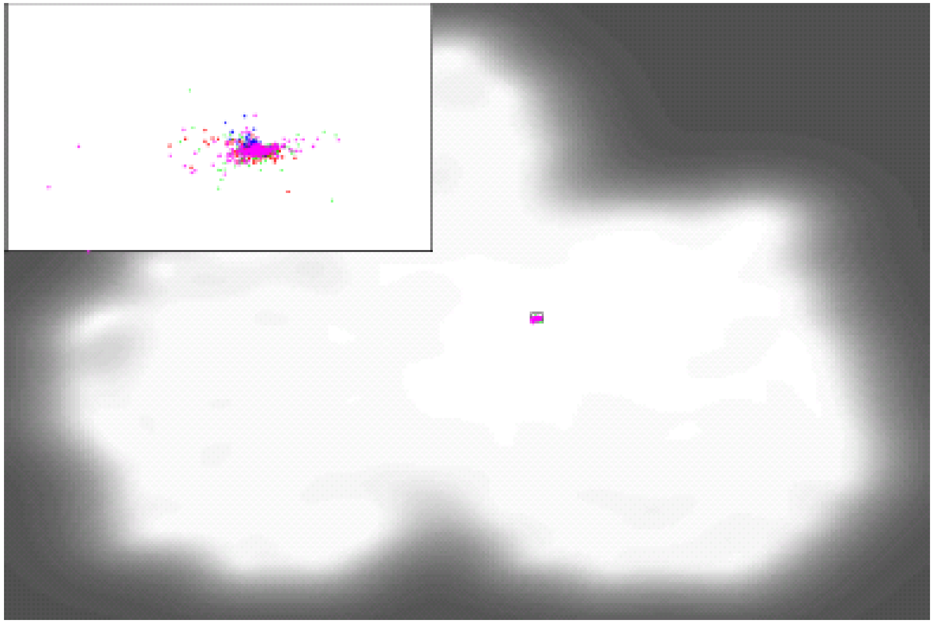
← simplicity, ease-of-use

M. Ciocarlie

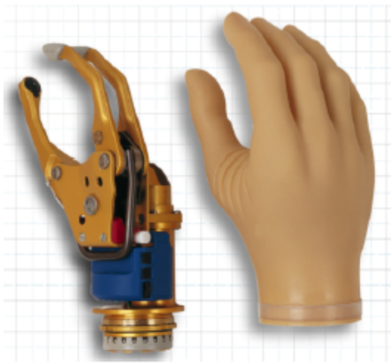
Results

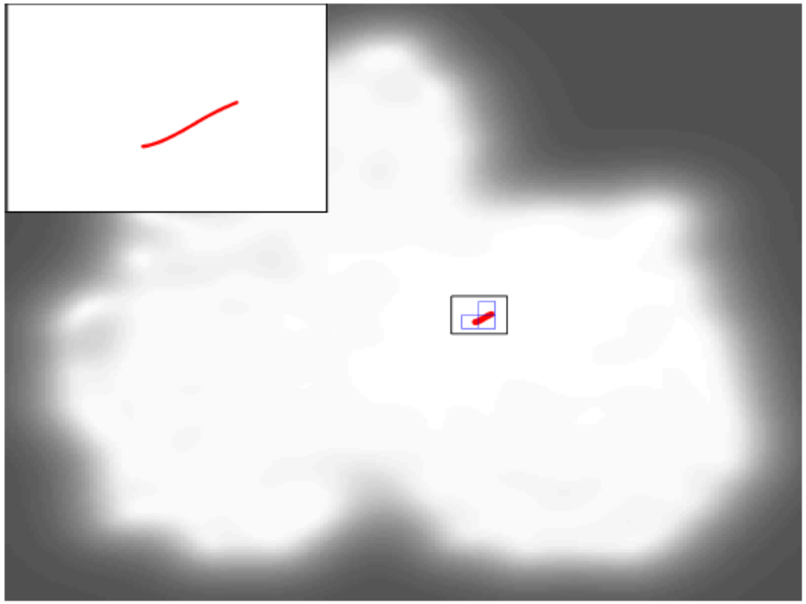


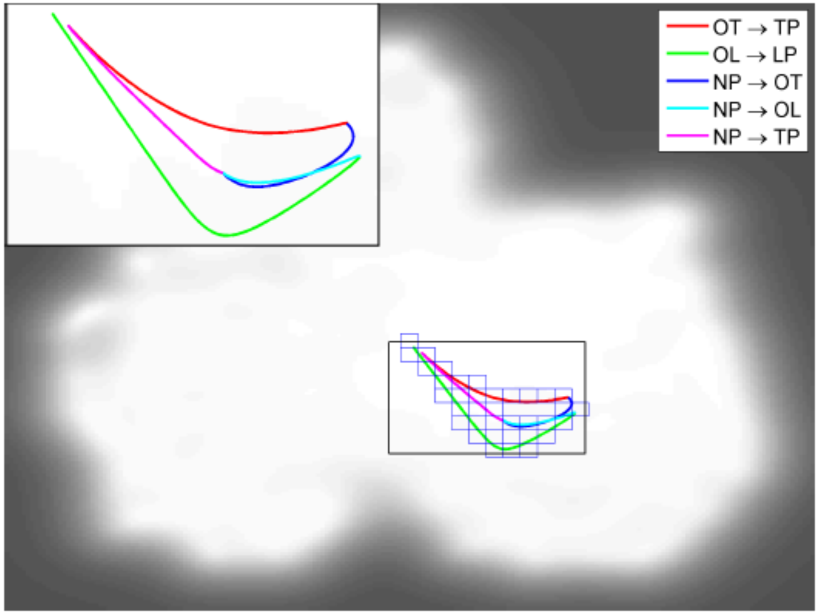




Examples







Mapping Human Intentions to Robot Motions via Physical Interaction Through a Jointly-held Object

Joint work with Francisco Vina, Yiannis Karayiannidis, Christian Smith

C. Smith, Y. Karayiannidis, L. Nalpantidis , X. Gratal, P. Qi, D.V. Dimarogonas and D. Kragic , *"Dual arm manipulation - a survey,"* Robotics and Autonomous Systems, 2012.

Y. Karayiannidis, C. Smith, and D. Kragic *"Mapping Human Intentions to Robot Motions via Physical Interaction Through a Jointly-held Object,"* IEEE Int Symposium on Robot and Human Interactive Communication, 2014

Physical Human-Robot Interaction

- Human-robot communicate through the haptic channel

Applications

- Cooperative manipulation of a jointly-held object
- Kinesthetic teaching

Physical Human-Robot Interaction

- Human-robot communicate through the haptic channel

Applications

- Kinesthetic teaching
- Cooperative manipulation of a jointly-held object

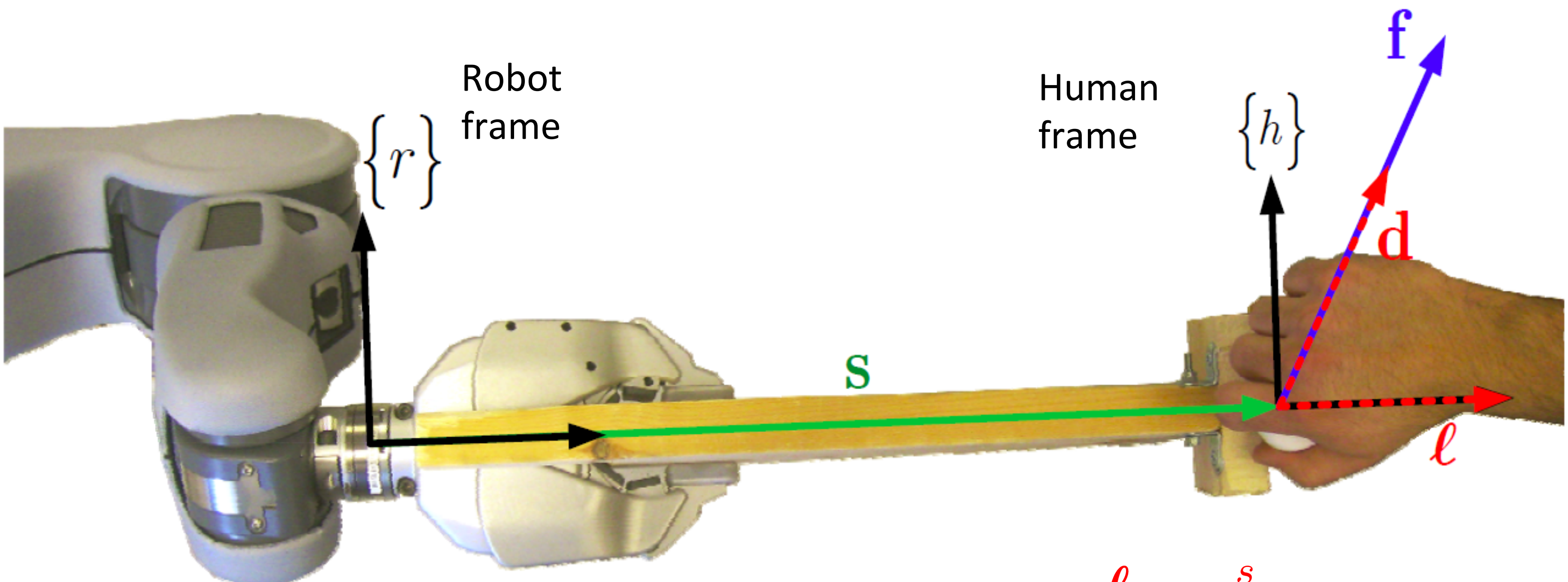
Physical Human-Robot Interaction

Human: active agent controls the motion of the object.

Robot: passive agen
(power amplifier –
reduce the apparent
mass of the object)

Admittance/Impedance control
M. Rahman et al. SMC99
K. Kosuge et. al, ICRA00, SMC01
Yokoyama et. al, ICRA03
T. Takubo et. al, IJRR, 2002

Human-robot setup - Notation



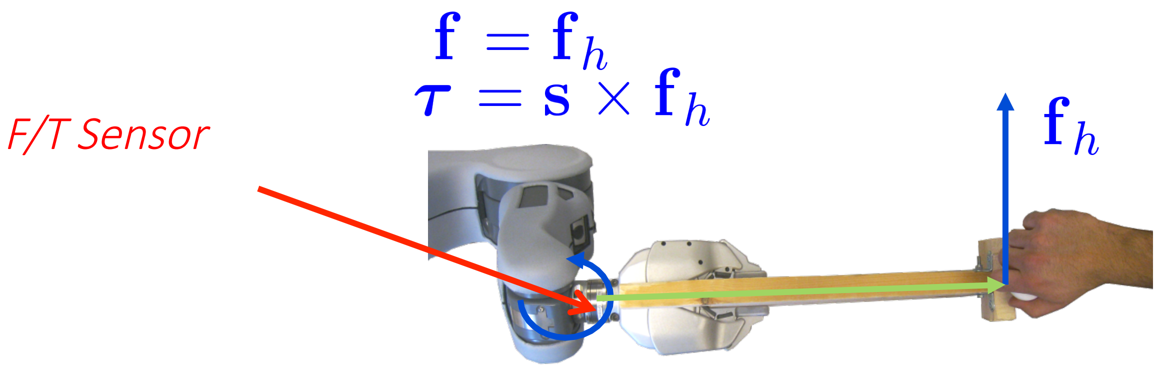
$\boldsymbol{\ell} = \frac{s}{\|s\|}$

$\mathbf{s} = \mathbf{p}_h - \mathbf{p}_r$ Virtual stick

$\mathbf{f}$ Force vector

$\mathbf{d} = \frac{\mathbf{f}}{f}$ Direction vectors

Rotation/Translation Problem (1)

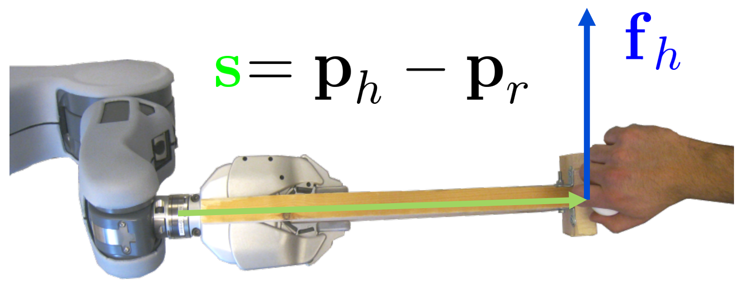


- Human can robustly control the exerted force
- Limitations to amount of torque that human can exert

- Large or massive objects
- Human can use only the one hand

- *Human control space* is of ***lower*** dimension compared to the *object state space*

Rotation/Translation problem (2)

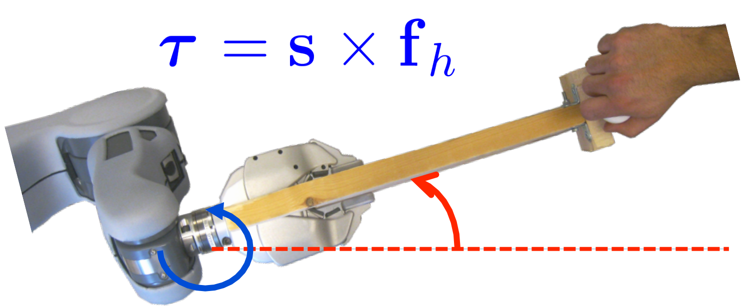


$$\boldsymbol{\omega} = \bar{b}_R \boldsymbol{\tau} = \bar{b}_R \mathbf{s} \times \mathbf{f}_h$$

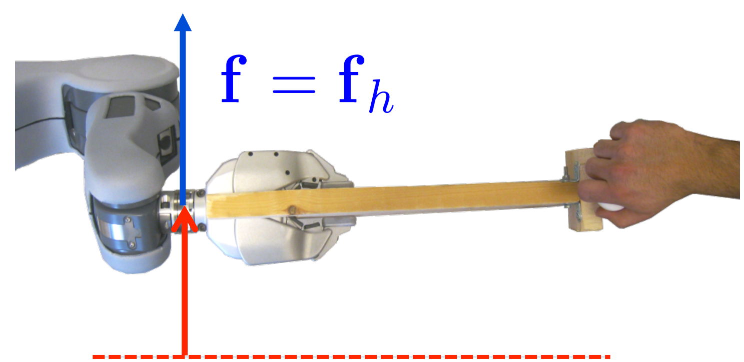
Rotation

$$\dot{\mathbf{p}}_r = \bar{b}_T \mathbf{f} = \bar{b}_T \mathbf{f}_h$$

Translation



+



Modes of operation

- Rotation mode

$$\sigma = 0$$

- Translation mode

$$\sigma = 1$$

Controller

$$\dot{\mathbf{p}}_r = \begin{cases} \sigma \bar{b}_T \mathbf{f}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

$$\boldsymbol{\omega} = \begin{cases} (1-\sigma)\,\bar{b}_R \boldsymbol{\tau}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

$f_{\min}$: motion threshold

Modes of operation

- Rotation mode

$$\sigma = 0$$

- Translation mode

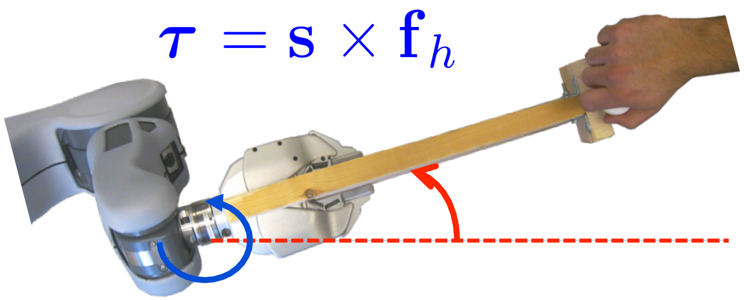
$$\sigma = 1$$

Controller

$$\dot{\mathbf{p}}_r = \begin{cases} \cancelto{\mathbf{0}}{\sigma \bar{b}_T \mathbf{f}}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

$$\boldsymbol{\omega} = \begin{cases} (\cancel{1-\sigma})\, \bar{b}_R \boldsymbol{\tau}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

$$\boldsymbol{\tau} = \mathbf{s} \times \mathbf{f}_h$$



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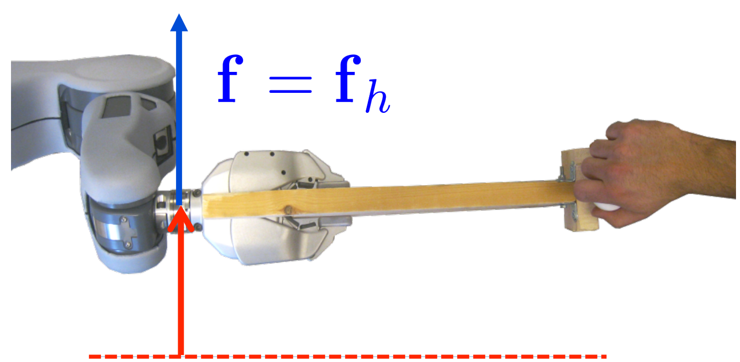


Controller

$$\dot{\mathbf{p}}_r = \begin{cases} \cancel{\sigma \bar{b}_T}\mathbf{f}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

$$\boldsymbol{\omega} = \begin{cases} \overset{0}{\cancel{(1-\sigma)\bar{b}_R \boldsymbol{\tau}}}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

$f_{\min}$: motion threshold

Modes of operation

- Rotation mode

$$\sigma = 0$$

- Translation mode

$$\sigma = 1$$

C_T → Translation mode

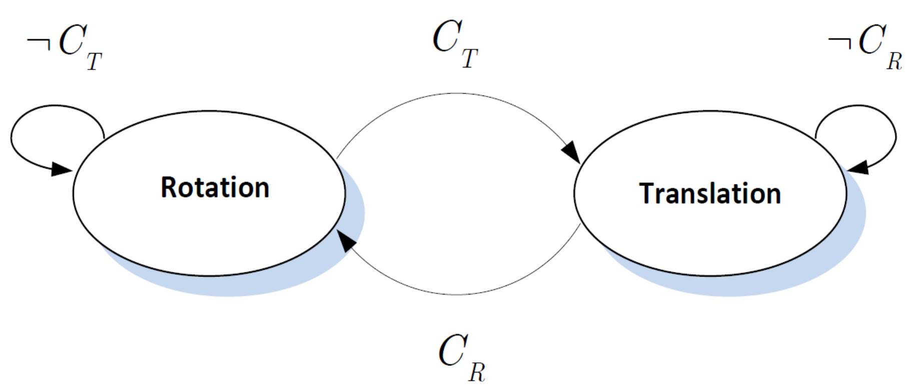
C_R → Rotation mode

Controller

$$\dot{\mathbf{p}}_r = \begin{cases} \sigma \bar{b}_T \mathbf{f}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

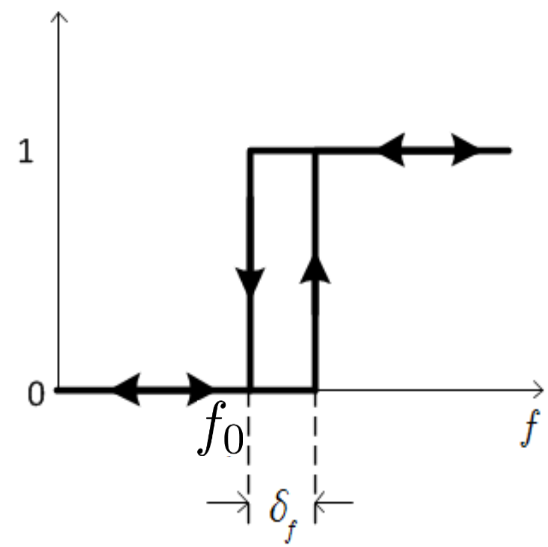
$$\boldsymbol{\omega} = \begin{cases} (1-\sigma)\, \bar{b}_R \boldsymbol{\tau}, & \|\mathbf{f}\| \geq f_{\min} \\ 0, & \|\mathbf{f}\| < f_{\min} \end{cases}$$

State machine describing the switching



Switching based on the force magnitude

1. Operation in the rotation mode:
   - Generation of ***internal forces*** for any commanded force that is not perpendicular to the virtual stick
2. Operation in the translation mode:
   - Compensation of forces in all possible directions



3. Proportional relation between human forces and the end-effector velocity

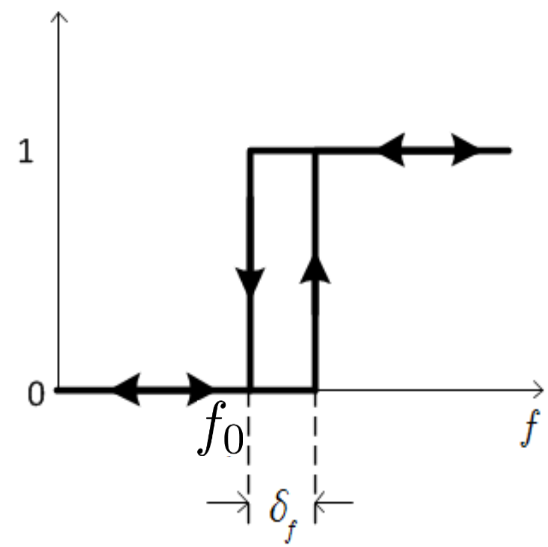
$$C_T \equiv (f > f_0 + \delta_f)$$

4. Intuition: Human must reduce speed to enter the rotation mode

$$C_R \equiv (f < f_0)$$

Switching based on the force magnitude

1. Operation in the rotation mode:
   - Generation of *internal forces* for any commanded force that is not perpendicular to the virtual stick
2. Operation in the translation mode:
   - Compensation of forces in all possible directions



3. Proportional relation between human forces and the end-effector velocity

4. Intuition: Human must reduce speed to enter the rotation mode

$$C_T \equiv (f > f_0 + \delta_f)$$

$$C_R \equiv (f < f_0)$$

socSMCs

Socializing Sensorimotor Contingencies

One of the main assertions of **sensorimotor contingency** theory is that sensory experience is not generated by activating an internal representation of the outside world through sensory signals, but corresponds to a mode of exploration and hence is an active process.

Sensorimotor Contingencies

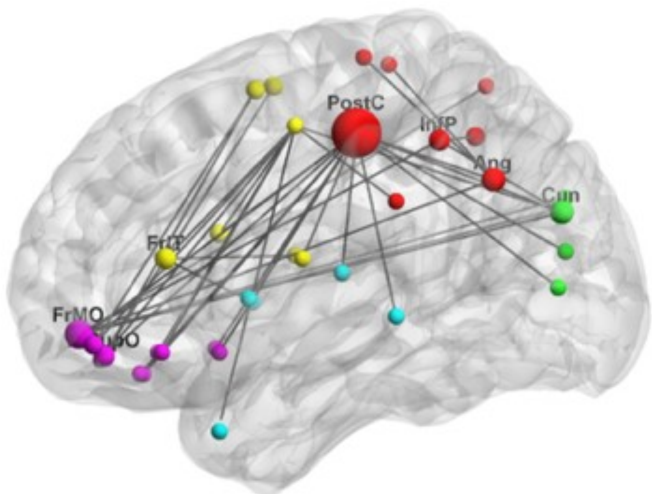
- Interpretation of sensory data depends on action context; requires a **forward model** that predicts how sensory inputs will change **as a consequence of movement**
- „Sensorimotor contingencies" (SMCs) are constitutive for perception, i.e., rules governing
  sensory changes produced by motor actions

  „We propose that seeing is a way of acting. It is a particular way of exploring the environment. …Vision is a mode of exploration of the world that is mediated by knowledge of what we call sensorimotor contingencies." (O'Regan & Noe, 2001)

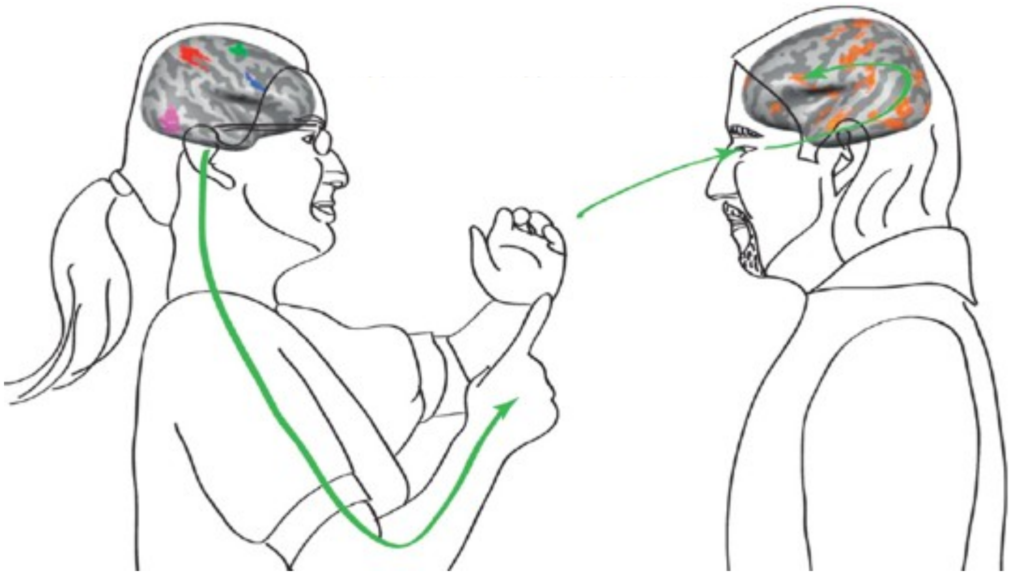
- Sensorimotor contingency theory claims that SMCs can be used to account for **differences between sensory modalities**
- Seeing differs from hearing mainly **because the SMCs differ**; i.e., the contingencies between movements and the ensueing sensory changes
- Can the concept of **SMCs**, generalized to learning action-effect contingencies, be applied to social contexts?

Coupling Within and Between Brains

Inspiration for the project: previous work on **within-brain** and **inter-brain coupling**



Andreou, Leicht, Nolte, Polomac, Moritz, Karow, Hanganu-Opatz, Engel & Mulert, Schizophr Res 2015



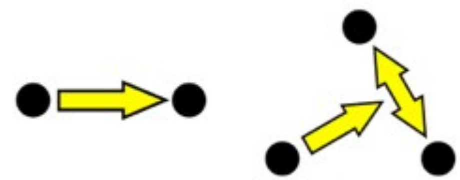
Hasson, Ghazanfar, Galantucci, Garrod & Keysers, TICS 2012

- Brains exhibit **rich dynamic coupling** within modules and across subsystems
- Brains are **mutually entrained** by interaction and joint actions; do similar coupling modes and dynamics apply?

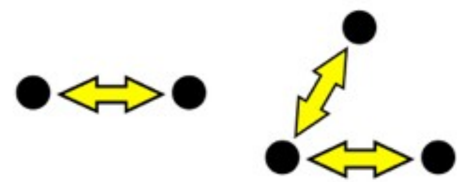
Levels of socSMCs

- Different **stages of social entrainment**; different **modes of dynamic coupling** between agents, involving an increasing set of degrees of freedom of the interacting multi-agent system

- **Check SMCs:**
  - **Unidirectional** coupling, one agent predicting another agent's actions or the interaction between two other agents
  - Entrainment of one agent to a group of other agents



- **Synch SMCs:**
  - **Bidirectional** coupling, both agents mutually predict each other
  - Mutual entrainment, allowing cooperation, joint attention, turn-taking, shared action goals



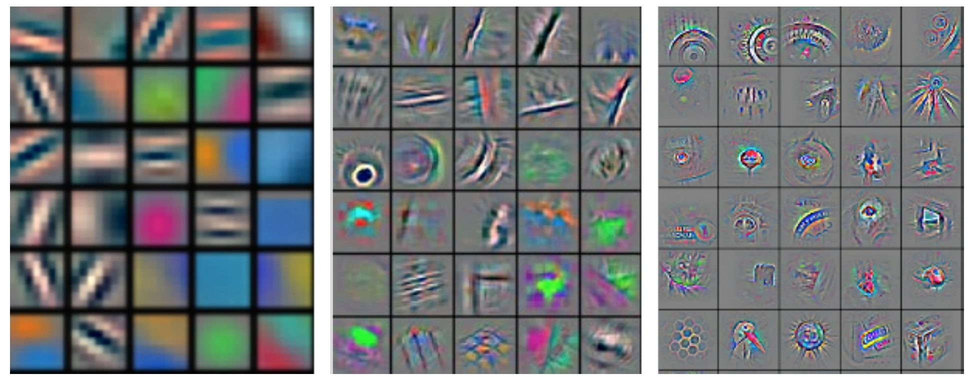
- **Unite SMCs:**
  - **Multidirectional** coupling; coupling mode characterized by emergence of higher-order interaction patterns that cannot fully be explained by bivariate interactions
  - Emergence of group mental states, group habits, group emotions

Social Sensorimotor Contingencies

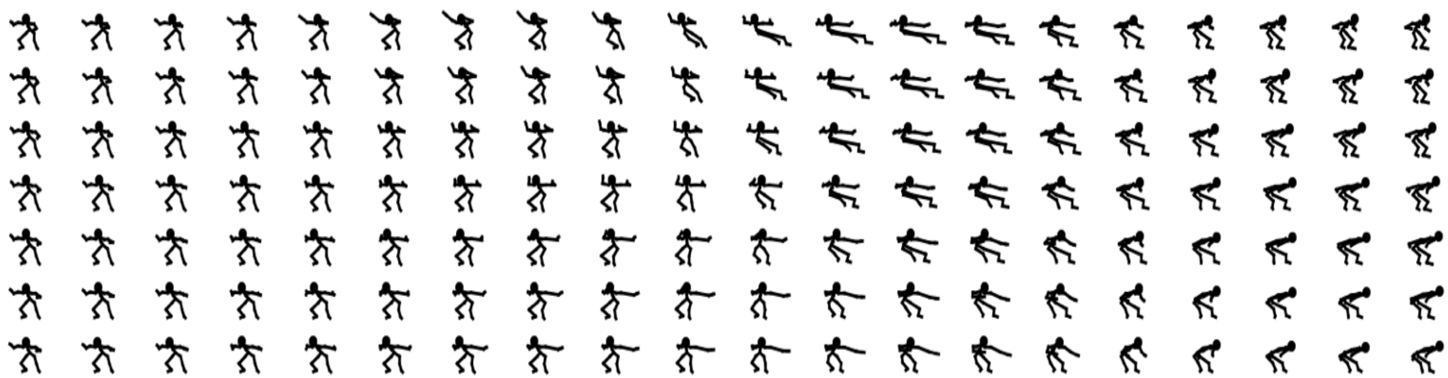
with Judith Bütepage

Deep learning is known to be an excellent feature extraction method for e.g. images …

[*]



… but what about human motion?



[*] http://www.cs.nyu.edu/~yann/talks/lecun-ranzato-icml2013.pdf

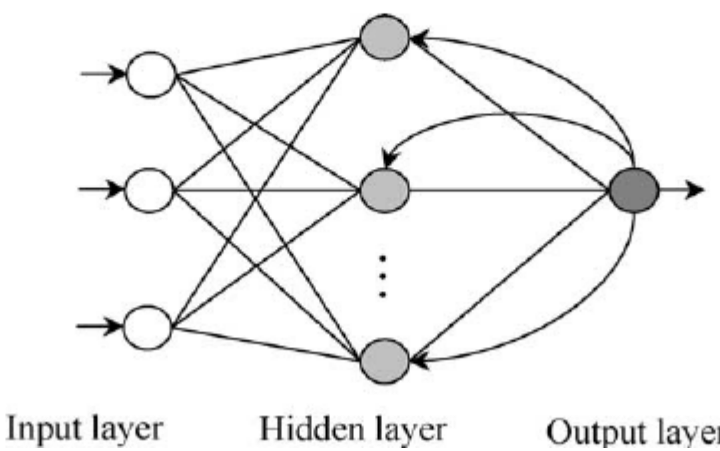
Our aim is to build a system that can give us long-term, 1-1.5 seconds, predictions of human motion. Since we will work in a HRI setting, this system needs to be:

- **general** - it needs to be able to predict everyday motion
- **online** - as the robot will base its own decisions on this
- **robust** - it should not fail in noisy situations and be able to handle occlusions

Ongoing work

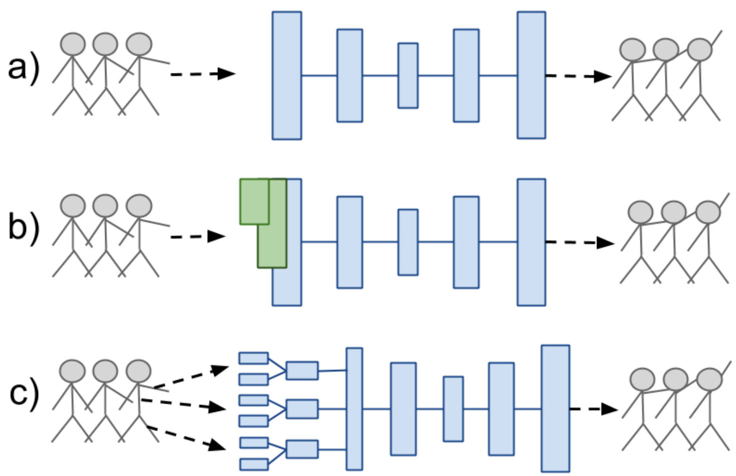
Recent related work has treated this problem with recurrent networks to capture the dynamics of the human motion. However, they do not meet our requirements:

- **general** - They learn a separate model for each motion.
- **online** - It takes long time to propagate the information through the network.
- **robust** - Recurrent networks are sensitive to noise since errors are propagated over time.



Ongoing work

We learn fully-connected temporal encoders as generative models of human motion.

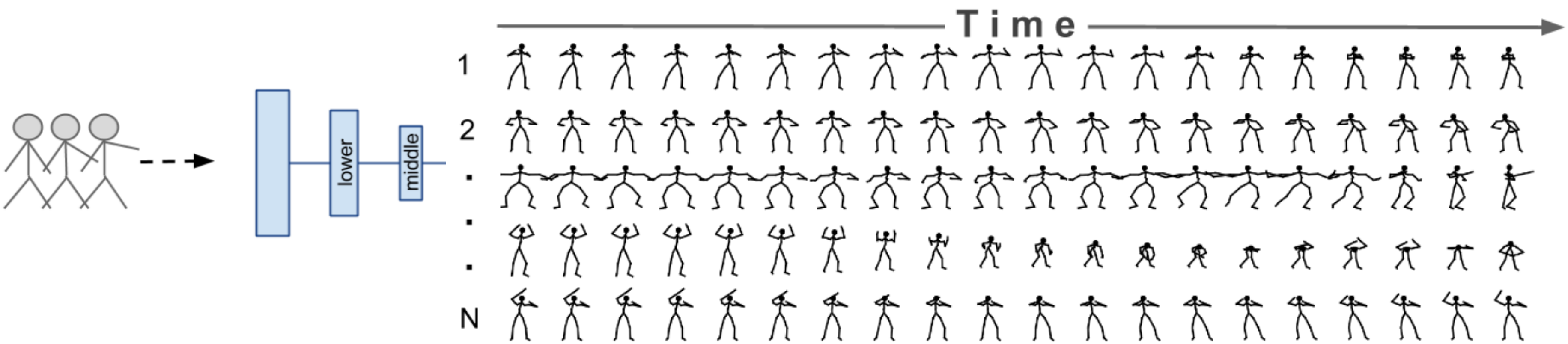


Symmetric temporal encoder

Convolutional temporal encoder

Hierarchical temporal encoder

Ongoing work

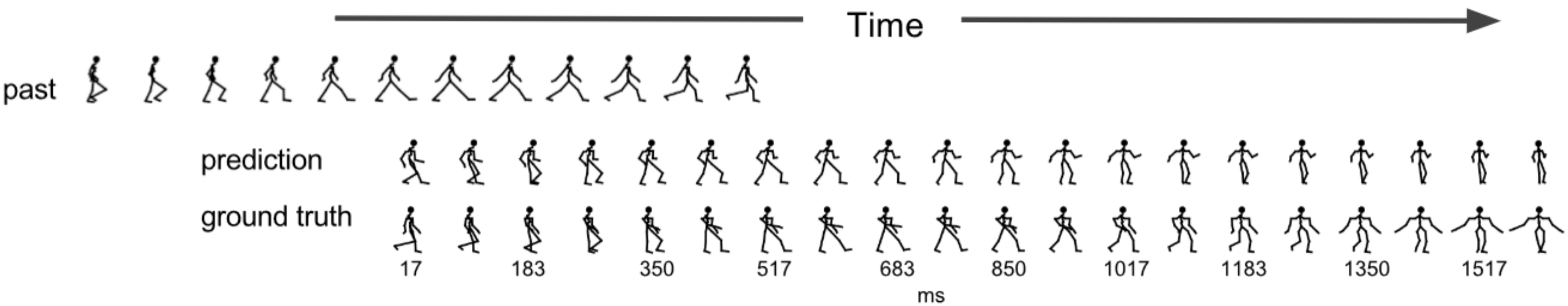


Average pose weighted by activity of neurons

Computed as an average over input pose windows weighted by the activity of a neuron if it exceeds a threshold.

We see that different neurons encode e.g. whole body turning, crouching or only arm movements. This suggests that the neurons learn meaningful features. The combined activity of the neurons acts in a way like PCA since we could reconstruct different motions as a linear combination of these poses.

Ongoing work



Predicted motion sequence

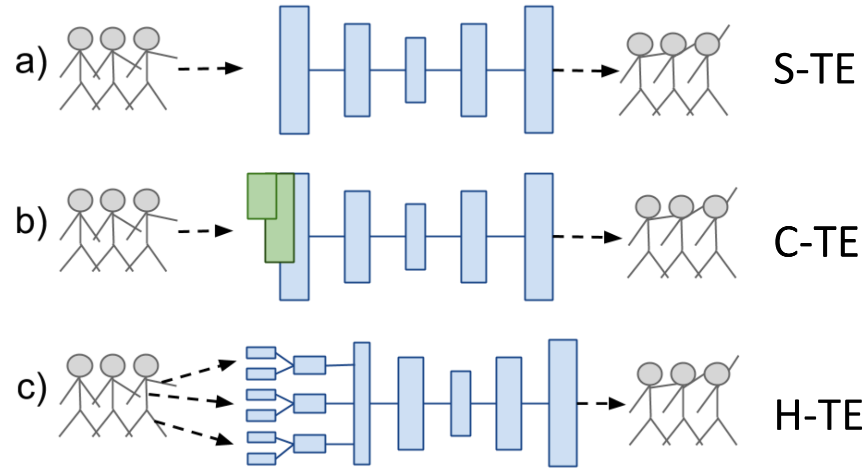
Based on the last pose window we predict the next pose window. This gives us coherent, longtime movement predictions that do not suffer from propagation errors as it is the case for e.g. recurrent networks.

Since we are working with feedforward models, the evaluation is fast and can be used in real-time interaction.

Related work predicts up to 560 ms.

Ongoing work

Method	Short Term			Long Term	
	80ms	160ms	320ms	560ms	1000ms
Walking					
ERD [8]	0.2	0.25	0.37	0.49	0.62
S-RNN [13]	0.19	0.23	0.31	0.44	0.57
LSTM3L	0.19	0.25	0.35	0.42	0.47
S-TE	0.33	0.35	0.37	0.37	0.4
C-TE	0.18	0.2	0.26	0.32	0.36
H-TE	**0.17**	**0.18**	**0.23**	**0.28**	**0.31**
H-TE-F	**0.16**	**0.17**	**0.2**	**0.24**	**0.24**
Smoking					
ERD [8]	0.38	0.42	0.47	0.53	0.63
S-RNN [13]	0.36	0.39	0.46	0.54	0.62
LSTM3L	0.28	0.33	0.4	0.46	0.52
S-TE	0.4	0.4	0.4	0.42	0.49
C-TE	**0.26**	0.27	0.33	0.4	0.49
H-TE	**0.26**	**0.26**	**0.29**	**0.35**	**0.41**
H-TE-F	**0.17**	**0.17**	**0.19**	**0.23**	**0.27**
Eating					
ERD [8]	0.25	0.29	0.37	0.46	0.56
S-RNN [13]	0.2	0.25	0.35	0.44	0.44
LSTM3L	**0.18**	0.25	0.35	0.4	0.44
S-TE	0.33	0.34	0.35	0.37	0.42
C-TE	0.19	0.21	0.25	0.31	0.37
H-TE	0.2	**0.2**	**0.23**	**0.29**	**0.37**
H-TE-F	**0.15**	**0.15**	**0.17**	**0.21**	**0.26**
Discussion					
ERD [8]	0.31	0.37	0.45	0.5	0.54
S-RNN [13]	0.38	0.4	0.52	0.6	0.58
LSTM3L	0.48	0.5	0.59	0.61	0.62
S-TE	0.22	0.23	0.32	0.26	0.27
C-TE	0.15	0.17	0.2	0.25	0.31
H-TE	**0.16**	**0.17**	**0.2**	**0.22**	**0.24**
H-TE-F	**0.13**	**0.14**	**0.18**	**0.2**	**0.22**



ERD,S-RNN and LSTM3L are all recurrent networks, i.e. for each action, there is a separate model that was trained on data from the same data set.

We trained on a different data set and have a single model for all predictions. If we fine-tune this model to each action (H-TE-F) the model gets better at long-term prediction.

A Sensorimotor Reinforcement Learning Framework for Physical Human-Robot Interaction

with Ali Ghadirzadeh, Judith Bütepage, Mårten Björkman

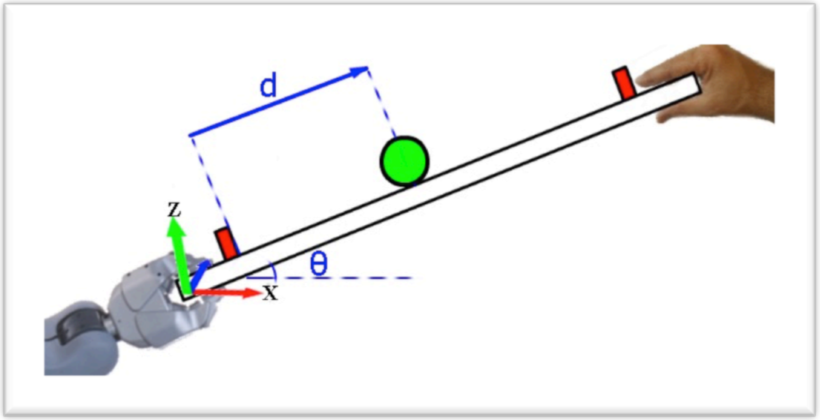
Physical Human-Robot Interaction - pHRI

Design of action policies of a robot to collaborate with human while being in physical contact with the human

Task

Learning a policy with the goals of

- Collaboratively **positioning the ball**
- Minimizing **the interaction force**



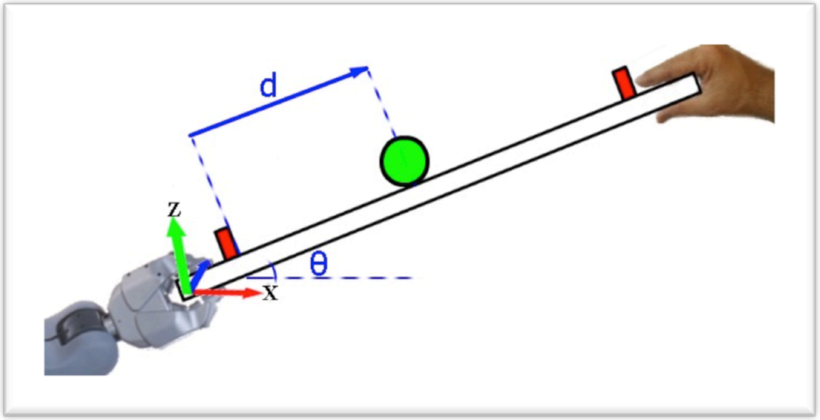
Task

Learning a policy with the goals of

- Collaboratively **positioning the ball**
- Minimizing **the interaction force**

Assumptions

- **No dynamic model** given
- Partners should **collaborate equally**
- **Few training data** available



Task

Learning a policy with the goals of

- Collaboratively **positioning the ball**
- Minimizing **the interaction force**

Assumptions

- **No dynamic model** given
- Partners should **collaborate equally**
- **Few training data** available

States

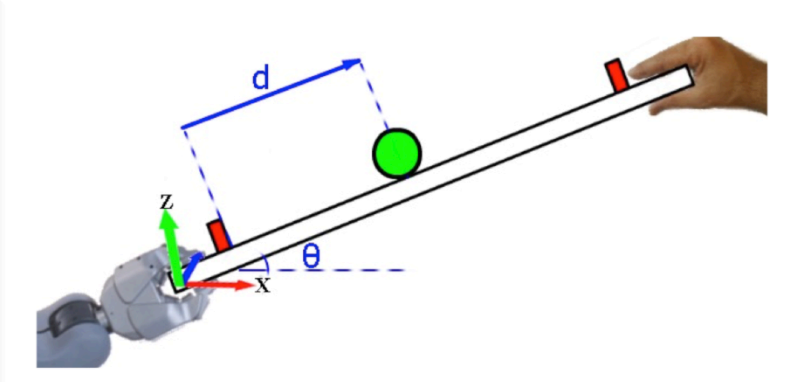
- end-effector position $[x_t, z_t]$
- Vision data $[\Delta d_t, d_t, d]$
- Force-torque $[\tau_t]$

Actions

- end-effector velocities $[v_x, v_z, \omega]$

Costs

- Ball positioning error
- Interaction force



Role-sharing in pHRI

- **Human leader, robot follower**
  - Load compensation *[Wojtara et al. 2009]*
  - Conveying human haptic command *[Dumora et al. 2012, Karayiannidis et al. 2014]*
  - Proactive motion planning *[Maeda et al. 2001, Thobbi et al. 2011, Gribovskaya et al. 2011]*
- **Robot leader, human follower**
  - Modeling humans as passive joints *[Karayiannidis et al. 2013]*
- **Equal role-sharing**
  - Role switching *[Ervard and Kheddar 2009]*
  - Impedance control *[Bussy et al. 2012, Agravante et al. 2013 and 2014]*

Modeling human behaviors

- **Motion trajectory predictions**
  - Minimum Jerk Model *[Maeda et al. 2001]*
  - Extended Kalman filters *[Thobbi et al. 2011]*
  - *Gaussian Mixture Models* *[Gribovskaya et al. 2011]*

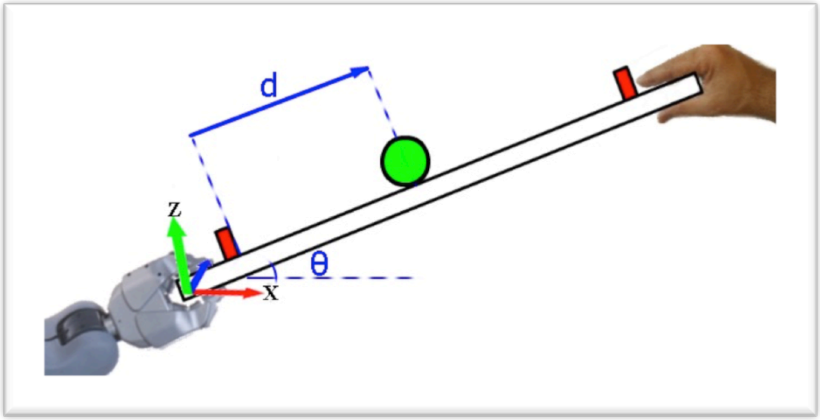
- **Geometrical modeling**
  - Revolute joint *[Karayiannidis et al. 2013]*

- **Disturbance modeling**
  - Impedance controller *[Bussy et al. 2012, Agravante, et al. 2013 and 2014]*

Role sharing and human modeling

Equal role-sharing

- Mutual modeling
- Cost function design

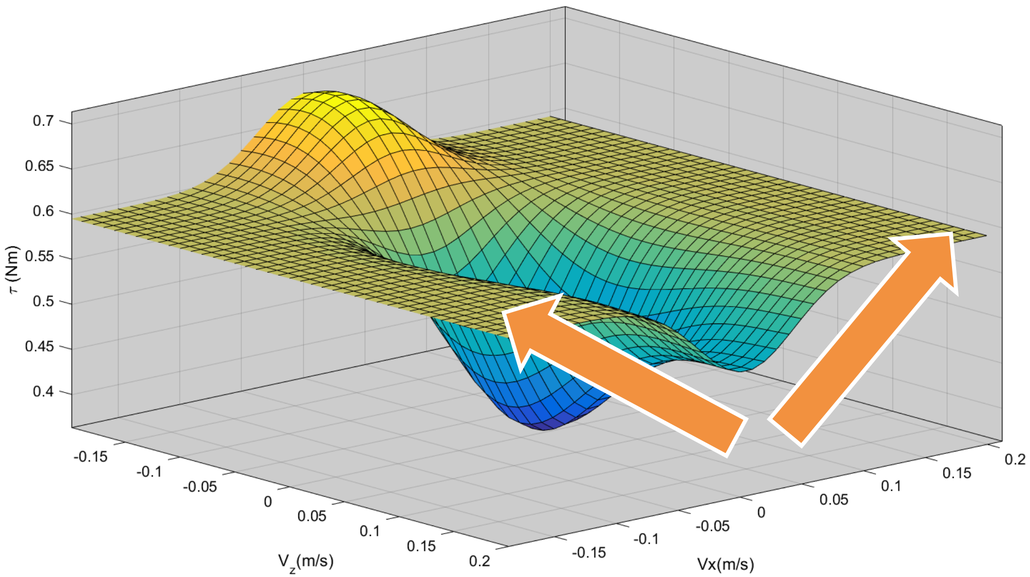


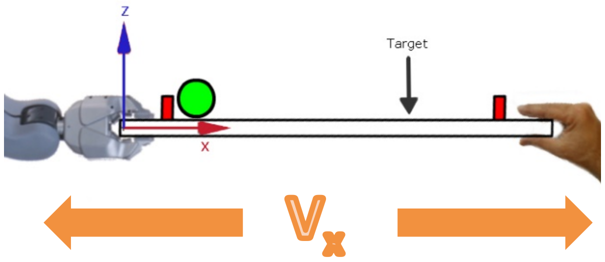
Sensorimotor modeling

- Representing human behaviors model by sensorimotor contingencies (SMCs) observed by the robot

Sensorimotor modeling

Example of sensorimotor modeling of human behaviors

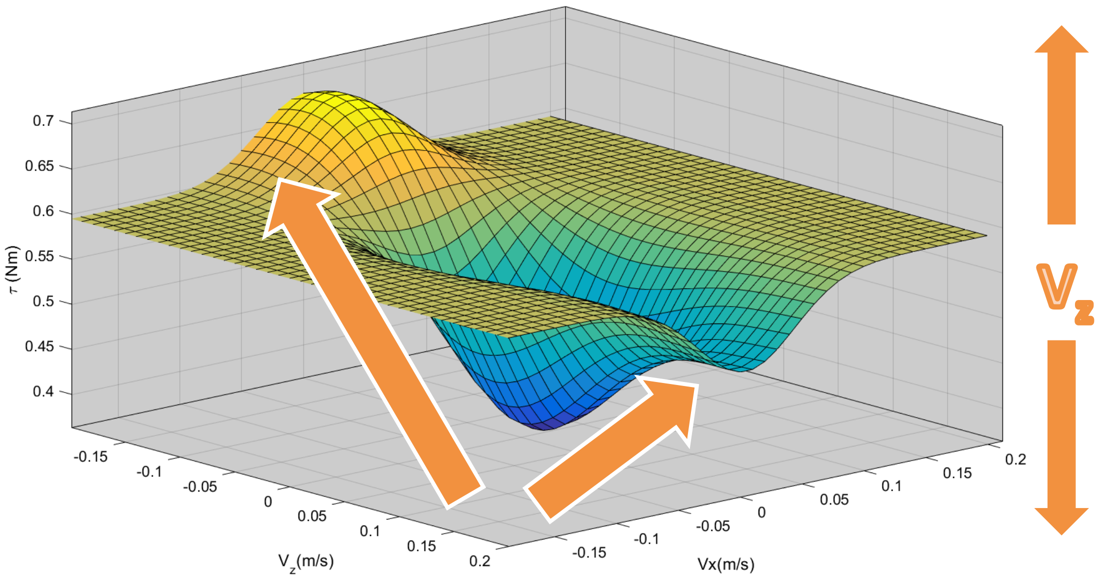


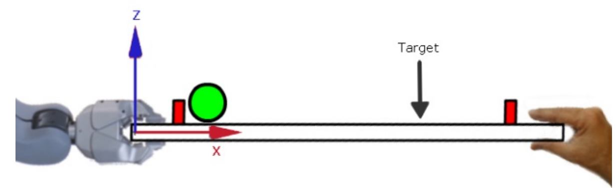


Predicted interaction force vs. commanded velocities

Sensorimotor modeling

Example of sensorimotor modeling of human behaviors



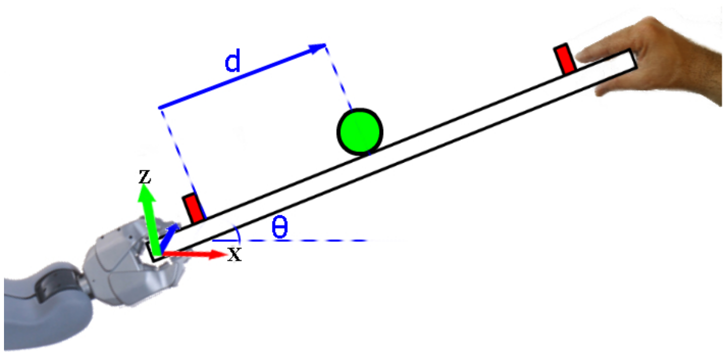


Predicted interaction force vs. commanded velocities

Forward model learning

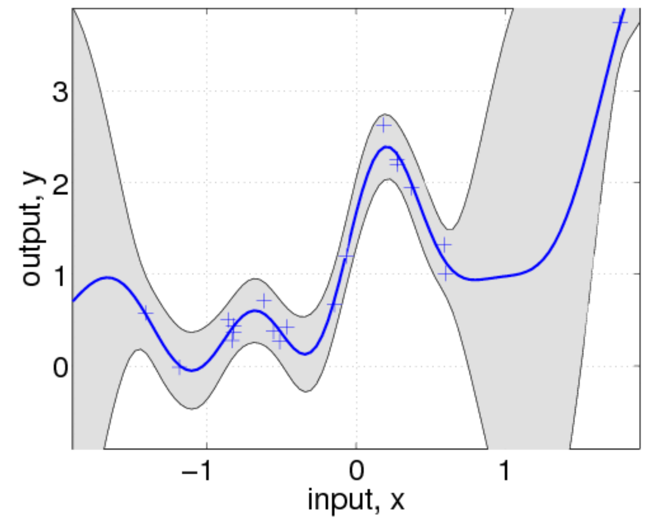
A forward model predicts future states given current state and action

$$\boxed{\Delta s_t = \mathscr{F}(s_t, a_t)}$$



Gaussian Processes

GP model - source: GPML documentation



Gaussian Processes represents both

- **Forward model**
- **Action-value function**

Benefits

- Model learning under **uncertainty** resulted from **stochastic human behaviors**
- **Data effieciency** due to non-parameteric representation
- Ensuring **optimal action selection** under uncertainty
- **Efficient Q-learning** with uncertain state-transisions

Bayesian optimization for optimal policy learning

Bayesian optimization

- **Optimal** action selection
- Staying **close** to the **previous action-state trajectories**

$$Q_{UCB}(x_t) = m_*(x_t) + \delta(k_*(x_t, x_t))^{\frac{1}{2}}$$

$$a_{t+1} = \operatorname*{argmin}_{a^*} Q_{UCB}([s_t, a^*])$$

Benefits

- **Safe exploration**
  - **Safety** to both partners – the human and the robot
- **Fast** policy learning
- Action selection under **uncertainty**

Model-based Gaussian processes Q-learning

Step 1) Predicting a <u>normal distribution</u> over the <u>next state</u> using the <u>forward model</u>

$$\Delta s_t = \mathscr{F}(s_t, a_t)$$

$$s_{t+1} \sim \mathcal{N}(\mu_{t+1}, \Sigma_{t+1})$$

Model-based Gaussian processes Q-learning

Step 1) Predicting a normal distribution over the next state using the forward model

Step 2) Finding the expected cost for the next state

$$\mathbb{E}_{s\sim s_{t+1}}[c(s)] = \int p(s'|\mu_{t+1}, \Sigma_{t+1})c(s')ds'$$

Model-based Gaussian processes Q-learning

Step 1) Predicting a normal distribution over the next state using the forward model

Step 2) Finding the expected cost for the next state

Step 3) Calculating the expected Q-value over the next state

$$\boxed{\mathbb{E}_{s\sim s_{t+1}}[Q(s,a)] = \iint p(q|s',a,\theta_q)p(s'|\mu_{t+1},\Sigma_{t+1})q\,ds'dq}$$

Model-based Gaussian processes Q-learning

Step 1) Predicting a normal distribution over the next state using the forward model

Step 2) Finding the expected cost for the next state

Step 3) Calculating the expected Q-value over the next state

Step 4) Updating Q-function

$$\boxed{Q(s_t, a_t) \leftarrow \mathbb{E}_{s \sim s_{t+1}}[c(s)] + \gamma \min_{a'} \mathbb{E}_{s \sim s_{t+1}}[Q(s, a')]}$$

END?