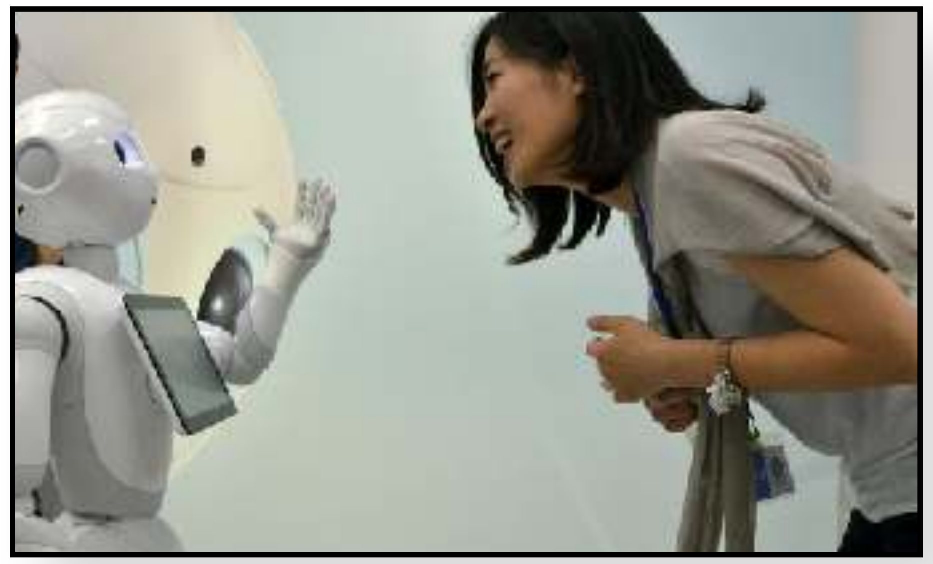
Human motion prediction for “human-aware” robots



Jim Mainprice, PhD

“HUMANS TO ROBOTS MOTION” (HRM)

Research Group Leader

Universität Stuttgart

MAX-PLANCK-GESELLSCHAFT

Human Space Sharing Skills

Human Interactive Manipulation

- Pick
- Place
- ➡ Give
- ➡ Receive
- ➡ Co-Manipulate

Dynamic Social Movement

Anticipation


Anticipation
Legibility
?


Anticipation
Legibility
Coordination


Anticipation
Legibility
Coordination
Learning

Human-Robot Interactions

[Multu, Springer Handbook of Robotics, 2016]

Robot Models

Model of the **human**, context of the task and the context of the interaction

Human Models

Mental model of the **robot**, social cognition and interpersonal perception difference

Interaction Models

Models of the communication and interaction

action

action

Task

Robot Models

Outline

1. Human Aware Motion Planning
2. Inverse Optimal Control of Collaborative Motion
3. Combining with Data Driven Dynamical Models

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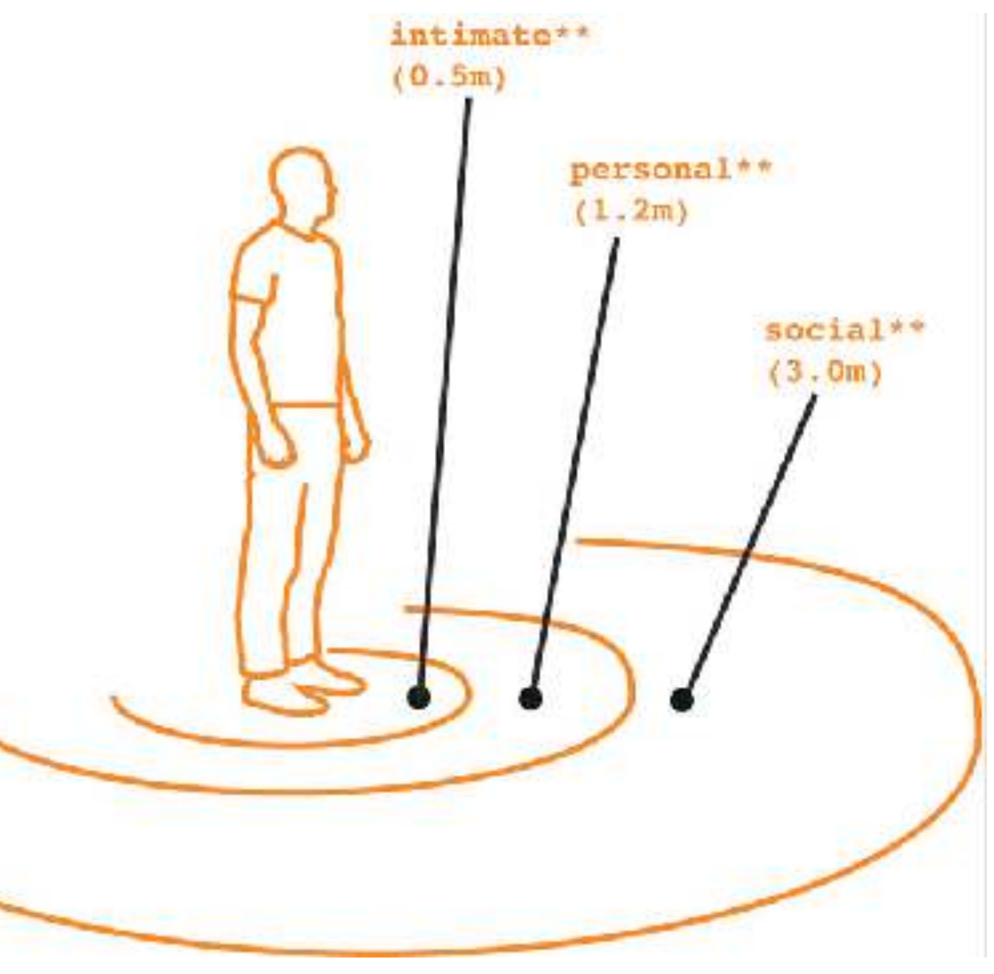
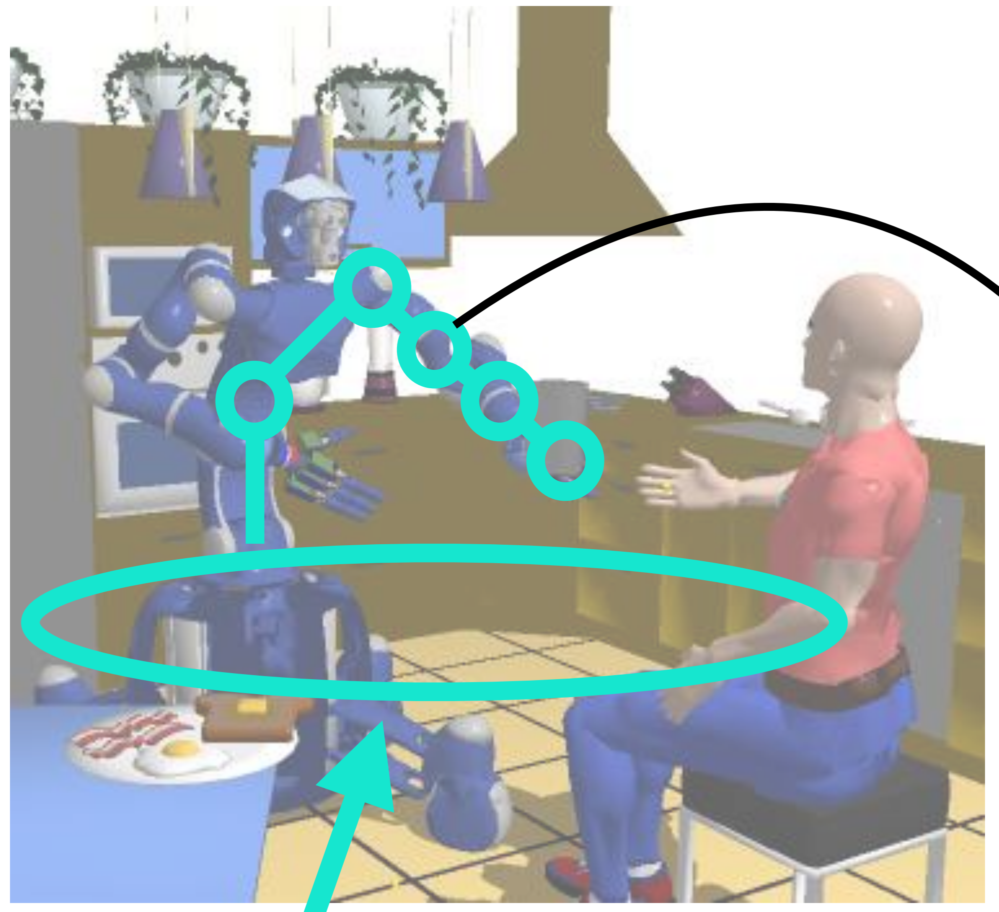
"Human-Aware" extension of motion planning algorithms



Anthropological Studies :
Theory of « proxemics » [Hall66]



Trajectory Space

$$\Xi = \{\xi \mid \xi : [0,1] \to \mathcal{C}\}$$

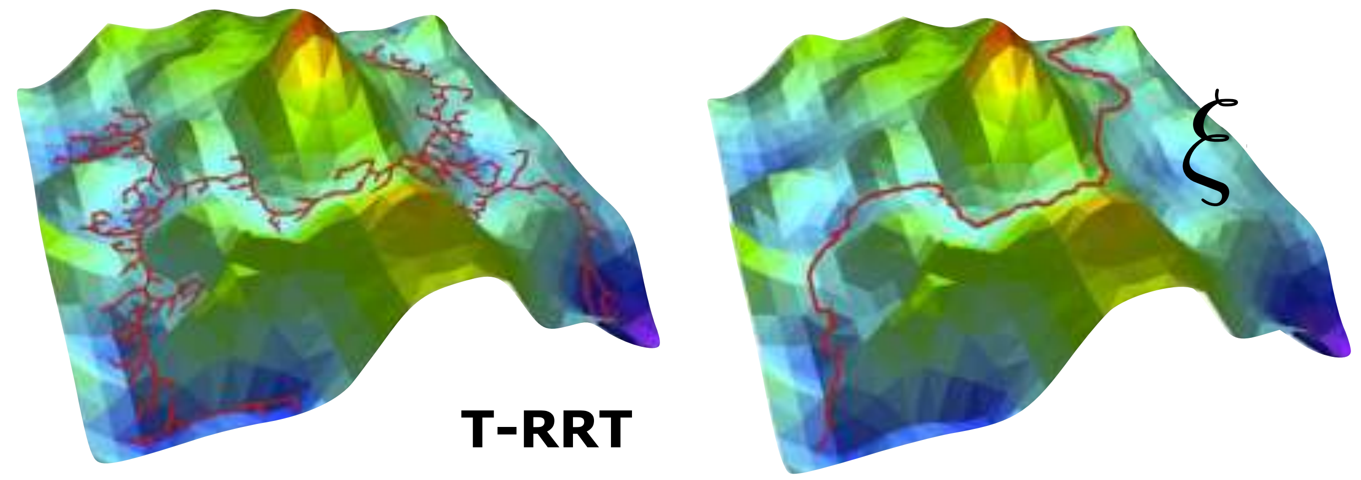
Configurations Space

$$\mathcal{C} = \{\boldsymbol{q} \in \mathbb{R}^d\}$$

Workspace

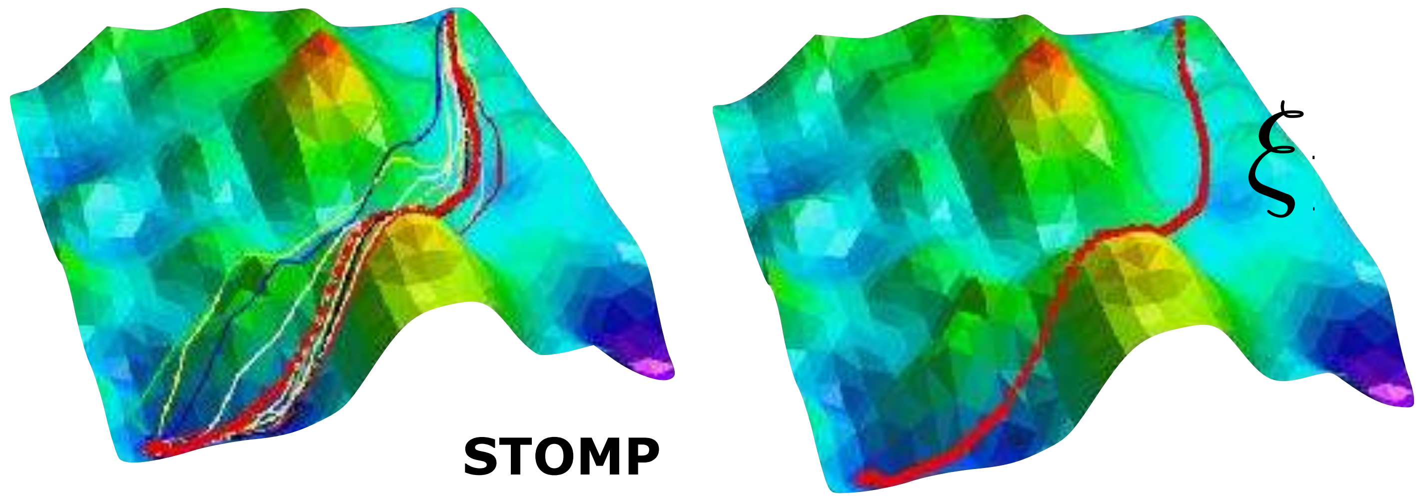
$$\mathcal{W} = \{\boldsymbol{x} \in \mathbb{R}^3\}$$

Explores trajectories globally



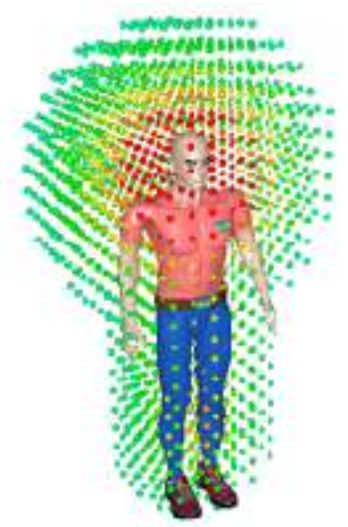
T-RRT

Explores trajectories locally

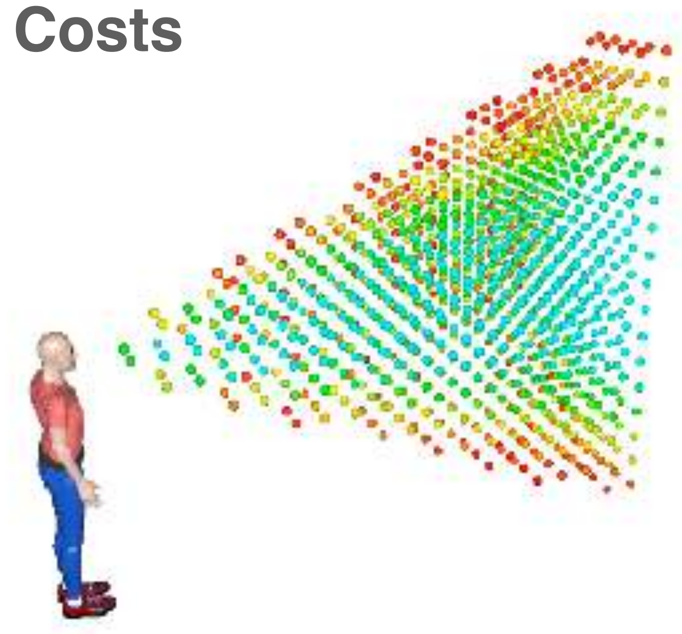


STOMP

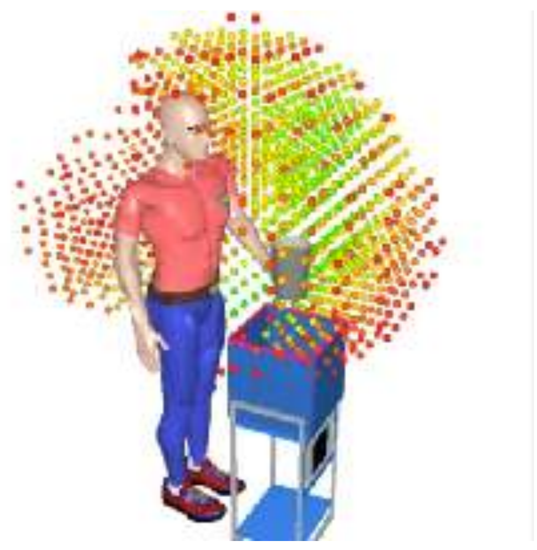
Elementary Interaction Costs



1 - Distance



2 - Visibility

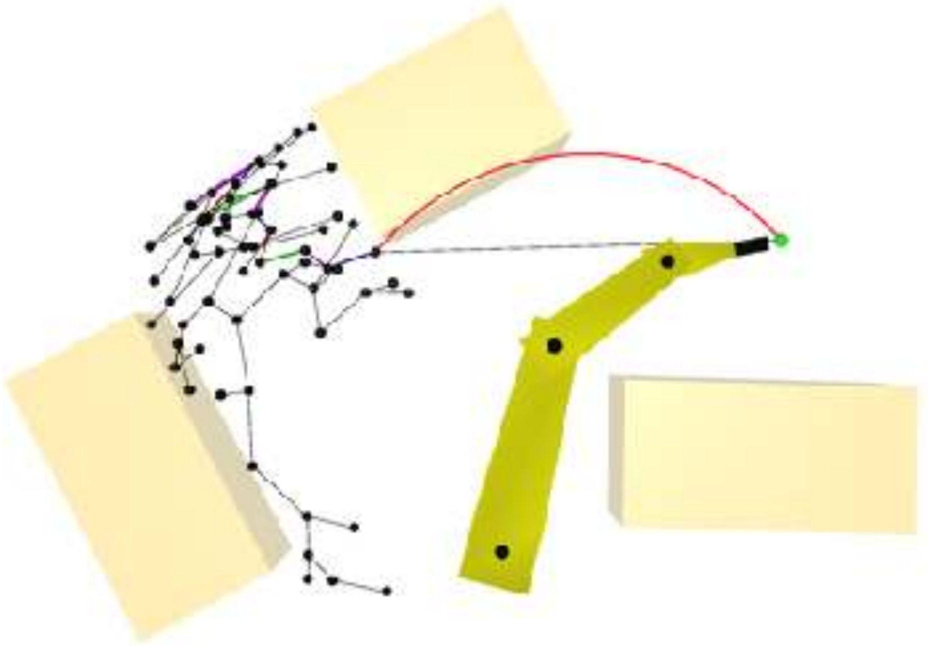


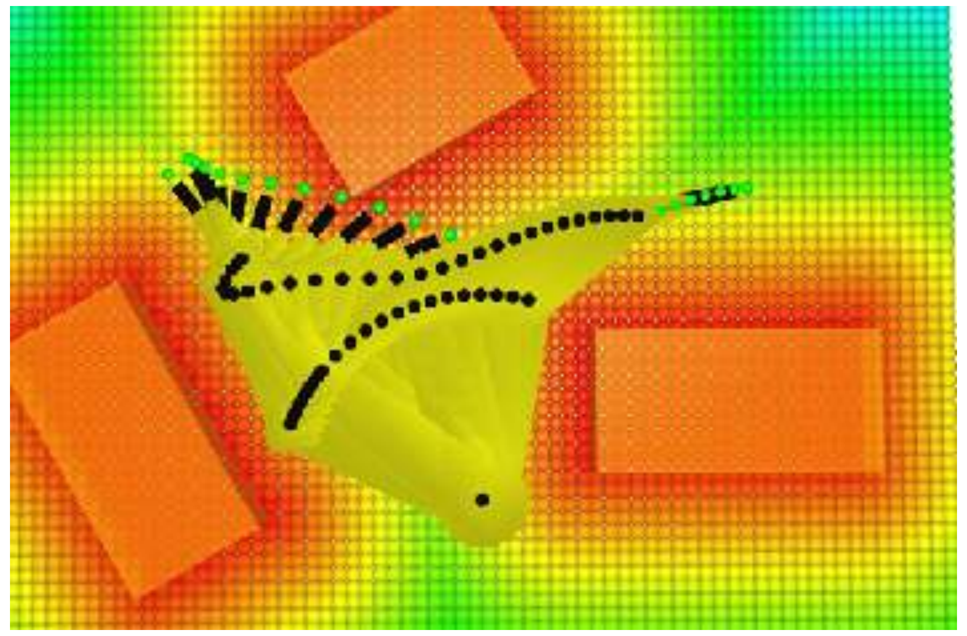
3 – Musculoskeletal Effort

Collaborators : *Rachid Alami, Thierry Siméon, Daniel Sidobre,* LAAS-CNRS
Publications : IARP 2010, ICRA 2011, ROMAN 2012, SORO 2014

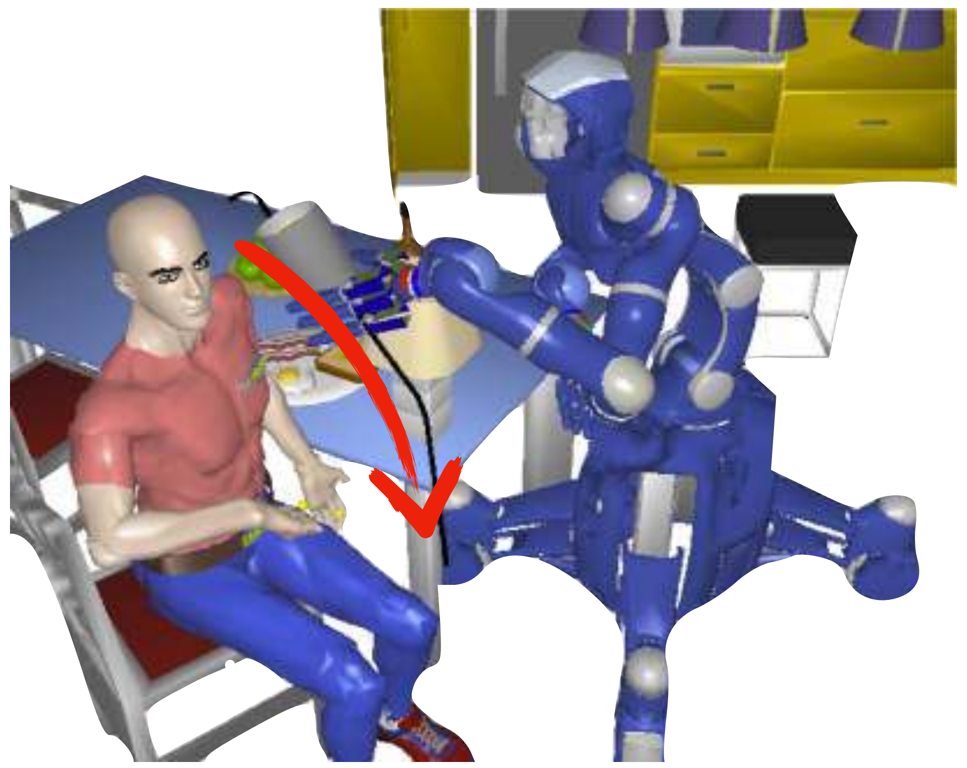
“Human-Aware” extension of motion planning algorithms

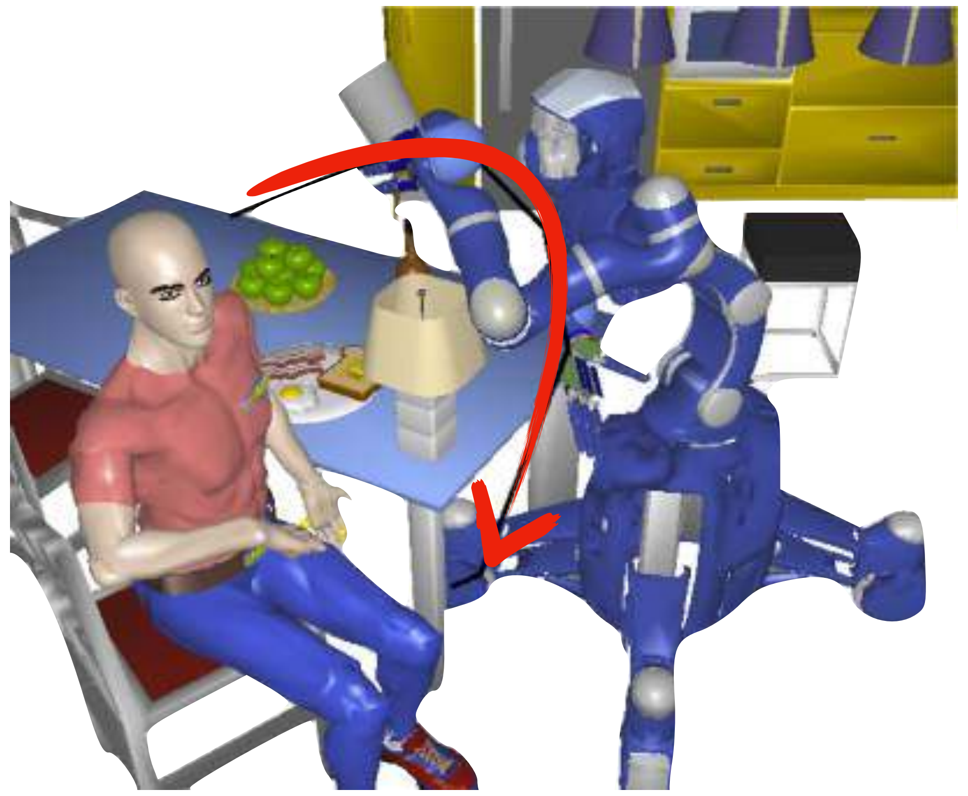
Motion planning with
binaire vs. continu cost maps



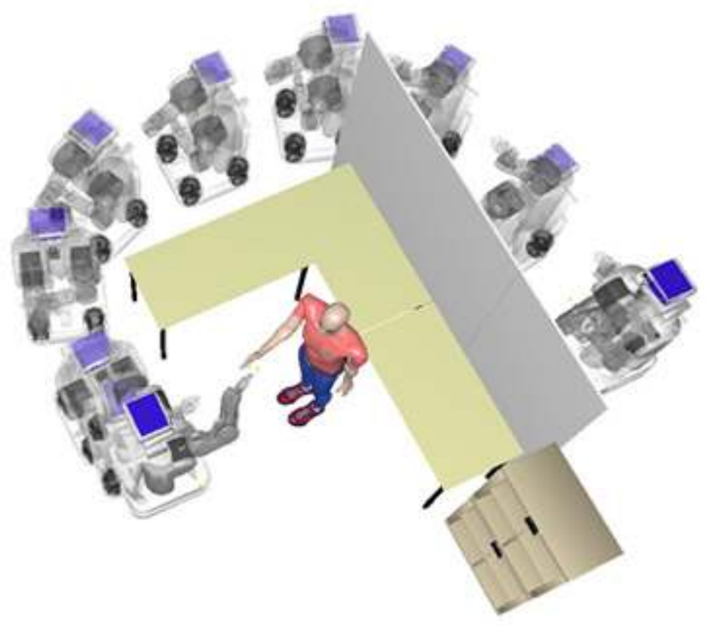


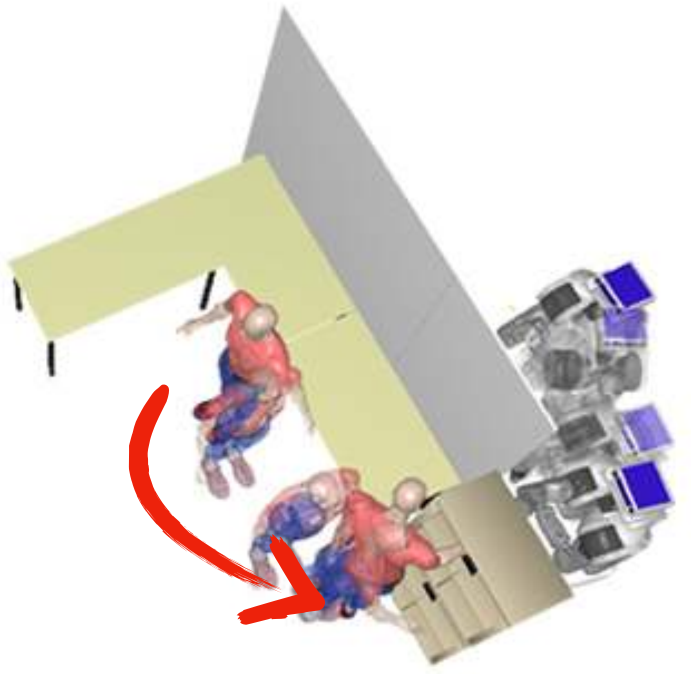
RRT **T-RRT + STOMP**





Motion planning with
statique vs. mobile human receiver

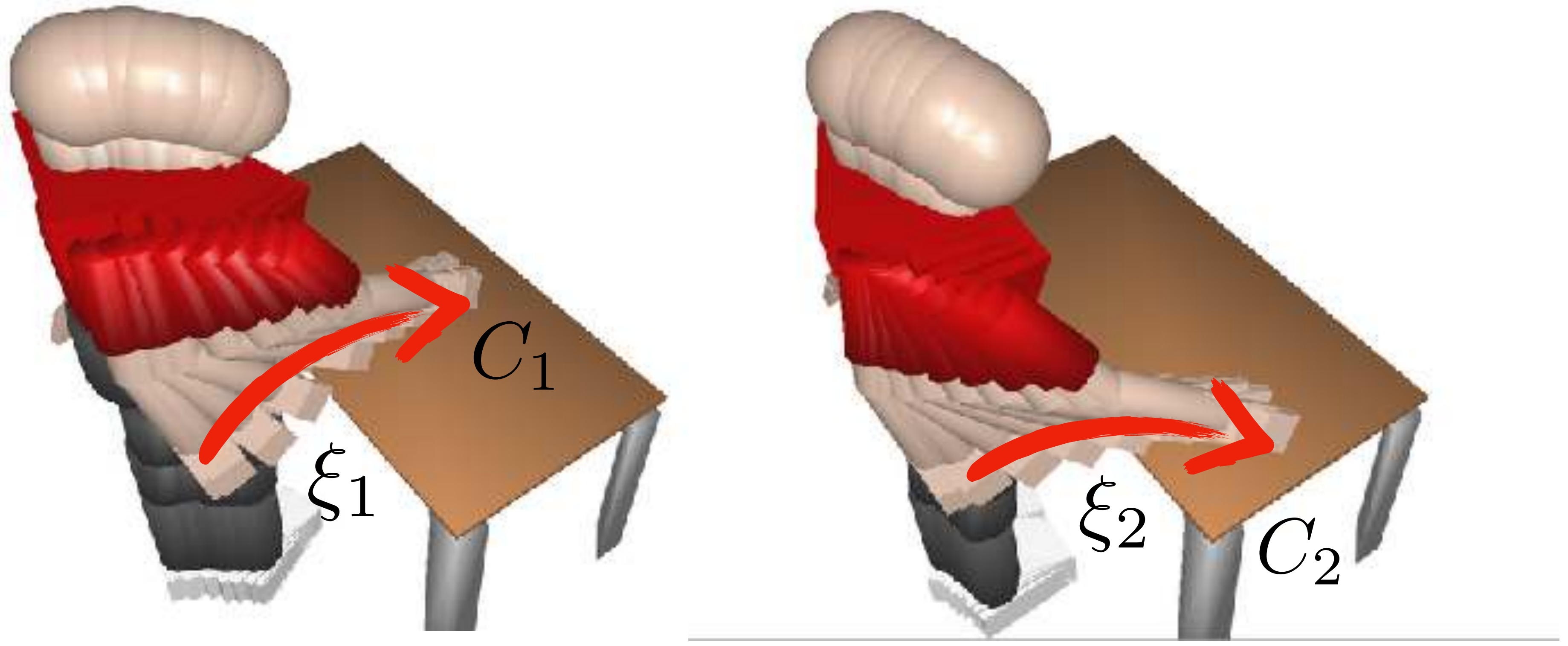




Statique **Mobile**

Collaborators : *Rachid Alami, Thierry Siméon, Daniel Sidobre,* et al. LAAS-CNRS
Publications : IARP 2010, ICRA 2011, ROMAN 2012, SORO 2014

Anticipation of human movement in dynamic motion planning



Number of classes

Voxel

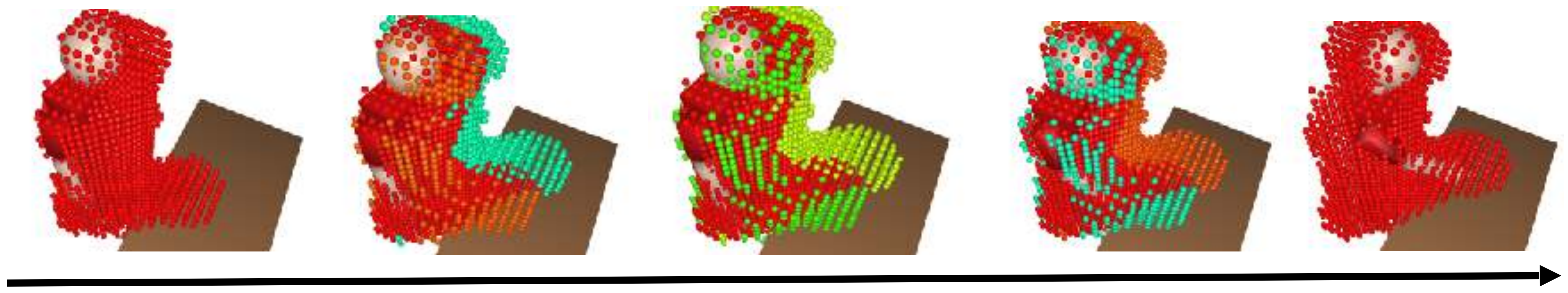
Probability of traverse in class *m*

$$p(x|\xi) = \sum_{m=1}^{M} p(x|C_m)p(C_m|\xi)$$

Partial trajectory

Probability to belong to class *m* encoded in a GMM

Solution : Prediction of swept volume



Red and green, high and low probability to be traversed

Collaborators : *Dmitry Berenson,* Worcester Polytechnic Institute
Publication : IROS 2013

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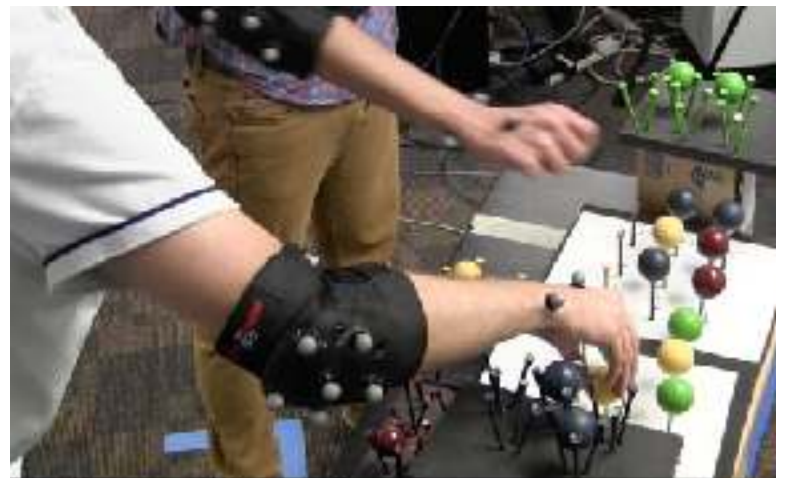
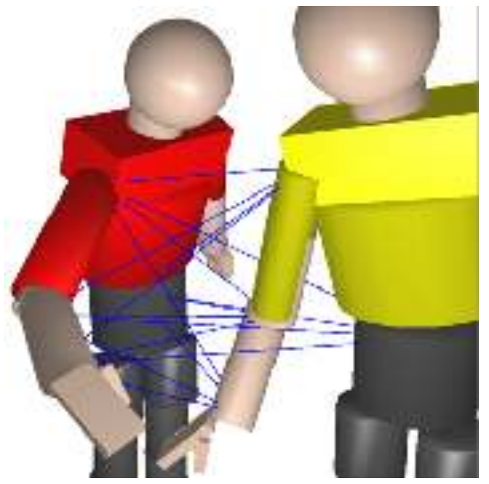
Imitation of interactive behaviors

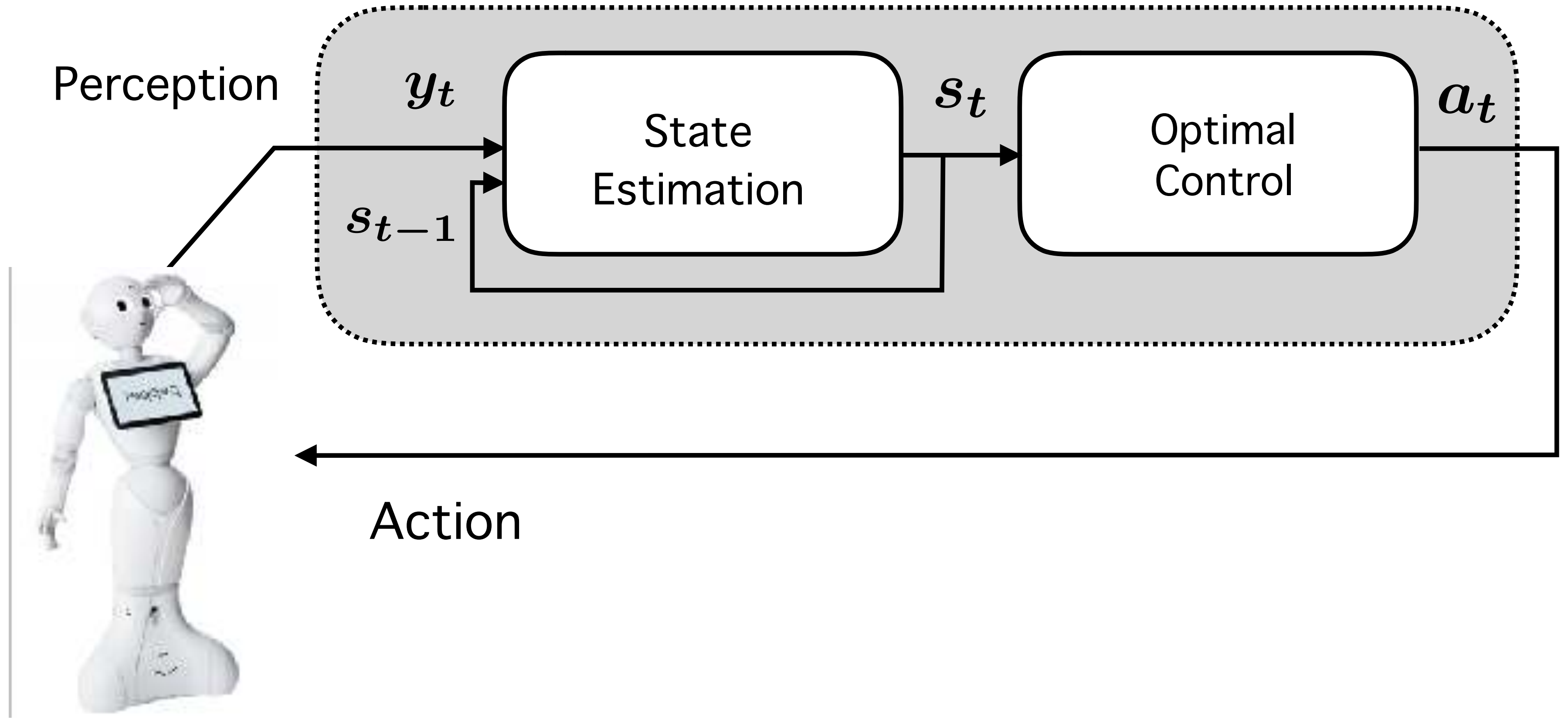
How to balance the elementary interaction features in the cost function ?

1) Demonstration

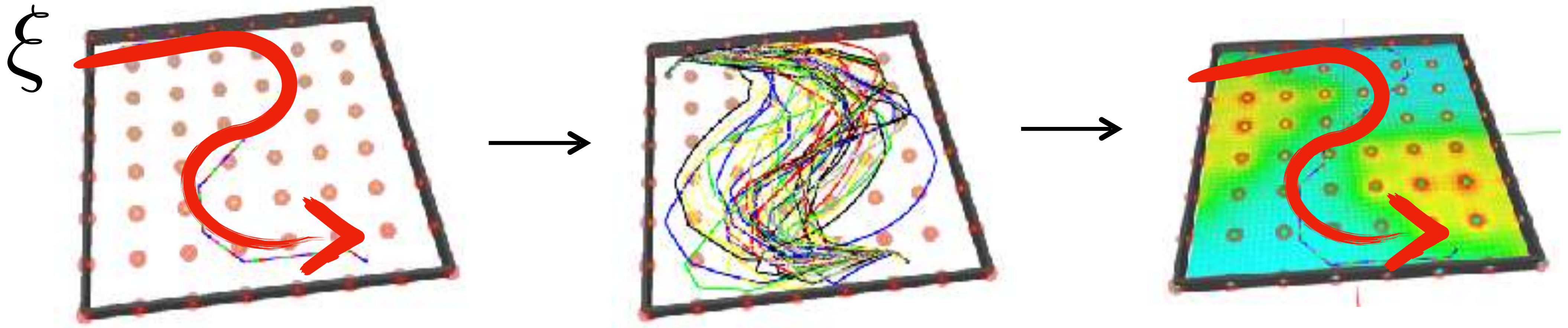


2) Features





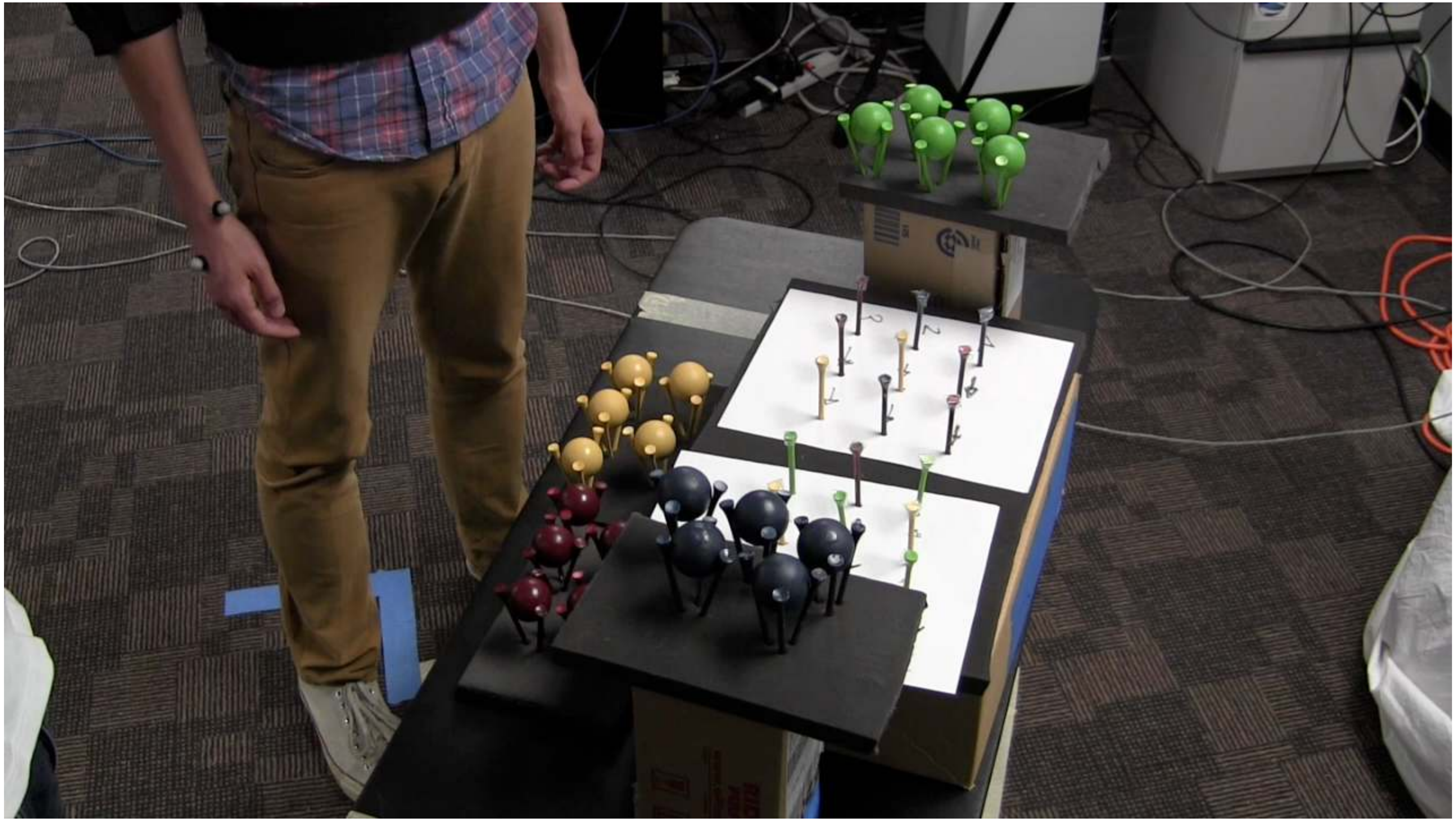
Solution : Inverse Optimal Control



$$\underbrace{c(\xi)}_{\text{cost function}} = \int_T \sum_{i=1:N} \underbrace{w_i}_{\text{weight}} \underbrace{e^{-\|\xi(t)-\mathbf{x}_i\|^2}}_{RBF} dt$$

Collaborators : *Rafi Haynes et Dmitry Berenson,* Worcester Polytechnic Institute
Publications : ICRA 2015, TRO 2016

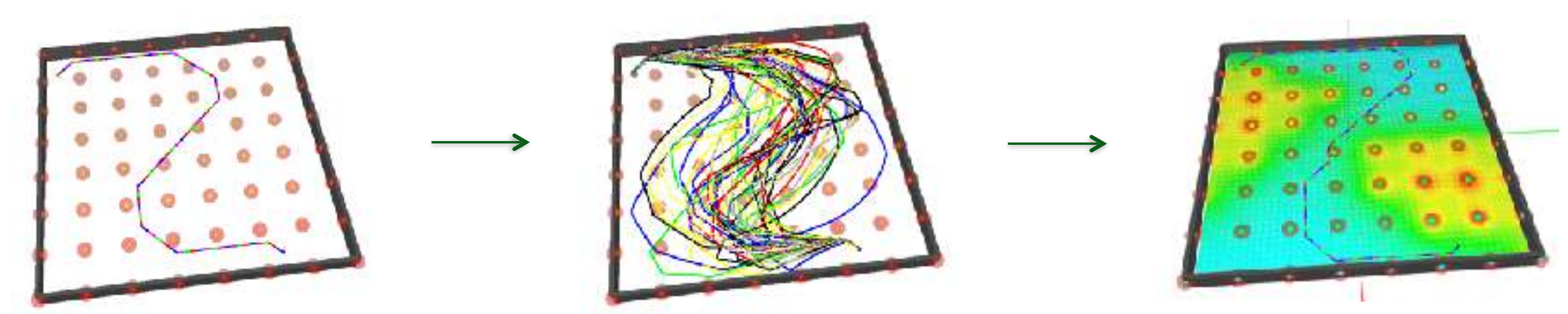
Collaborative Manipulation Experiment



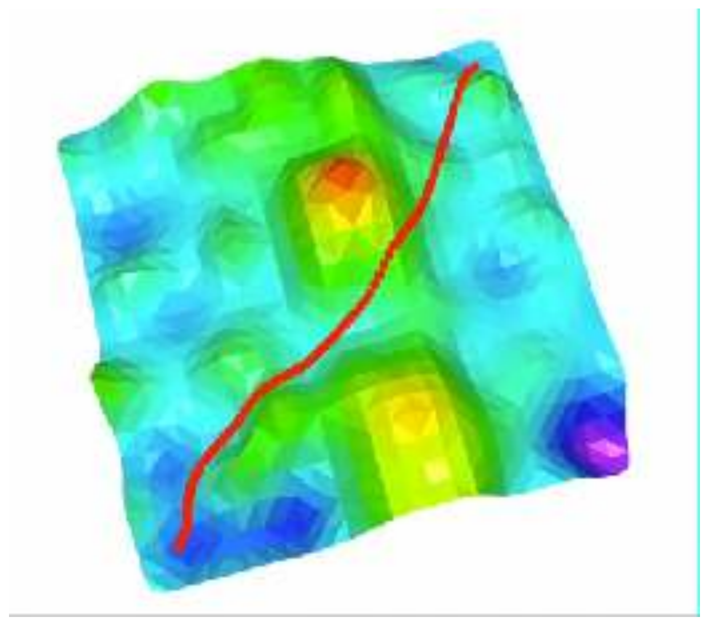
Collaborators : *Rafi Haynes et Dmitry Berenson,* Worcester Polytechnic Institute
Publications : ICRA 2015, TRO 2016

Goalset Stochastic Inverse Optimal Control

Learning PIIRL [Kalakrishnan 13]



Prediction STOMP [Kalakrishnan 11]



Trajectory vector

$$\boldsymbol{\xi} = [\ \boldsymbol{q}_1\ \ldots\ \boldsymbol{q}_N\ ]^T$$

Smoothness Metric

$$\mathbf{R} \leftarrow K^T K$$

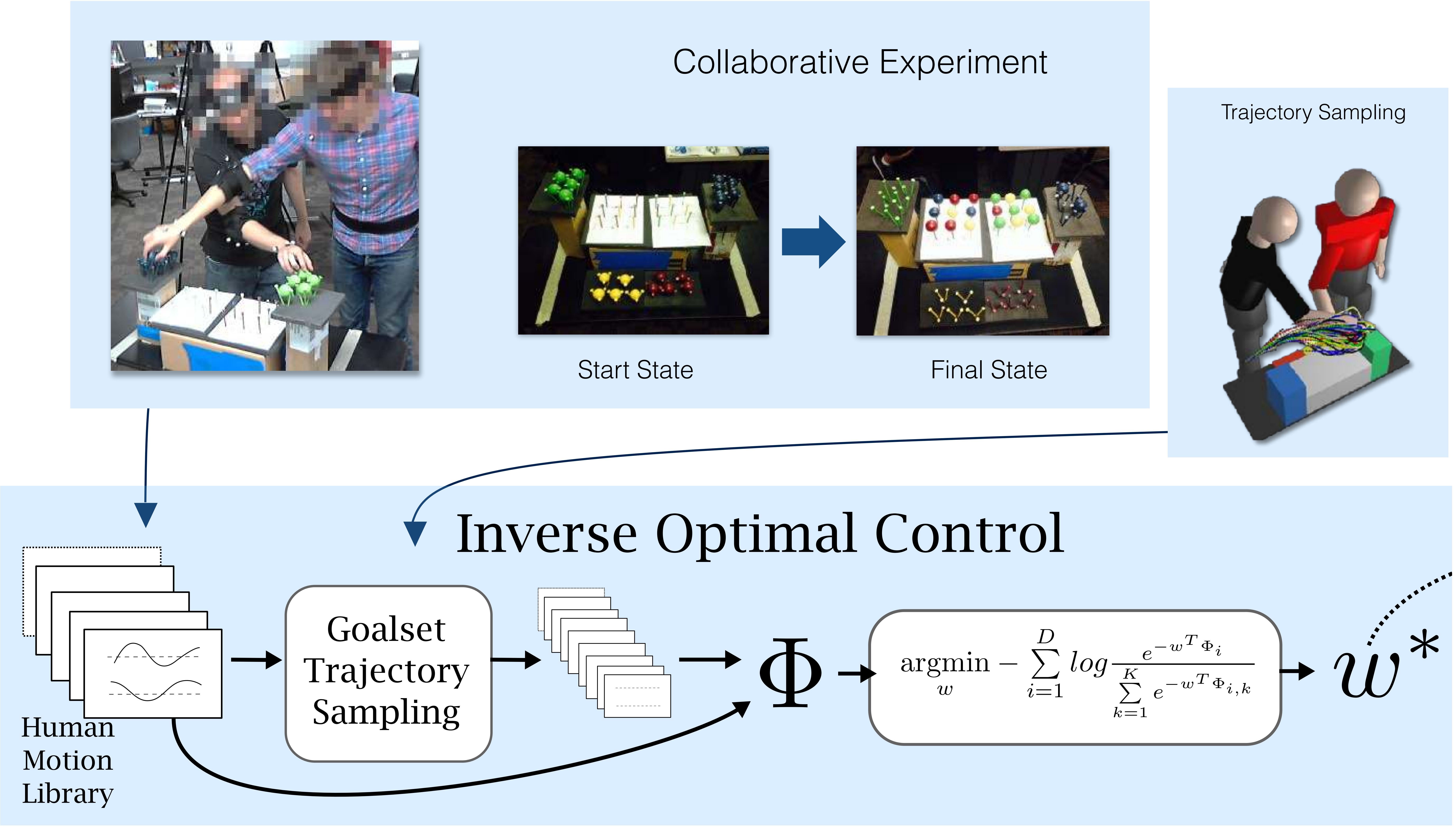
Goalset Trajectory Sampling

- Modified covariance
- Project the samples to the goal region with respect to the smoothness metric

$$\begin{array}{ll} \underset{\Delta\xi}{\text{minimize}} & \frac{1}{2}||\Delta\xi||_R^2 \\ \text{subject to} & h(\xi_t + \Delta\xi) = 0 \end{array}$$

Collaborators : *Rafi Haynes et Dmitry Berenson*, Worcester Polytechnic Institute
Publications : ICRA 2015, TRO 2016

Learning Collaborative Motion Objectives



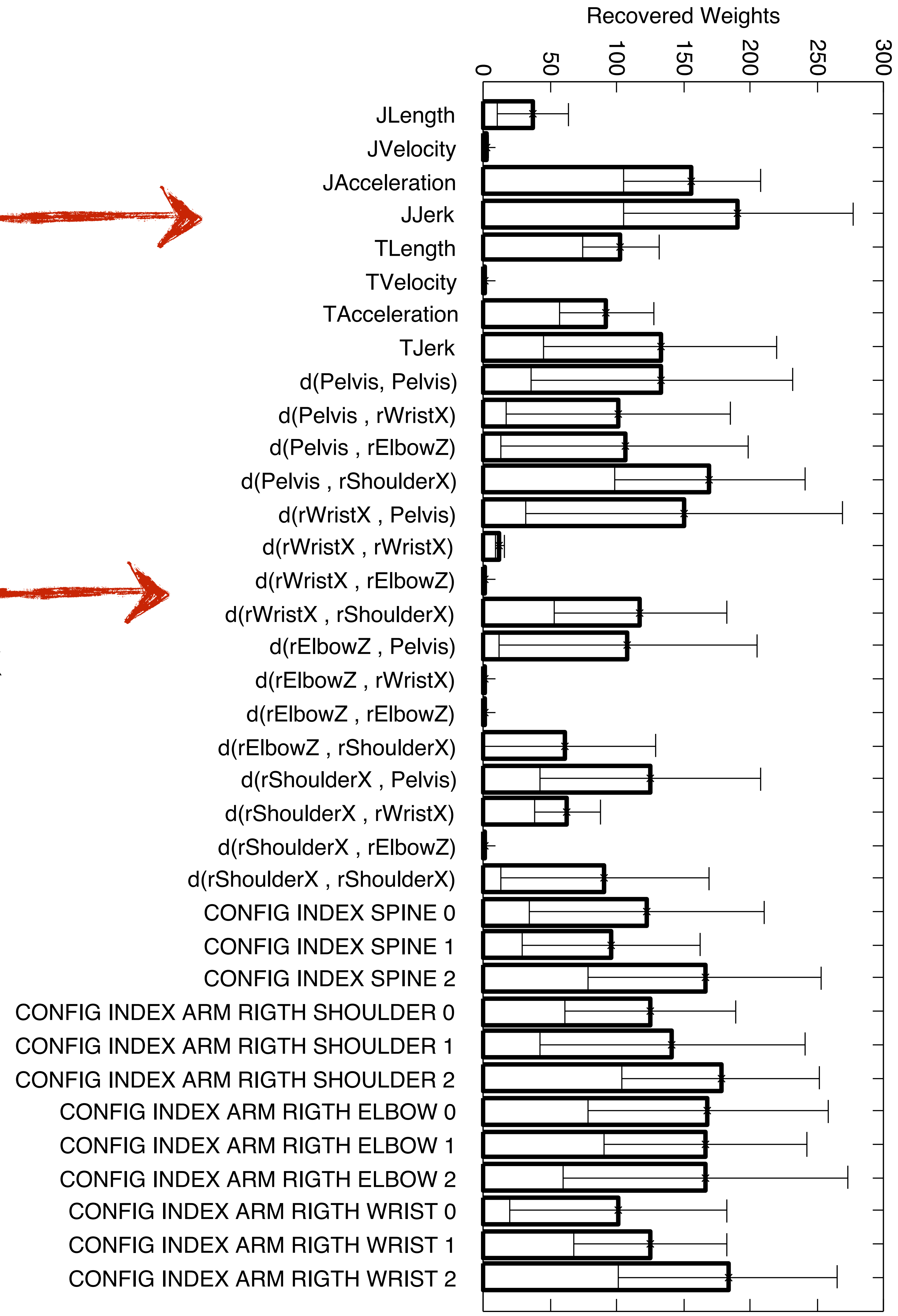
Collaborators : *Rafi Haynes et Dmitry Berenson,* Worcester Polytechnic Institute
Publications : ICRA 2015, TRO 2016

Interactive Features Importance

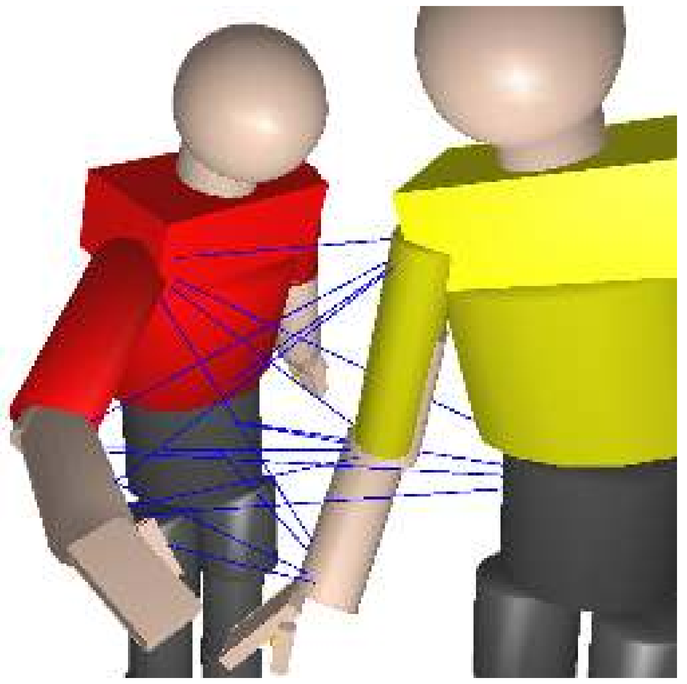
- Smoothness
  - Length
  - Sum of squared velocity, acceleration and jerk

- Interpersonal distances
  - Between the center of each link
    - Shoulder
    - Elbow
    - Wrist

- C-space distance to a resting posture
  - 12 DoFs considered



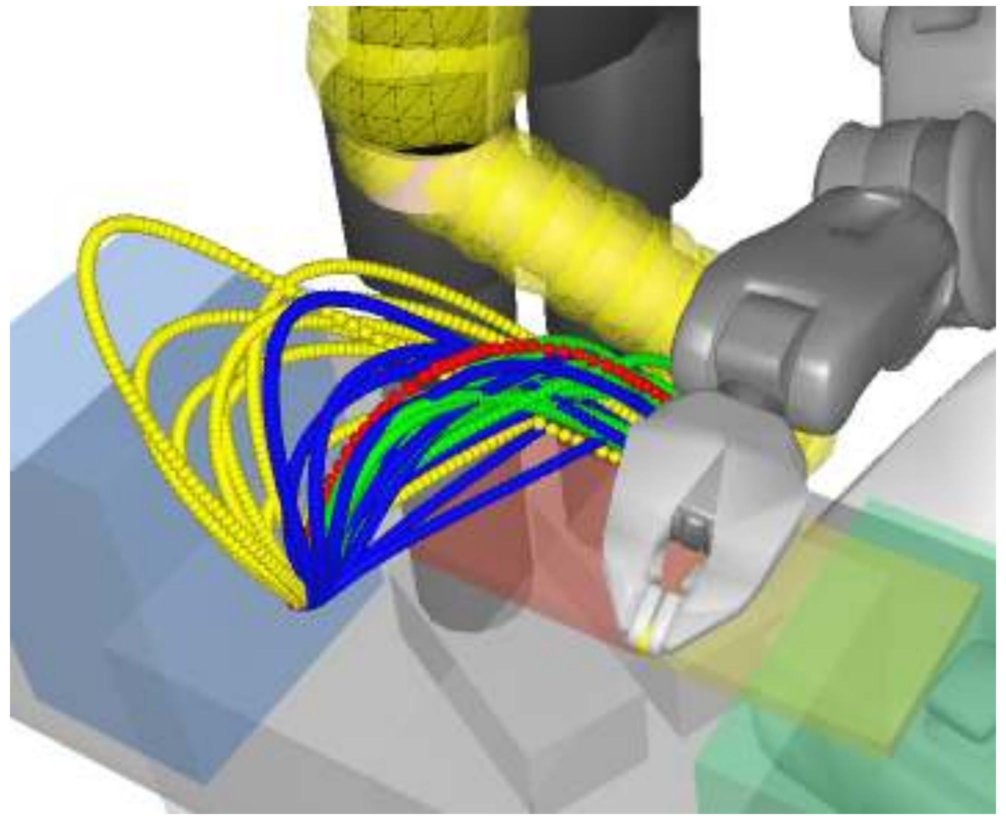
Significant interference example

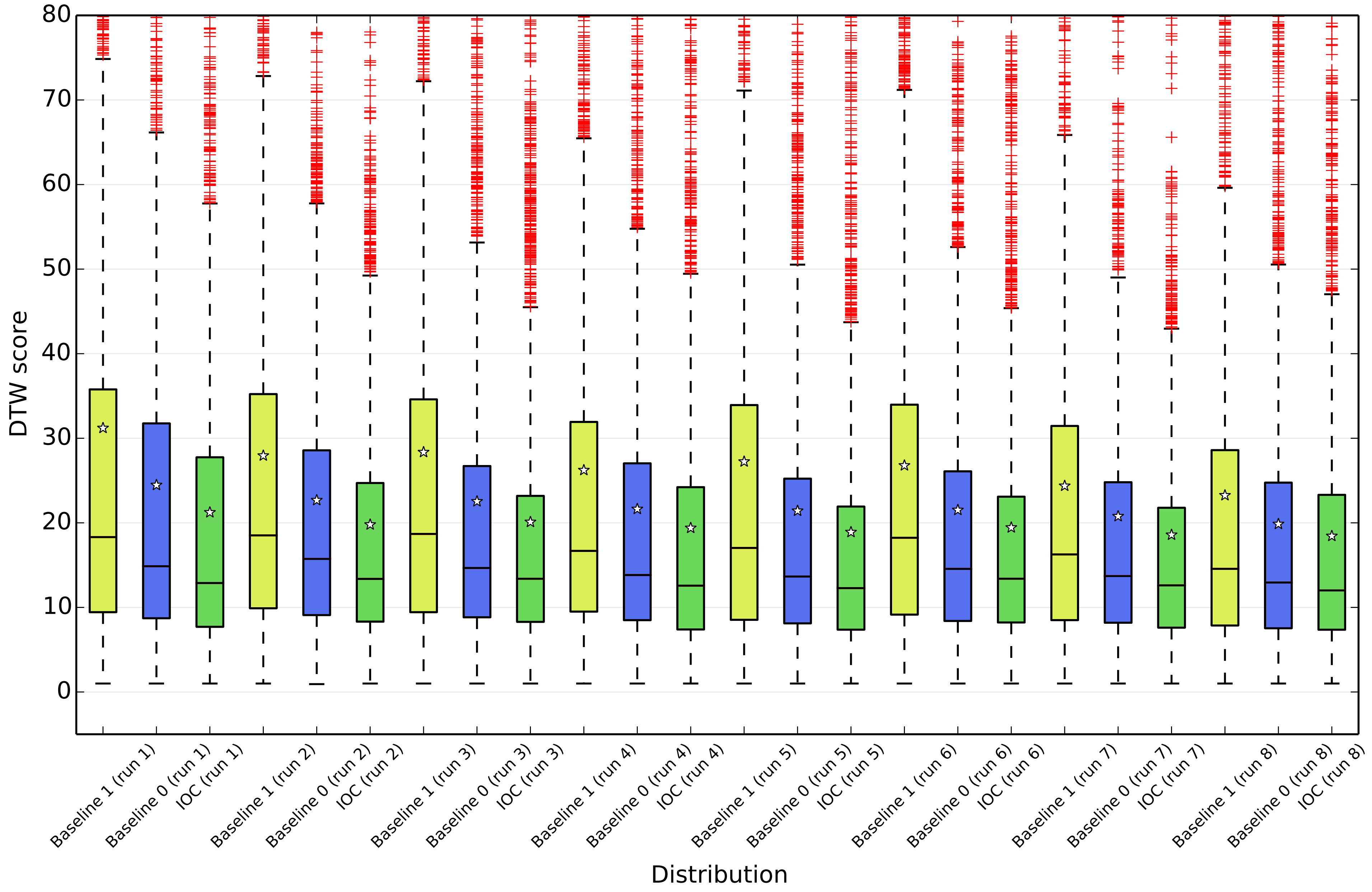


Interpersonal distances

Collaborators : *Rafi Haynes et Dmitry Berenson,* Worcester Polytechnic Institute
Publications : ICRA 2015, TRO 2016

Anticipation of Human-Robot movement by **Inverse Optimal Control**





15 users x 8 execution = 2120 trajectories

IOC better than **manual tuning** of the cost function and **GMMs**

- **The robot is executing fixed trajectories**
- **Compare against baseline tunings**
  - Conservative : all distances active
  - Agressive: no-interlink distances

- **Compare with multiple metrics**
  - Joint center distances
  - Task space metric

$$d(T_1, T_2) = \|p_1 - p_2\| + 0.1 * cos^{-1}(|\langle v_1, v_2 \rangle|)$$

Collaborators : *Rafi Haynes et Dmitry Berenson*, Worcester Polytechnic Institute
Publications : ICRA 2015, TRO 2016

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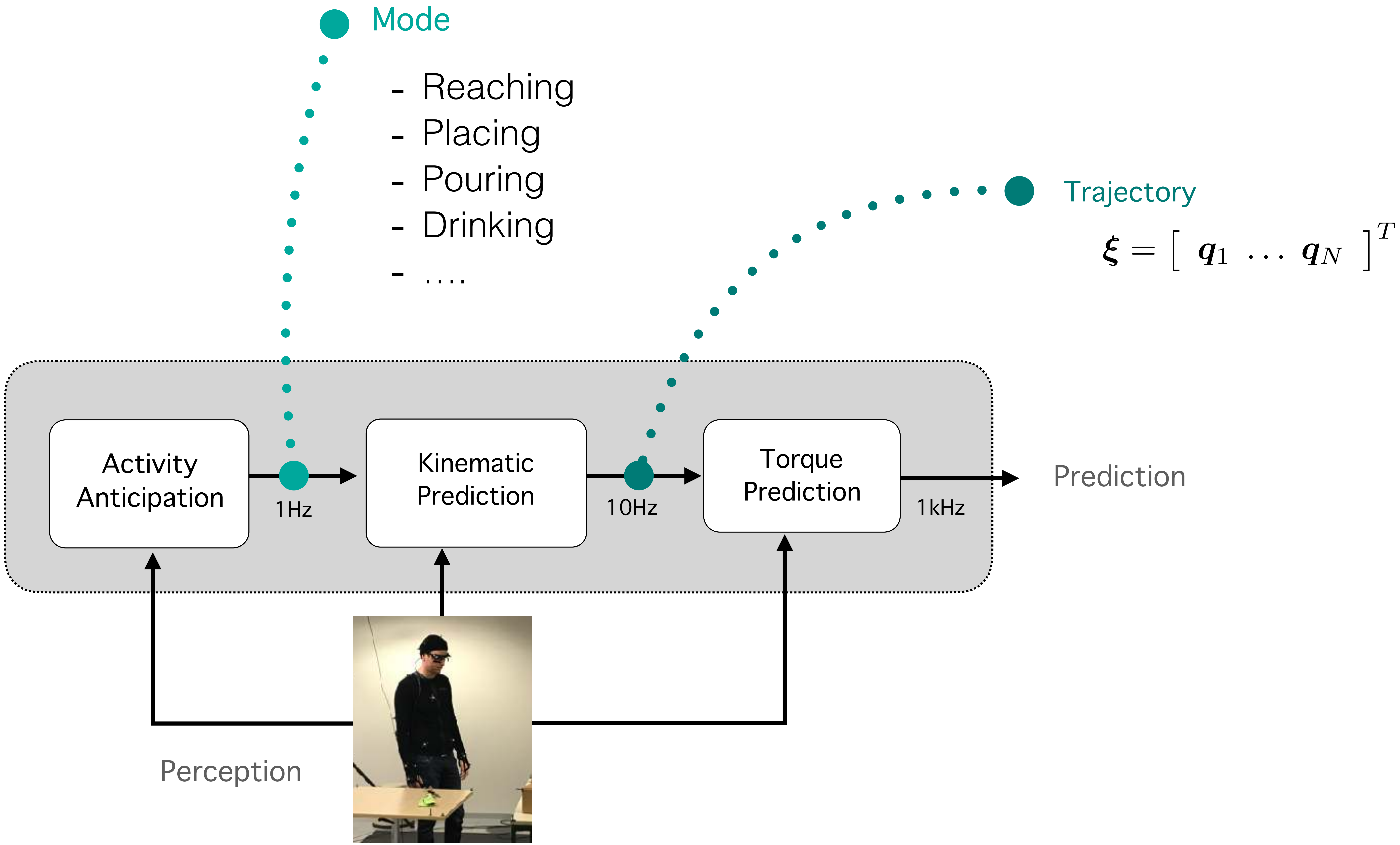
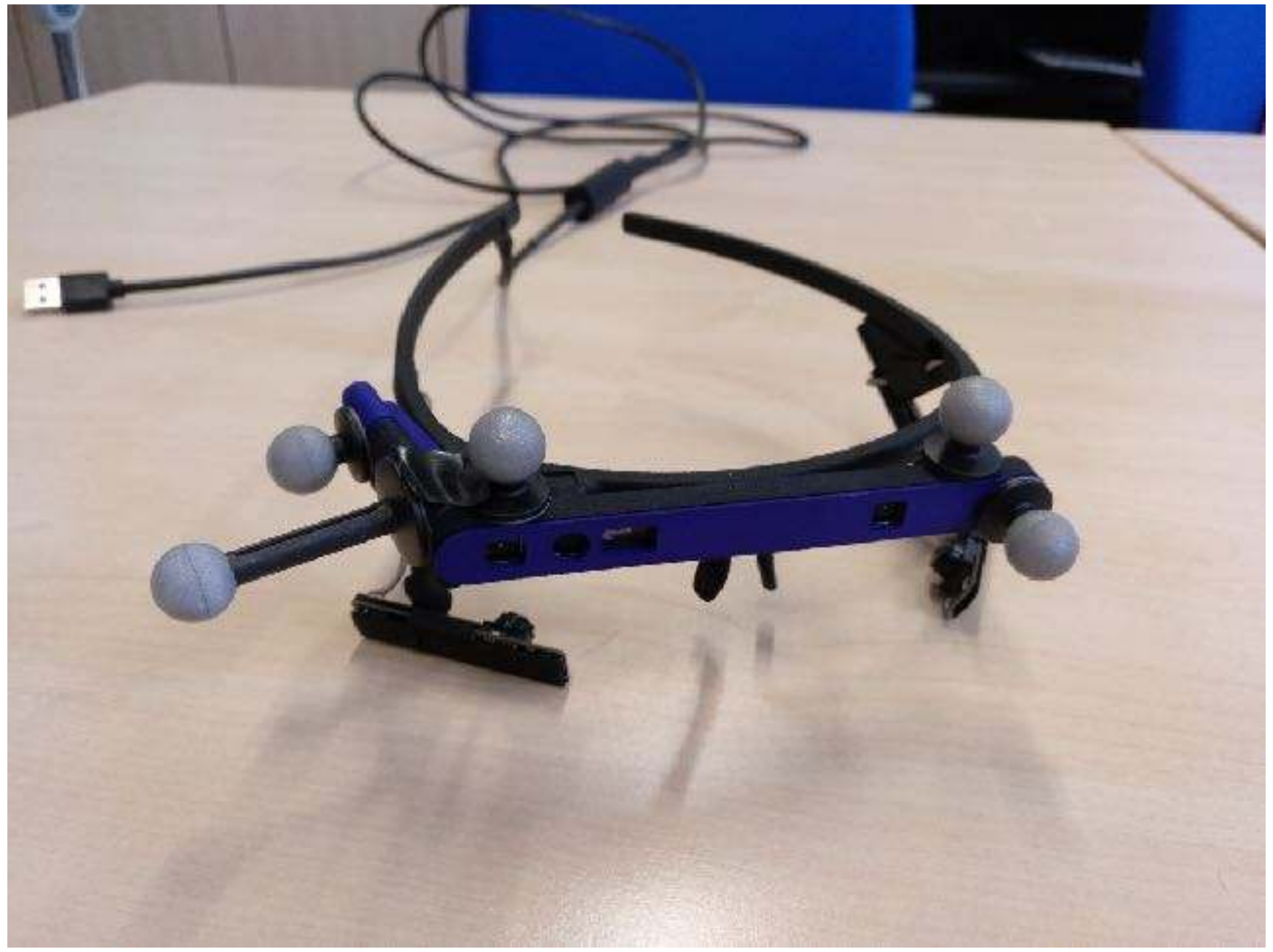
Long-term activity and motion prediction



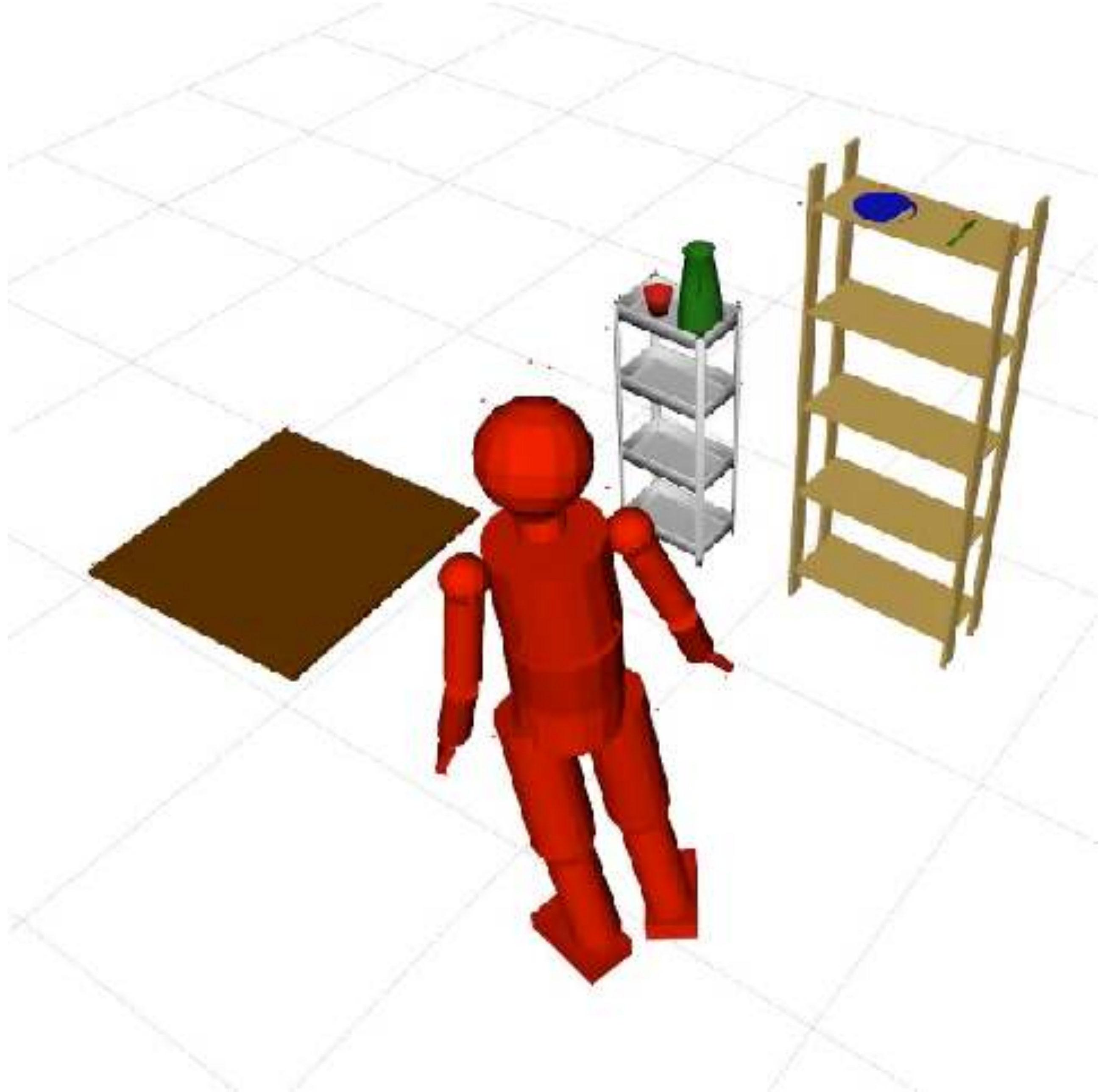
Collaborators : *Philipp Kartzer,* Stuttgart Uni.
Publication : IEEE Humanoids 2018, IROS Workshop 2018, ECCV Workshop 2018

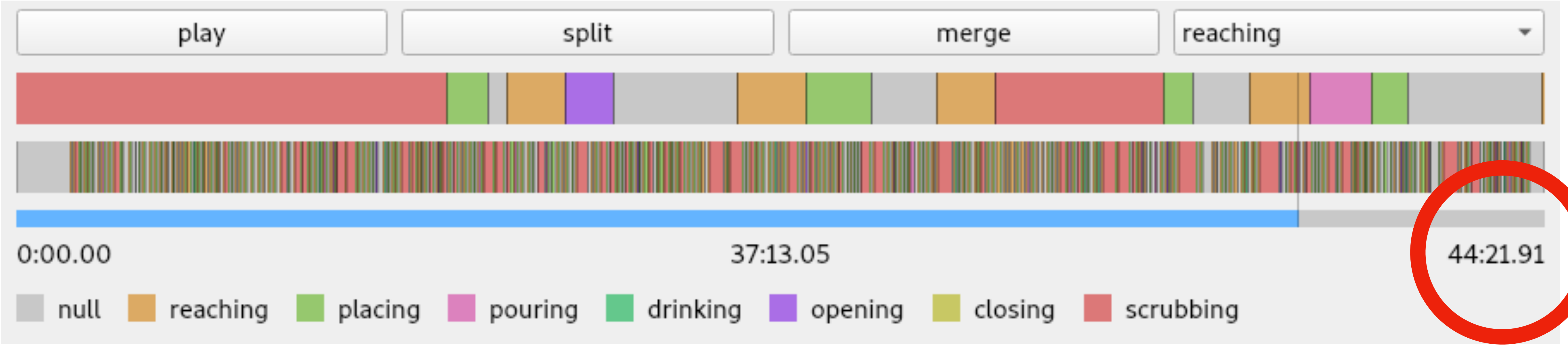
Data gathering of activity and motion

PUPIL sensor



Fullbody Data



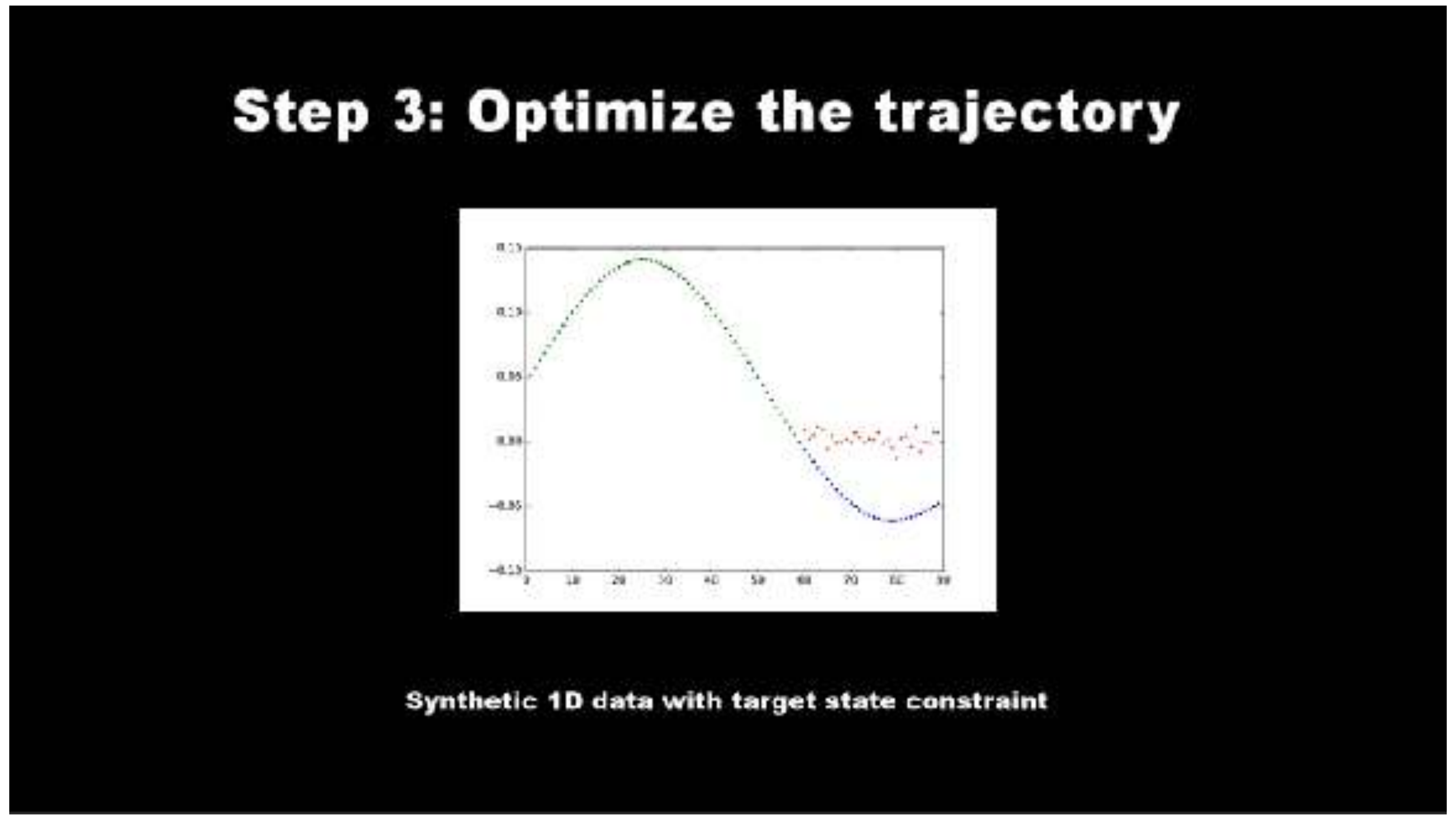


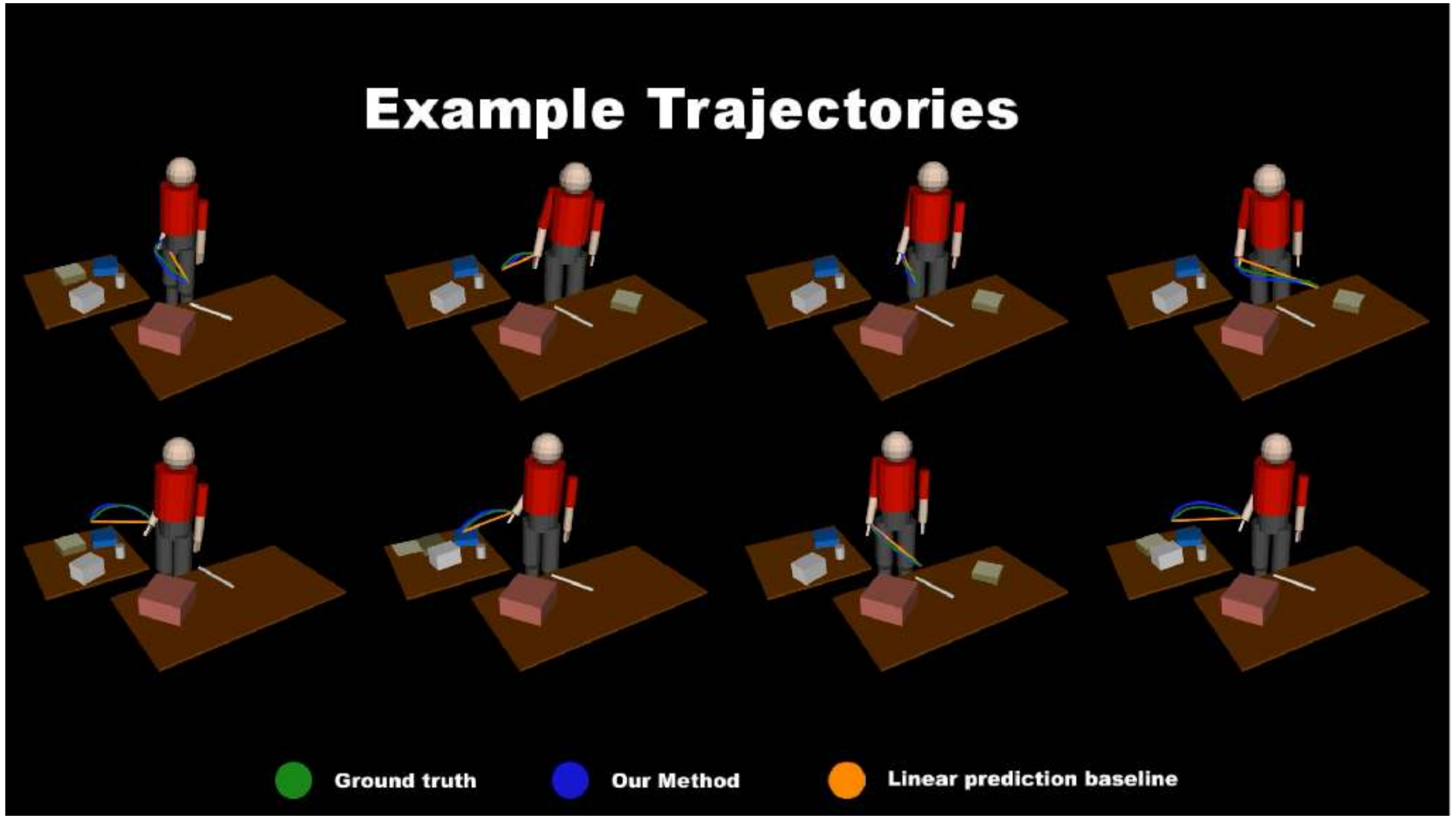
~1 hour of data
7 different activities
Tracking objects and human

Collaborators : *Philipp Kartzer, Jan Hoffman* Stuttgart Uni.

Combining Data Driven Dynamical Models with Trajectory Optimization

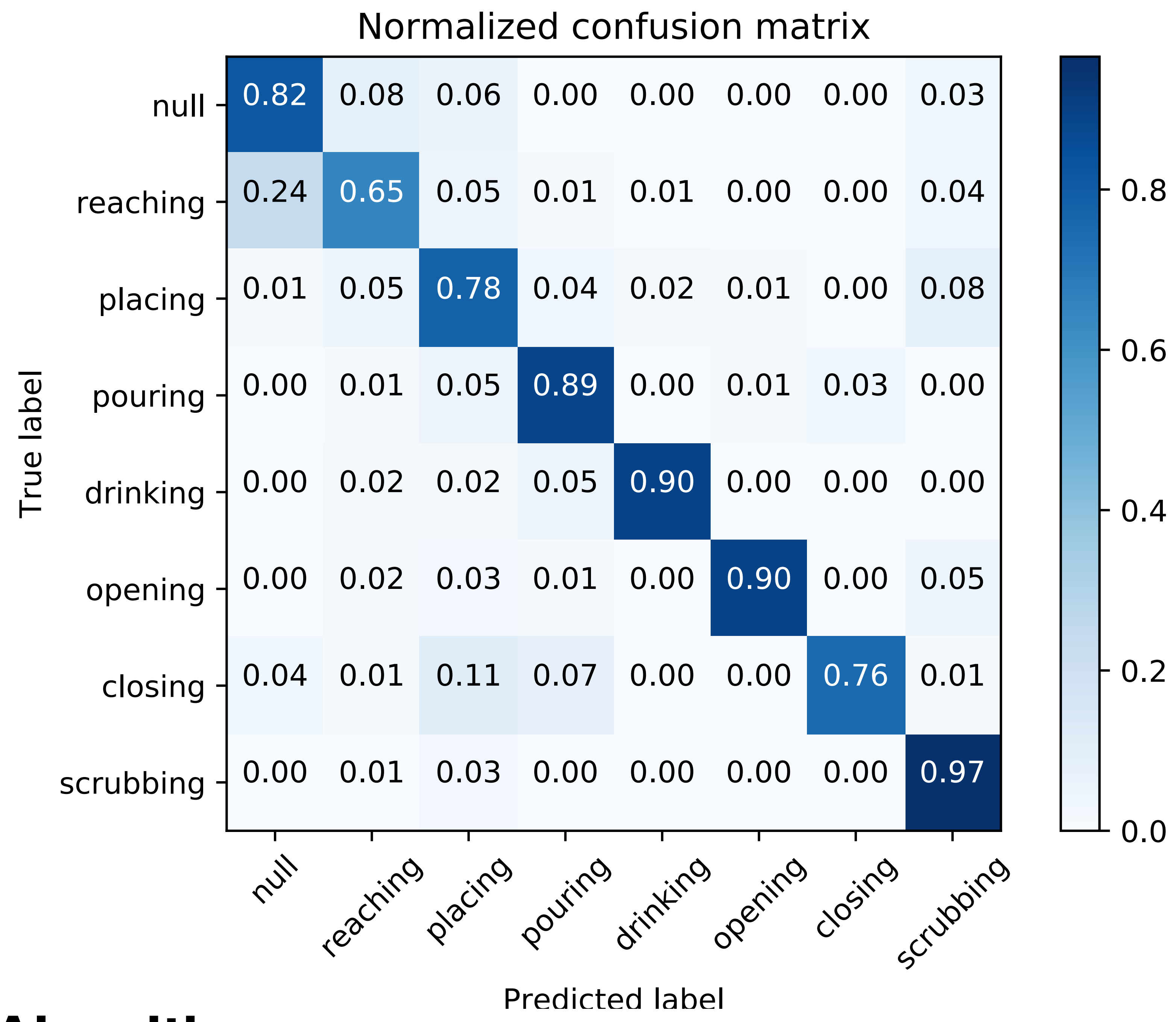
- Discrete trajectory of states: $\xi_t = (s_0, \ldots, s_t)$
- Step 1:
  - Learn dynamic behavior of humans: $s_{t+1} = f(\xi_t)$
  - We do this using a Gaussian process (GP)
- Step 2:
  - Unroll the prediction
  - Iteratively apply $s_{t+1} = f(\xi_t)$
- Step 3:
  - Account for constraints e.g. target state
  - Optimize the trajectory





Collaborators : *Philipp Kartzer, Jan Hoffman* Stuttgart Uni.
Publications : IEEE Humanoids 2018, IROS Workshop 2018, ECCV Workshop 2018

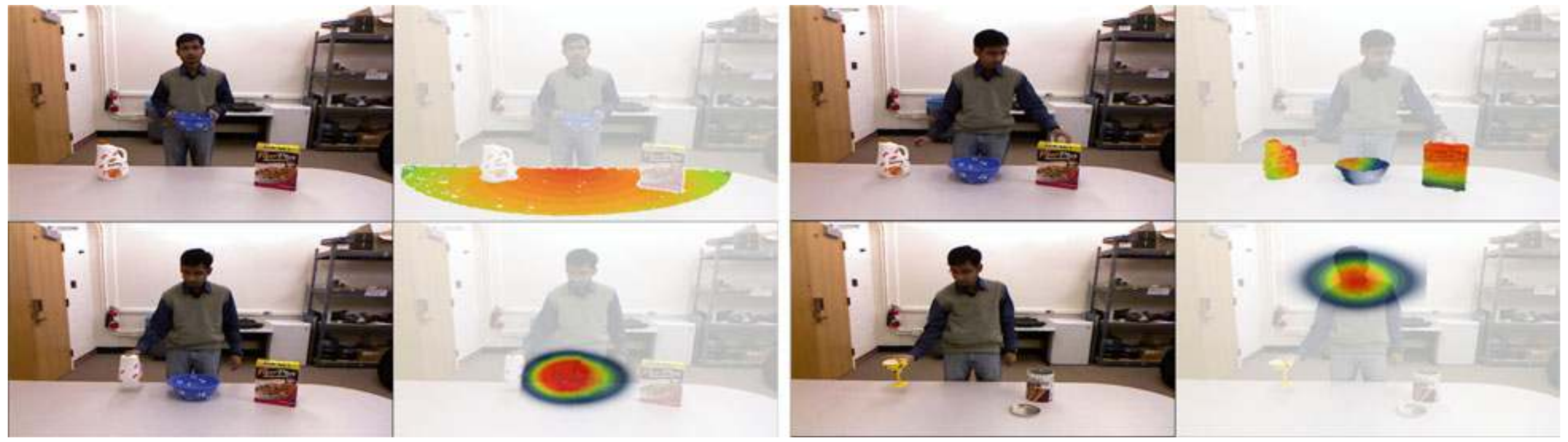
Prediction of human activity



Algorithm:

- Sample Affordances
- Generate Spline Trajectories
- Evaluate the features
- Evaluate Energy/Cost for sampled frame

[Koppula 16]



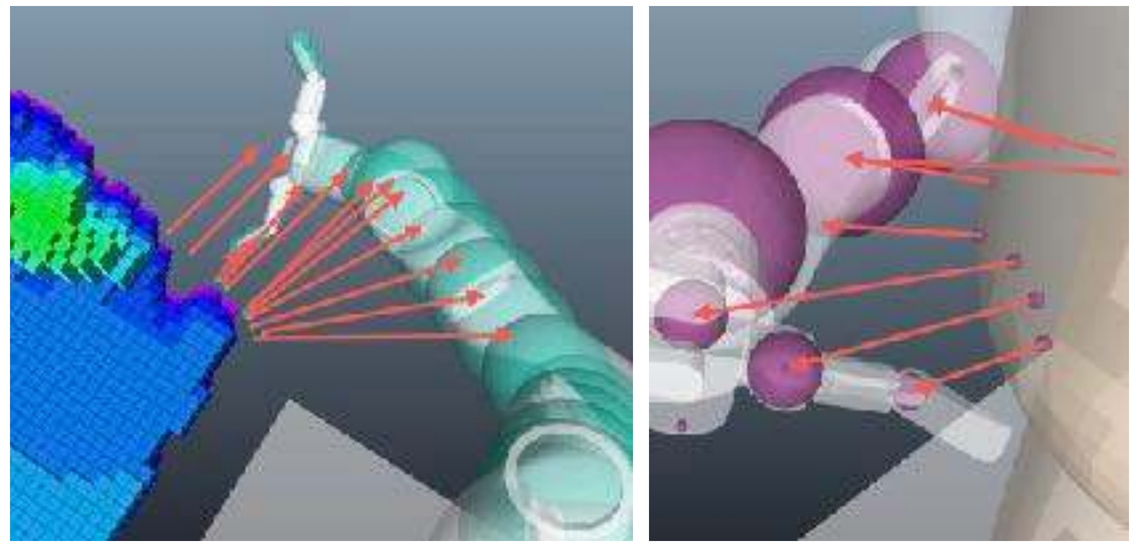
Affordance Sampling

Collaborators : *Jan Hoffman, Philipp Kartzer,* Stuttgart Uni.
Publications : IROS Workshop 2018

Outline

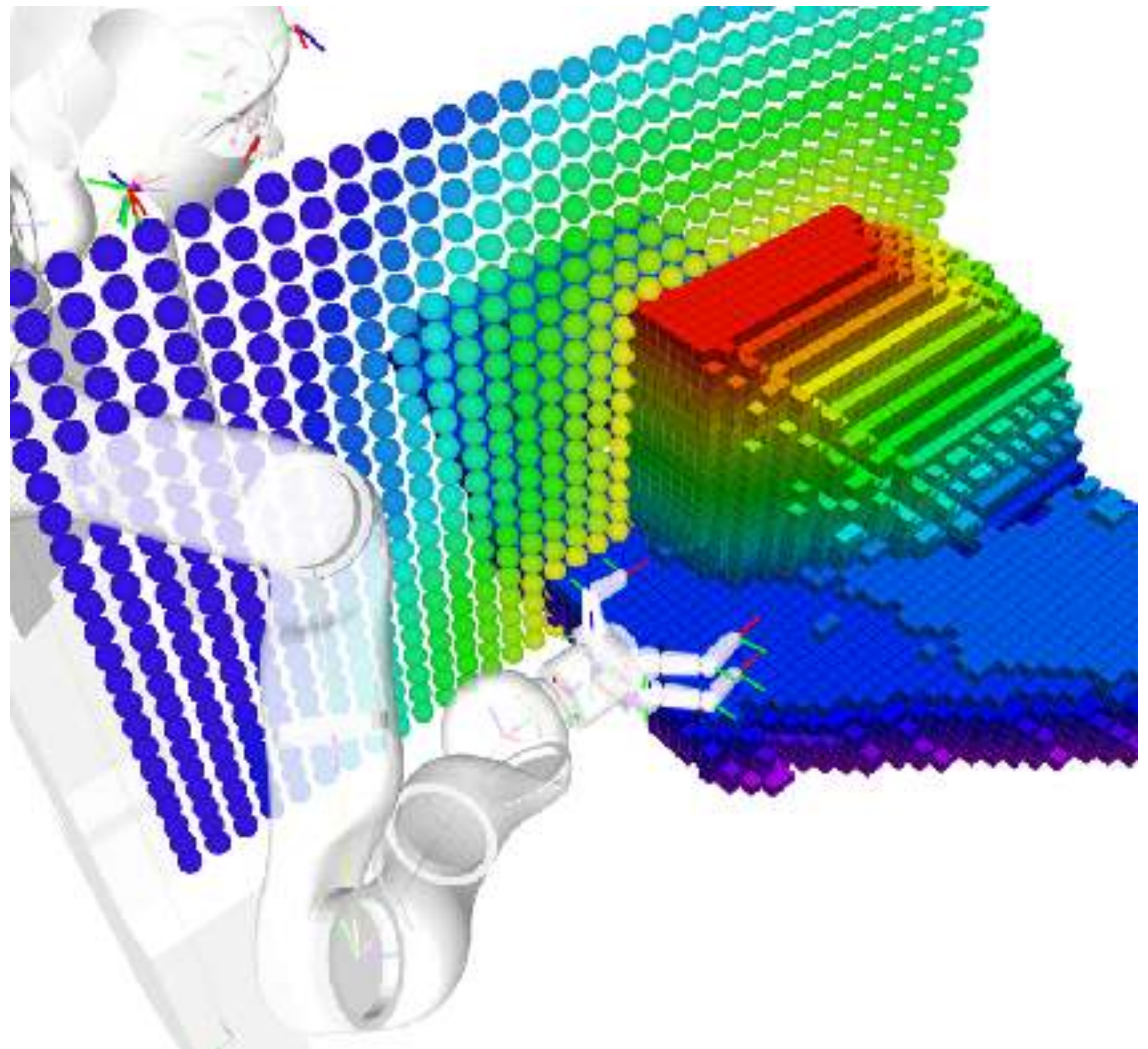
Architectures for Reactive Manipulation

Integrating **feedback** at multiple time scales

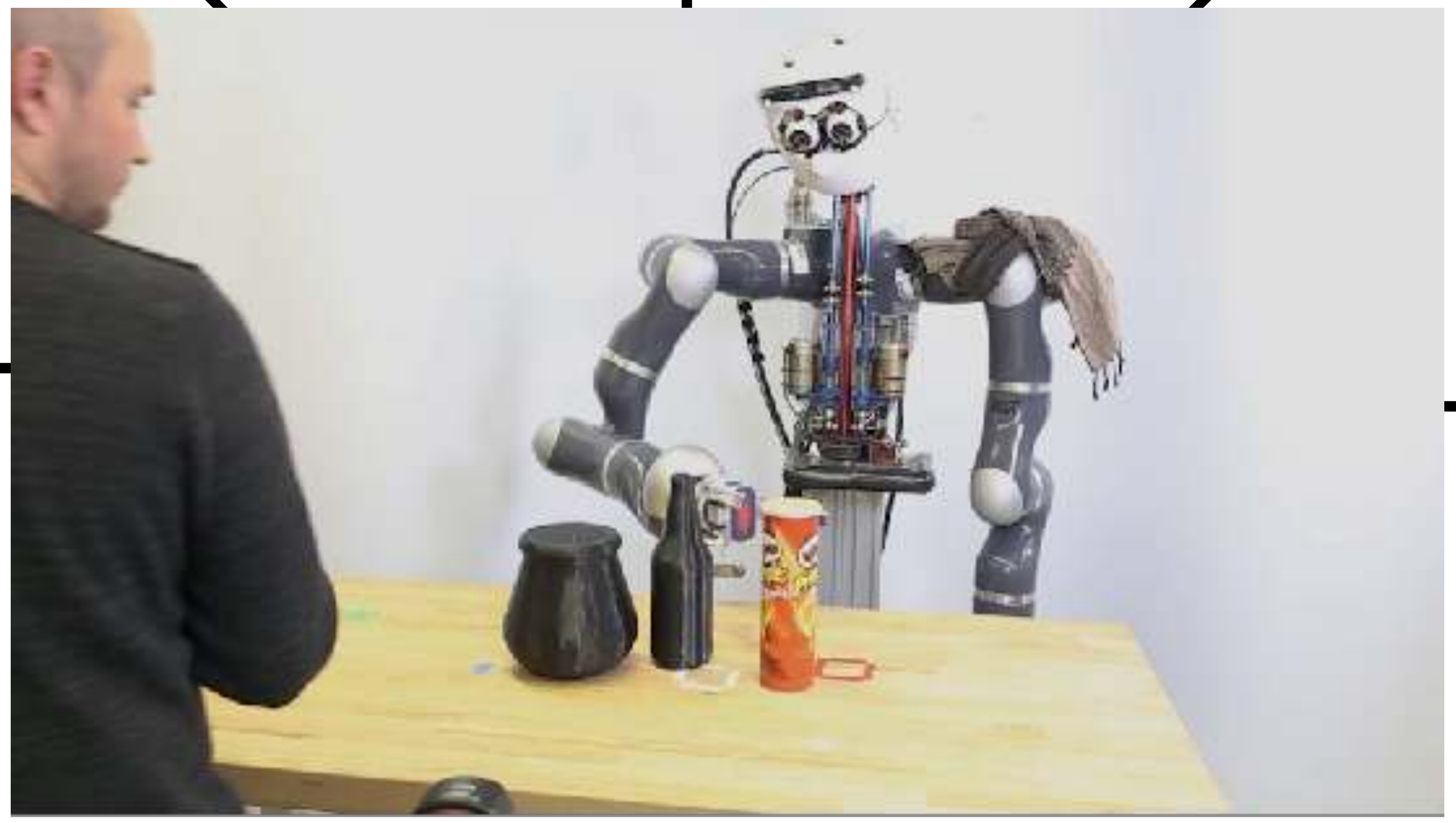


Closest Points, 100Hz

World Model → Trajectory Optimization → 10Hz → Kinematic Control → 100Hz → Torque Control → 1kHz



Distance Field, 10Hz



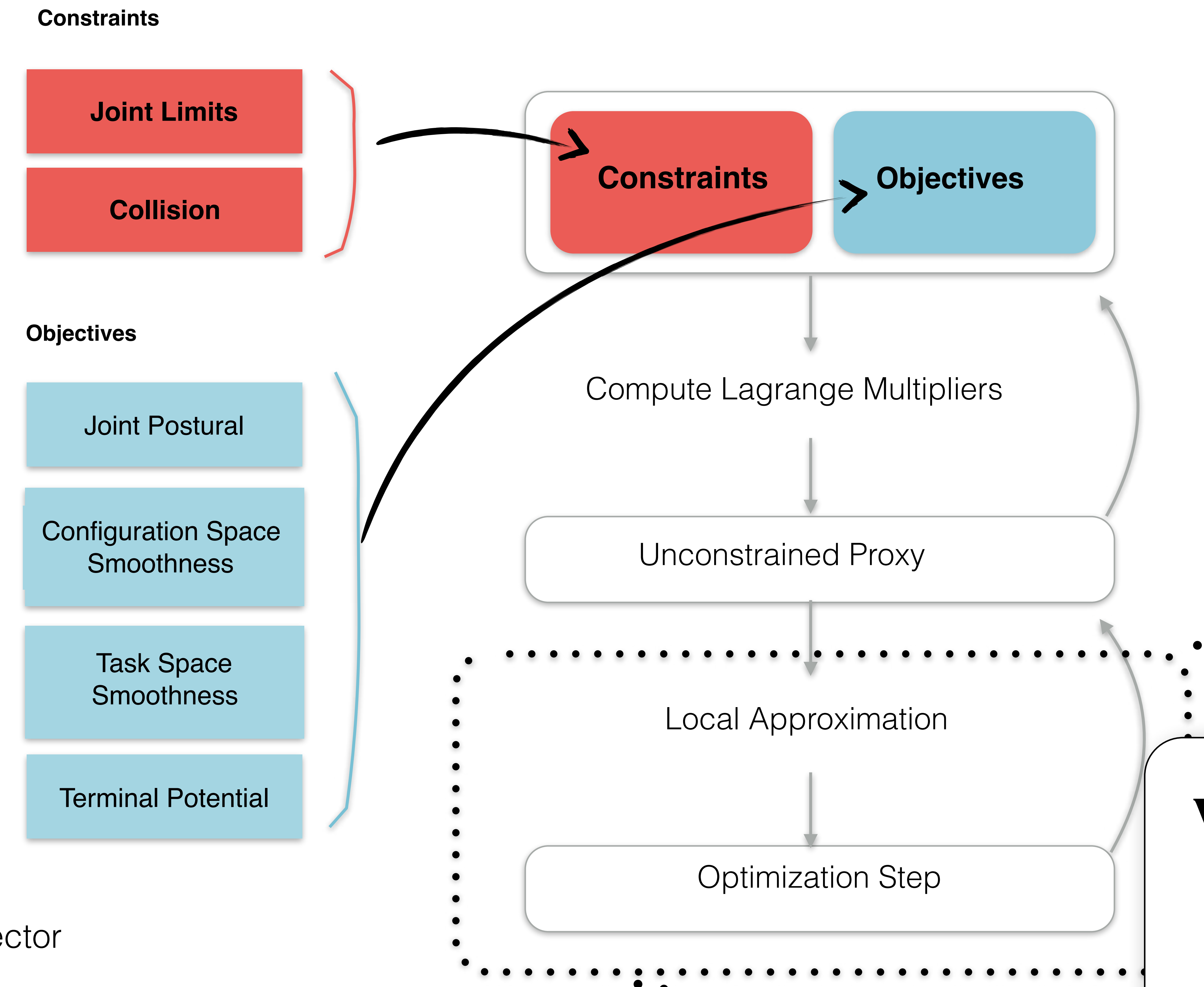
Perception

Action

300+ experiments on 4 dynamic scenarios with dynamical geometries

Collaborators : *Nathan Ratliff, Jeannette Bogh et al.,* Max Planck Institute, Tübingen
Publications : IROS 2016, LBR-ICRA 2017, RA-L 2018

“Gauss-Newton” for motion planning



Local Optimizer

while not $\texttt{StopCondition()}$ **do**

$$v \leftarrow f(\boldsymbol{\xi}_i) \;;$$
$$g_{\boldsymbol{\xi}} \leftarrow \nabla f(\boldsymbol{\xi}_i) \;;$$
$$\boldsymbol{\xi}_{i+1} \leftarrow \boldsymbol{\xi}_i - \eta_i \boldsymbol{B}_i^{-1} g_{\boldsymbol{\xi}_i} \;;$$

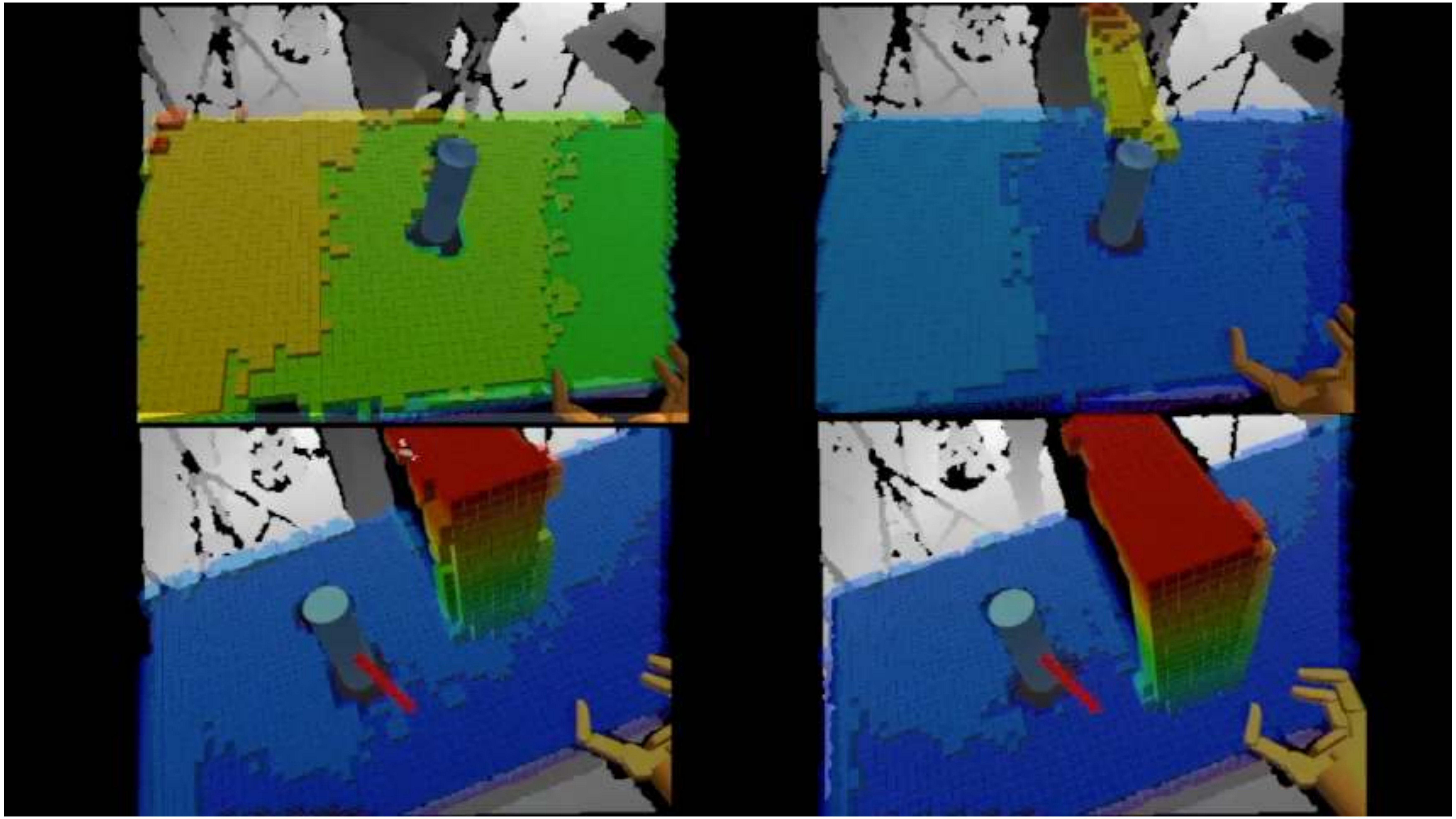
Trajectory vector

$$\boldsymbol{\xi} = [\ \boldsymbol{q}_1 \ \ldots \ \boldsymbol{q}_N \ ]^T$$

Collaborators : *Nathan Ratliff et al.*, Max Planck Institute, Tübingen
Publications : IROS 2016

Modeling the Environment

Smooth occupancy grids
using tri-cubic splines



Collaborators : *Nathan Ratliff et al.,* Max Planck Institute, Tübingen
Publications : IROS 2016, LBR-ICRA 2017, RA-L 2018

Conclusion

- Motion planning for manipulation
  ➡ High-DOF, Continuous state-space
  ➡ Sampling-based + local methods

- Human-awareness requires a predictive models of human motion
  ➡ safety, comfort (i.e, social awareness)

- Challenges:
  ➡ Model environment : affordances
  ➡ Model awareness : theory of mind
  ➡ Hierarchical representations

Collaborators Past and Present

Questions

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Thierry Siméon**
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**Dmitry Berenson, Sonia Chernova,
Rafi Haynes, Paul Oh**
Worcester Polytechnic Institute, MA, USA

**Nathan Ratliff, Daniel Kappler,
Jeannette Bogh, Stefan Schaal**
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Martin Giese
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