Task-informed grasping: from Perception to Physical interaction

A full day workshop at RSS 2019

Robotics: Science and systems

Freiburg

22 June 2019

Organisers: A. Ghalamzan, H. Kasaei, G. Neumann

FAST LEARNING AND SEQUENCING OF OBJECT-CENTRIC MANIPULATION SKILLS

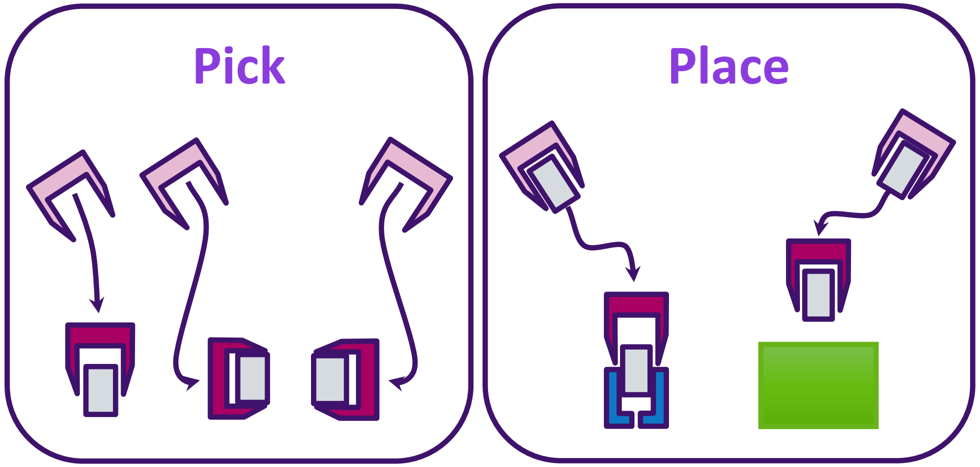
LEONEL ROZO, ANDRAS KUPCSIK, MENG GUO, MARCO TODESCATO,
PHILIPP SCHILLINGER, NICOLAI WANIEK, MARKUS GIFTTHALER, MATHIAS BÜRGER

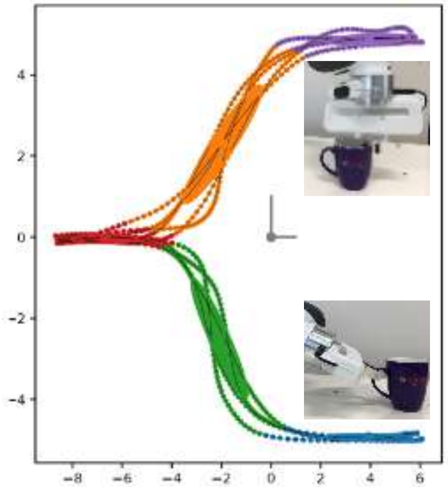
Bosch Center for Artificial Intelligence (BCAI)

BOSCH

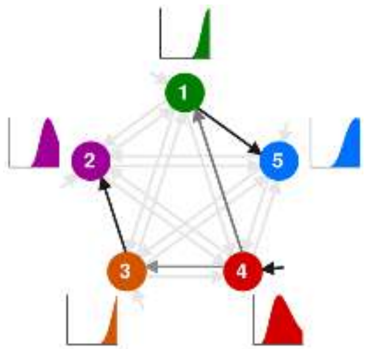
Fast Learning and Sequencing of Skills

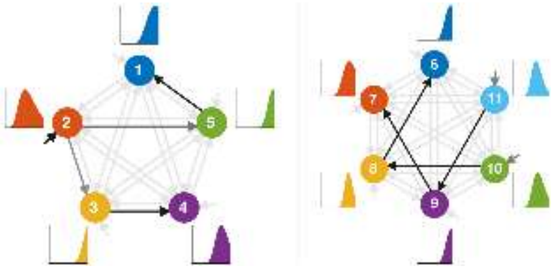
Combining high-level task planning and low-level motion primitives



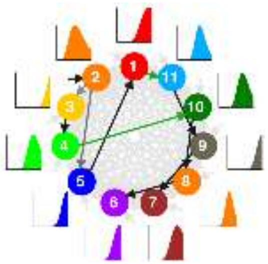


Task Parametrized Hidden semi-Markov Models



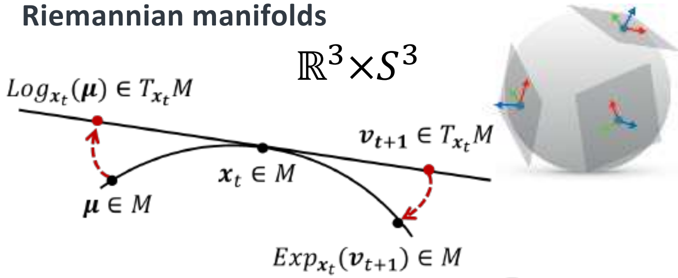


Cascading TP-HSMMs with KL-divergence



Viterbi sequencing

Riemannian manifolds



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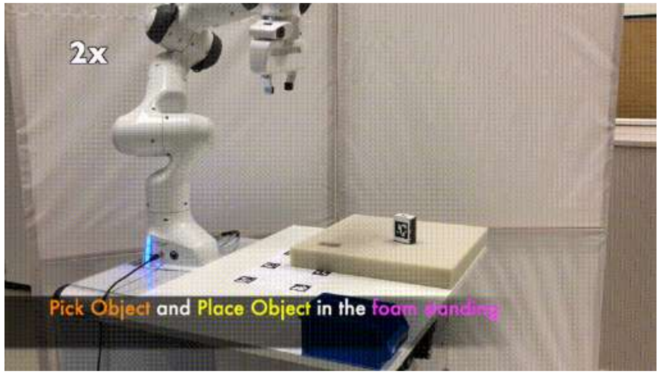
Experiments

Demonstrations

Reproductions



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Online Learning of Forward Models for Variable Impedance Control in Manipulation Tasks

Michael Mathew, Saif Sidhik, Mohan Sridharan, Morteza Azad, Akinobu Hayashi

June 22, 2019

Inspiration from Human/Animal Motor Control

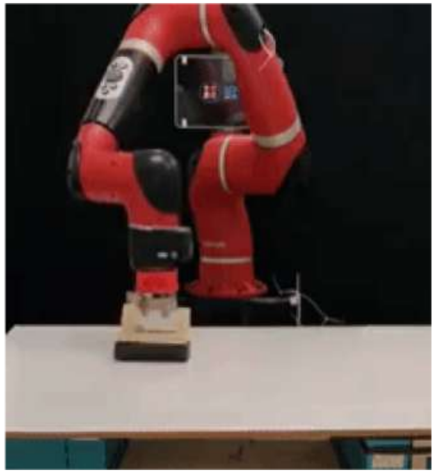
Behavior of humans performing a **new manipulation task**.

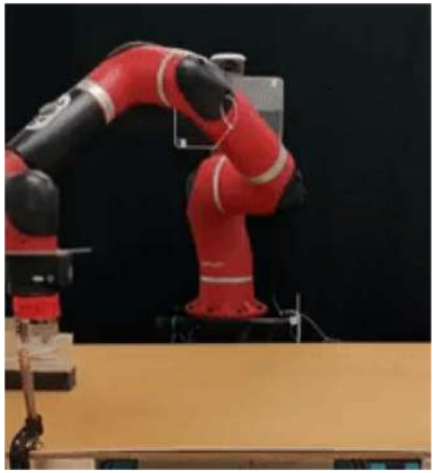
- Initially very **stiff** in order to:
  - Counter **unforeseen disturbances**.
  - Perform task accurately.

- With experience, evidence indicates humans:
  - Create **internal models** to predict forces.
  - Use prediction error to adapt stiffness.
  - Minimize **energy consumption**, achieve **compliance** (if and when needed).

Proposed Approach

- **Incremental online revision** of **forward model** of task learned from a small set of examples.
- Stiffness parameters as **time-independent, state-dependent** property in **task space**.
- **Quick online adaptation** of stiffness parameters to task based on forward model's prediction error.
- **Hybrid force-motion controller** to separate directions in which arm has to be stiff or **compliant**.

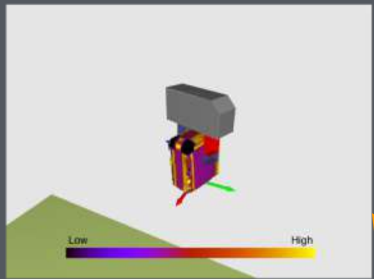


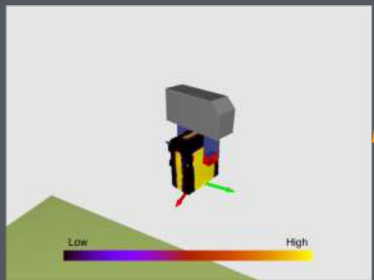


Generative grasp synthesis from demonstration using parametric mixtures

Ermano Arruda, Claudio Zito, Mohan Sridharan, Marek Kopicki and Jeremy L. Wyatt
University of Birmingham, UK

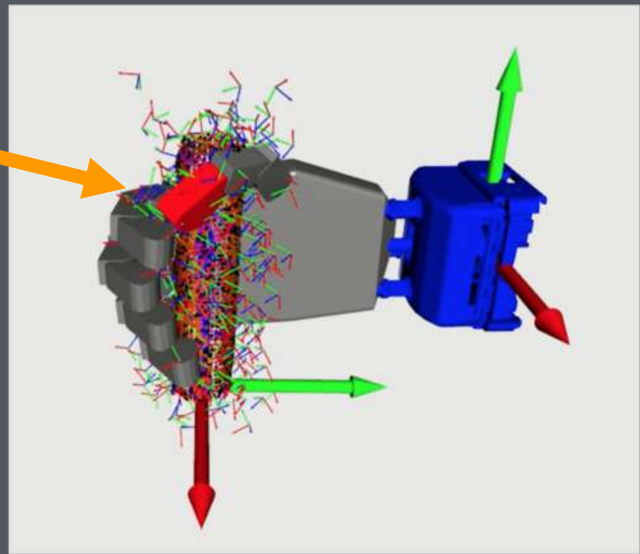
Approach





Thumb contact query density

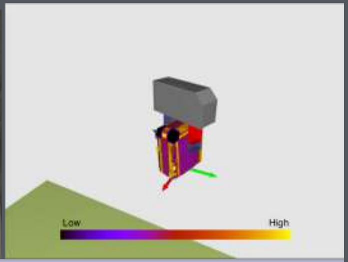
highlighting finger link affinities from a demonstration

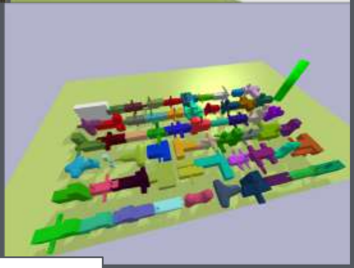


- **Given a grasp demonstration, learn generative models for grasp synthesis using Gaussian Mixture Models (GMMs).**
- **Can incorporate task-specific constraints, potential for real-time grasp generation.**
- **Computationally faster, better grasp success rate.**

Experiments

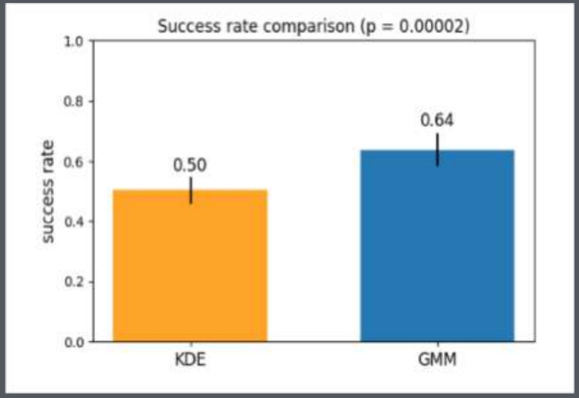
1. **60 trial objects (x10 trials per object). One grasp demo; four experimental conditions:**
   a. Depth noise (with/without)
   b. Grasp optimisation (with/without)

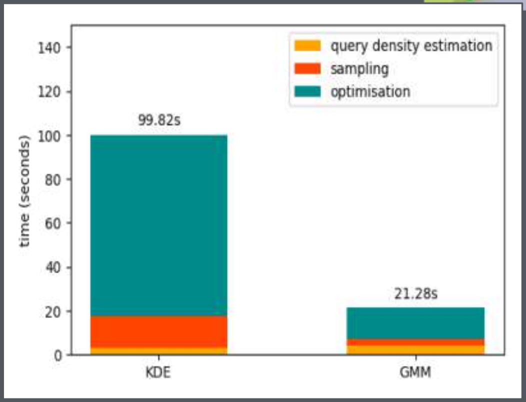




1. **Performance comparison:**
   a. Non-parametric approach (KDE-based)
   b. Parametric approach (GMM-based)

1. **Deployment on robot platform (Boris)**





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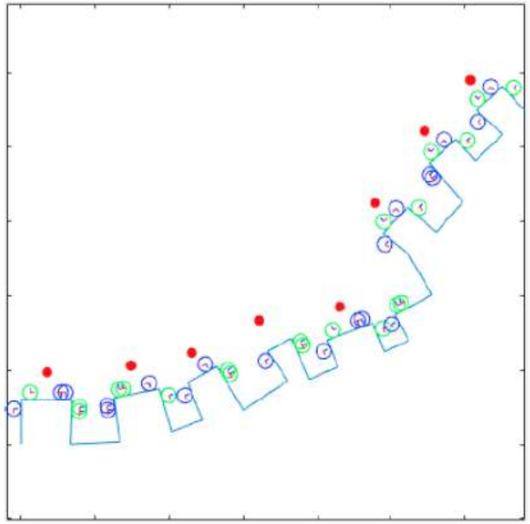
Claudio Zito*, Tomasz Deregowski, and Rustam Stolkin

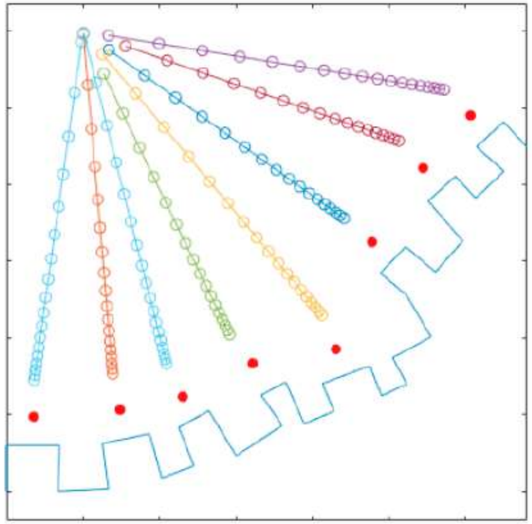
2D Linear Time-Variant Controller for Human's Intention Detection for Reach-to-Grasp Trajectories in Novel Scenes

Contributions

- Improving accuracy and usability of semi-autonomous robots
- Our framework accounts for context- and user-awareness
- Context-awareness:
  - Understand the scene
  - Generate a set of candidate grasps
  - Plan reach-to-grasp trajectories
- User-awareness:
  - Linear time-variant LQR (LTV-LQR) feedback controller
  - Facilitate motion towards the most promising grasp
  - Recover from wrong assumptions (i.e. enable user to switch between trajectories)

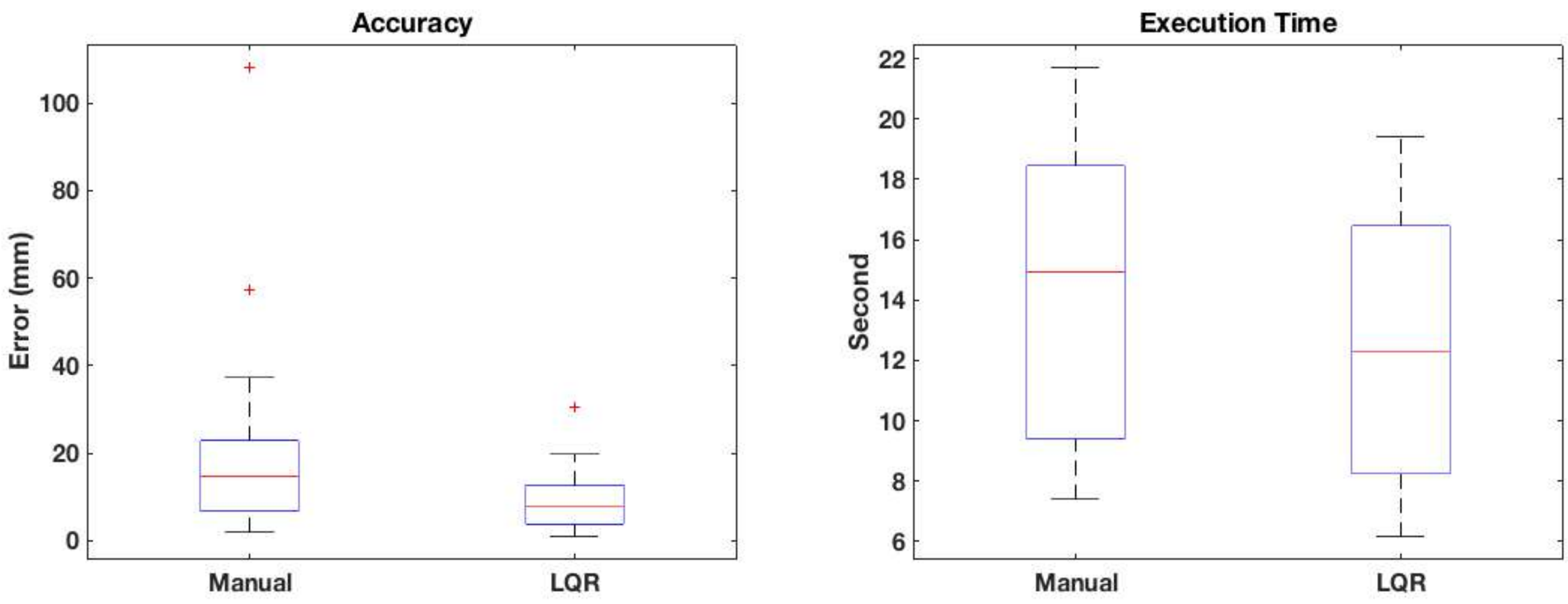


Grasp generation



Trajectory planning

Results


Accuracy
Error (mm)
0
20
40
60
80
100
Manual
LQR
Execution Time
Second
6
8
10
12
14
16
18
20
22
Manual
LQR

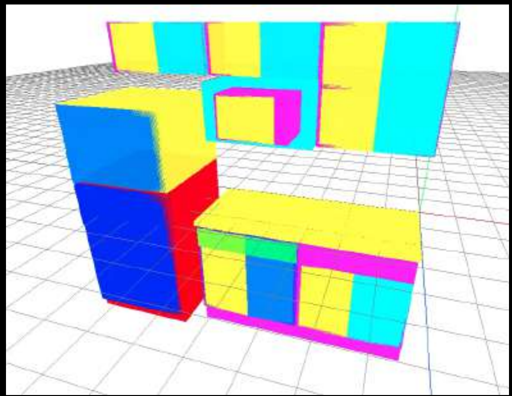
Tracking Large Scale Articulated Models with Belief Propagation

for Task Informed Grasping and Manipulation

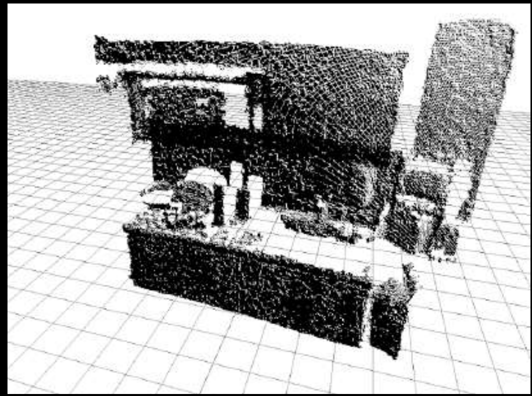
Karthik Desingh, Jana Pavlasek, Cigdem Kokenoz, Odest Chadwicke Jenkins

Laboratory for Progress

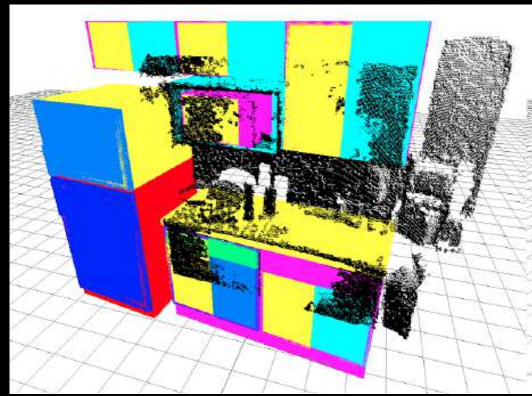
University of Michigan, Ann Arbor, MI, USA



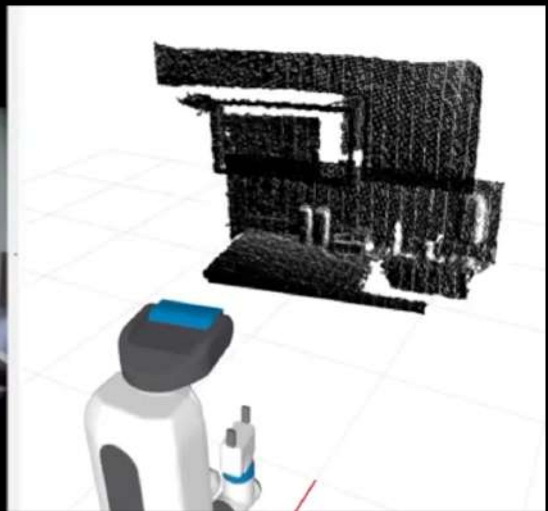
Articulated Kitchen Model



3D Point Cloud



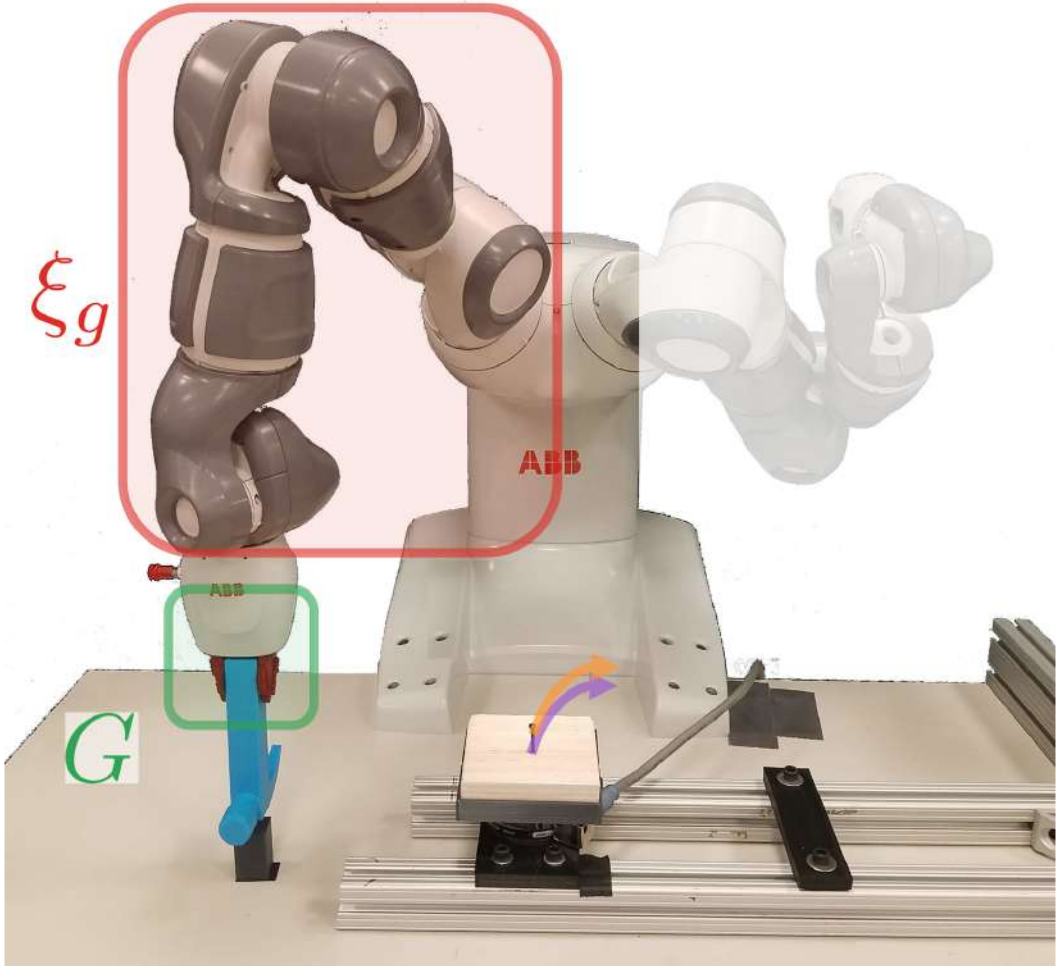
Pose Estimate



Challenges

- Limited view of the scene,
- Occlusions due to external objects & agents,
- Noisy sensor observations.

Previous work: Efficient Nonparametric Belief Propagation for Pose Estimation and Manipulation of Articulated Objects



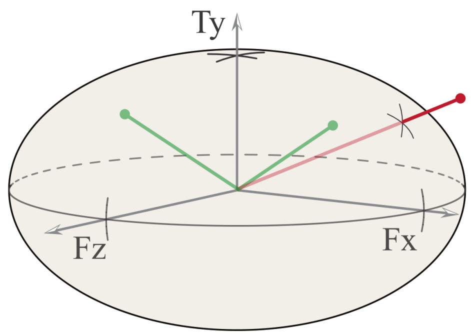
Force-and-Motion Constrained Grasp Planning for Tool Use

Rachel Holladay
Tomás Lozano-Pérez
Alberto Rodriguez

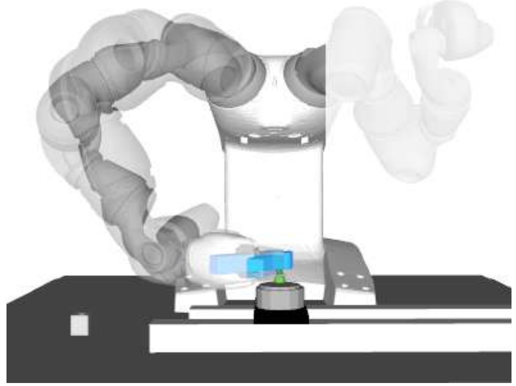
RSS 2019 Workshop: "Task-Informed Grasping (TIG-II): From Perception to Physical Interaction"

Key Insight:
Tool use as a *constraint satisfaction* problem, with high-dimensional continuous variables

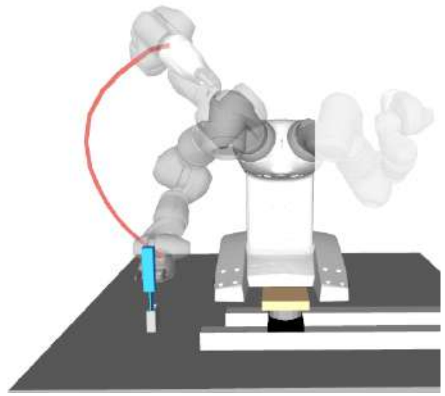
Choose a grasp such that:



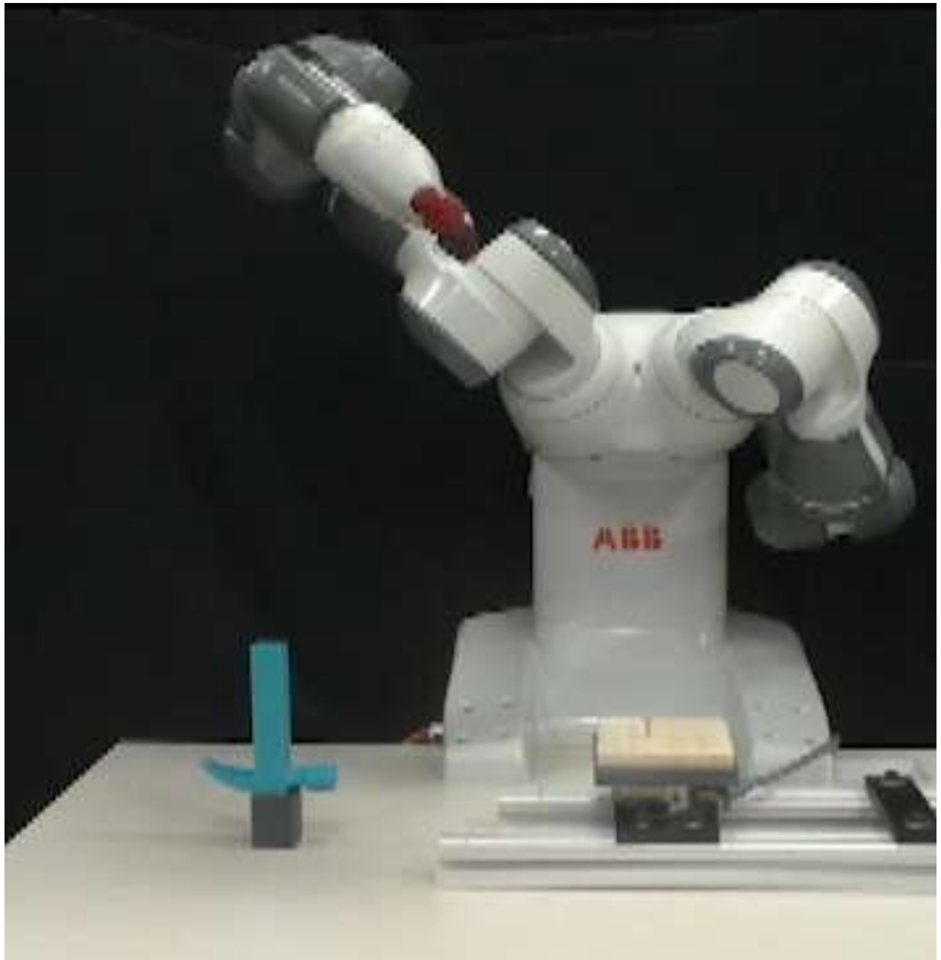
Force Suitable



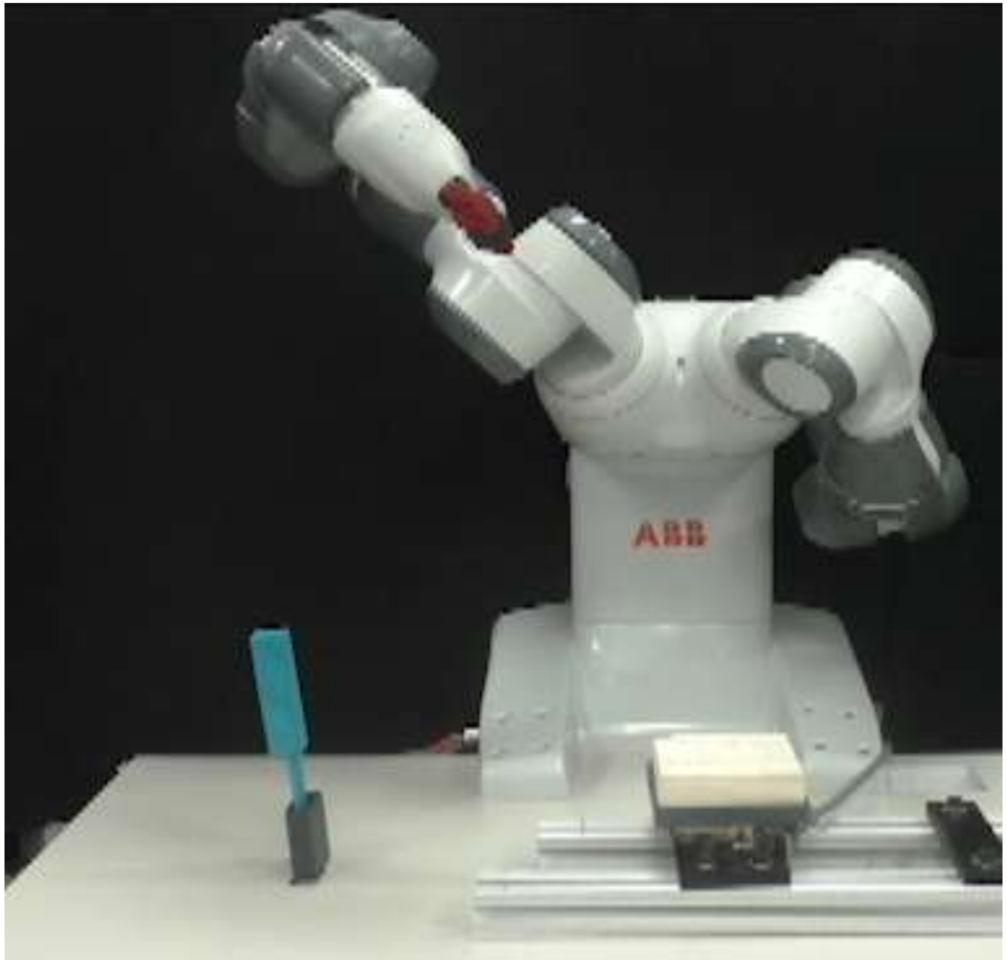
Kinematically Suitable



Reachable



hammer_pulling



knife_cutting

Bite Acquisition of Soft Food Items via Reconfiguration

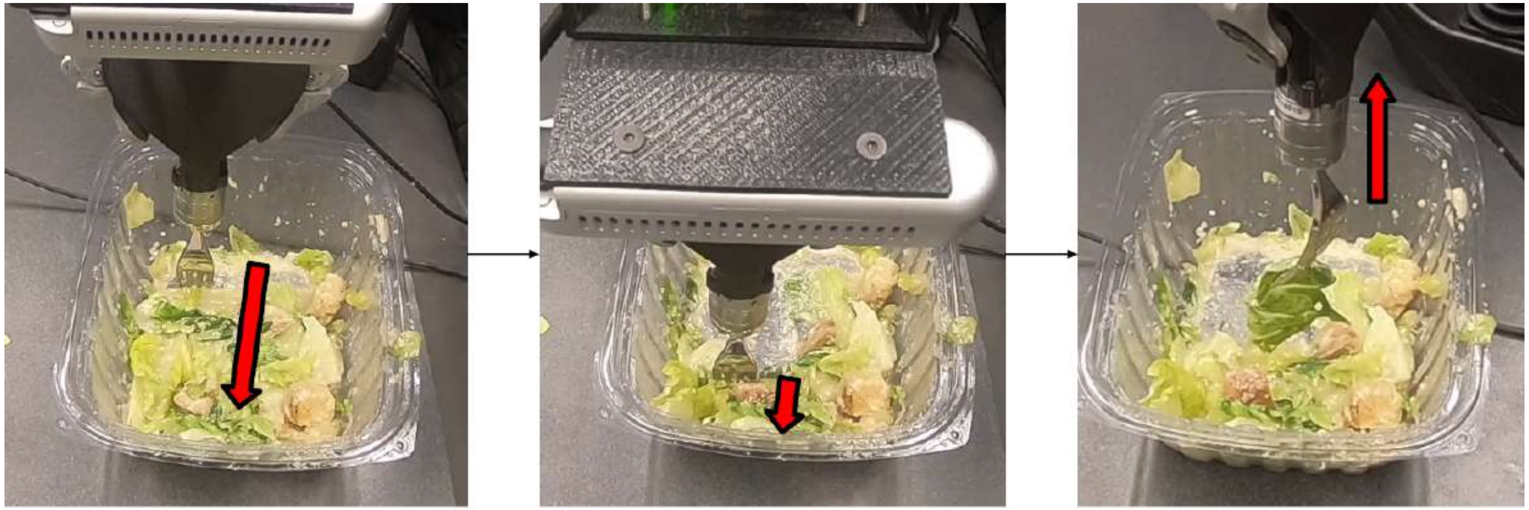
Gilwoo Lee, Tapomayukh Bhattacharjee, and Siddhartha S. Srinivasa

Personal Robotics Lab, CSE

University of Washington

PAUL G. ALLEN SCHOOL OF COMPUTER SCIENCE & ENGINEERING

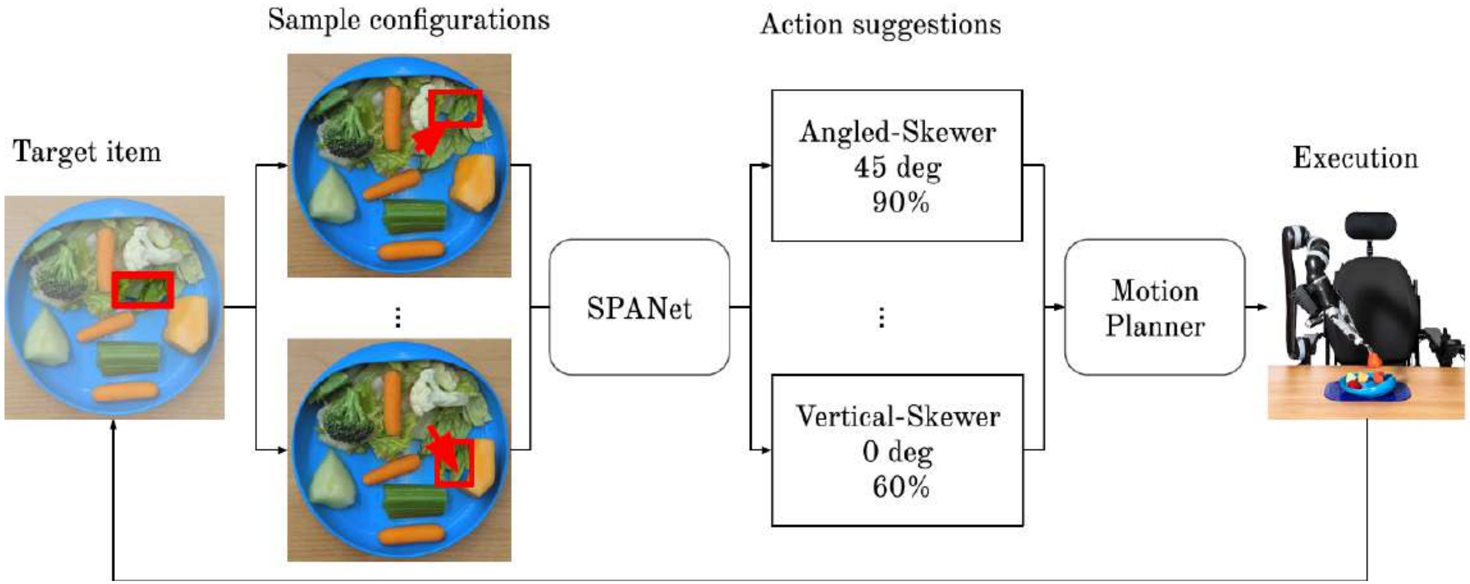
Preliminary results validate the need for reconfiguration



Push Stack against the wall Skewer

- Preliminary results with *Push-then-Skewer* experiments
- Pushing helps in stacking soft and highly deformable lettuce, thus helping in acquiring it from a salad bowl.

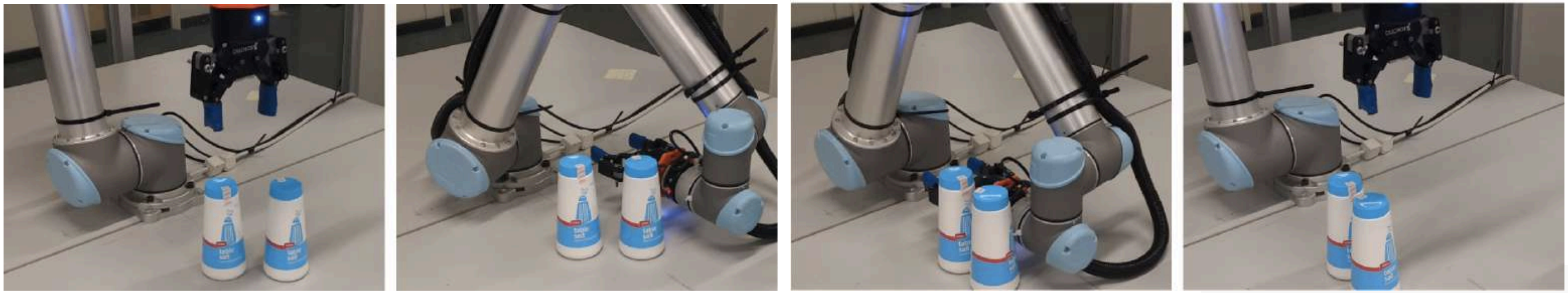
Search in the joint space of pre-acquisition and acquisition actions



- *Configuration Generator*: Generate candidate configurations
- *Prediction Model*: Predict pre-acquisition actions
- *SPANet*: Predict most successful acquisition action and success probability

Embracing Contact: Pushing Multiple Objects with Robot's Forearm

Akansel Cosgun, Luke Ditria, Shayne D'Lima, Tom Drummond



- Sorting Task
  - 2 types of objects (red, blue), randomly placed on table
  - Goal: Cluster red/blue objects in given circular red/blue goal regions
  - Metric: Complete task in shortest amount of wall time
- Research Question
  - Can forearm-push actions increase task efficiency?

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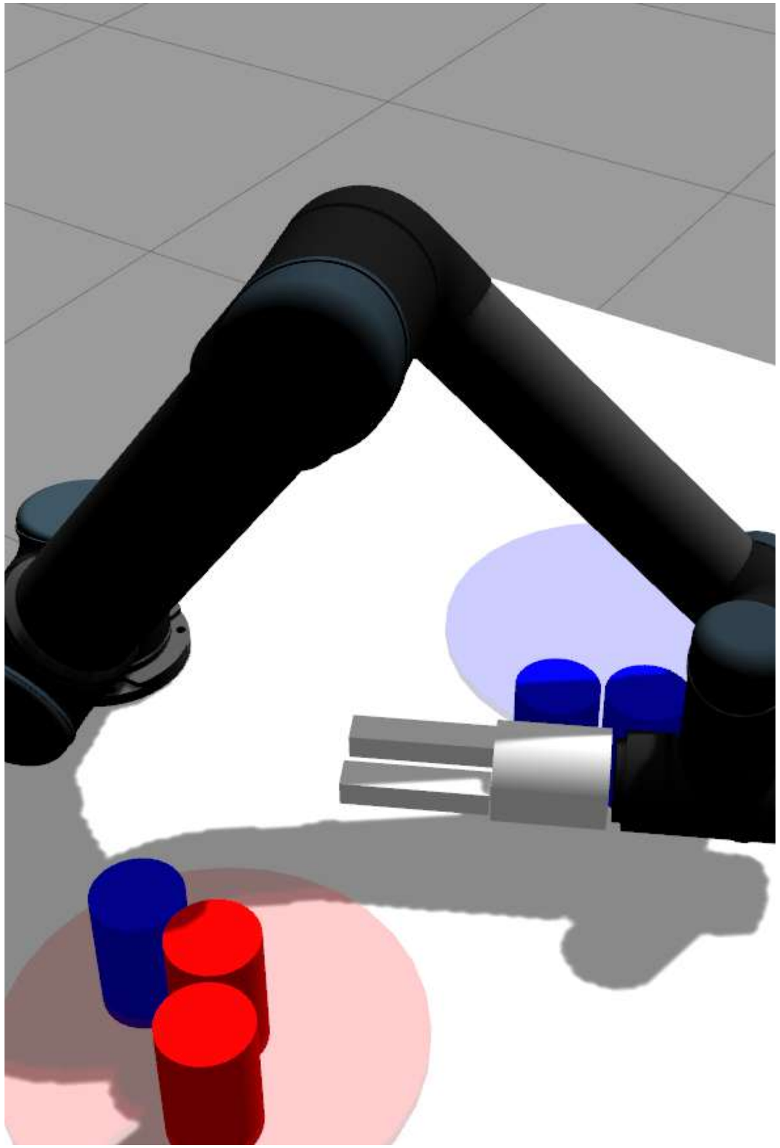
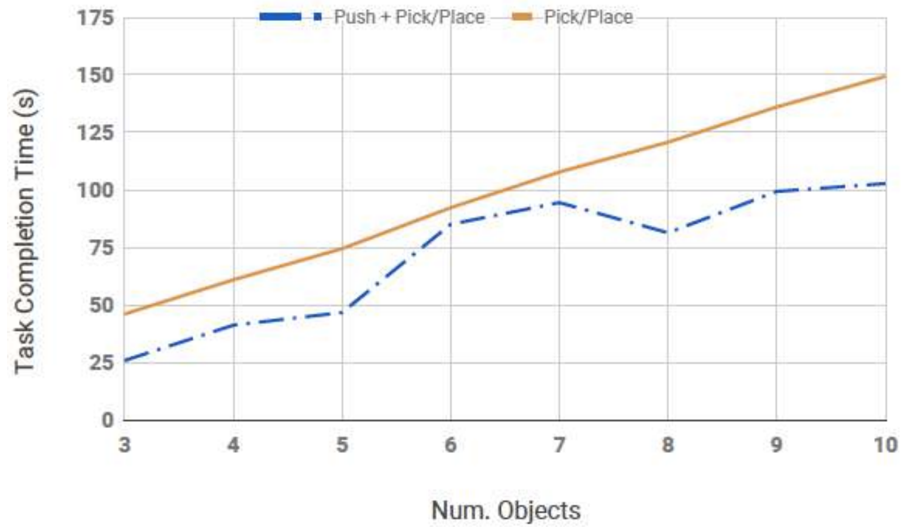


Approach

- Action space (high level)
  - Pick&Place: Place an object to its goal region (randomly sampled)
  - Forearm-push: Push an object to the center of its goal region. Other objects might also be inadvertently pushed
- Forearm-Push
  - First collision-free pre-push pose is found and trajectory is checked for kinematic feasibility
  - End effector pose constrained w.r.t. table surface during push motion
  - 2D physics simulator (Box2D) used to predict new table configuration
- Planning Algorithm
  - 1-step lookahead greedy search
  - Heuristic: Sum of distances of all objects to their goal regions
- Implementation
  - UR5. Point-cloud based object detection. [not robust yet!]
  - Gazebo. Experiments are carried in sim

Experiments

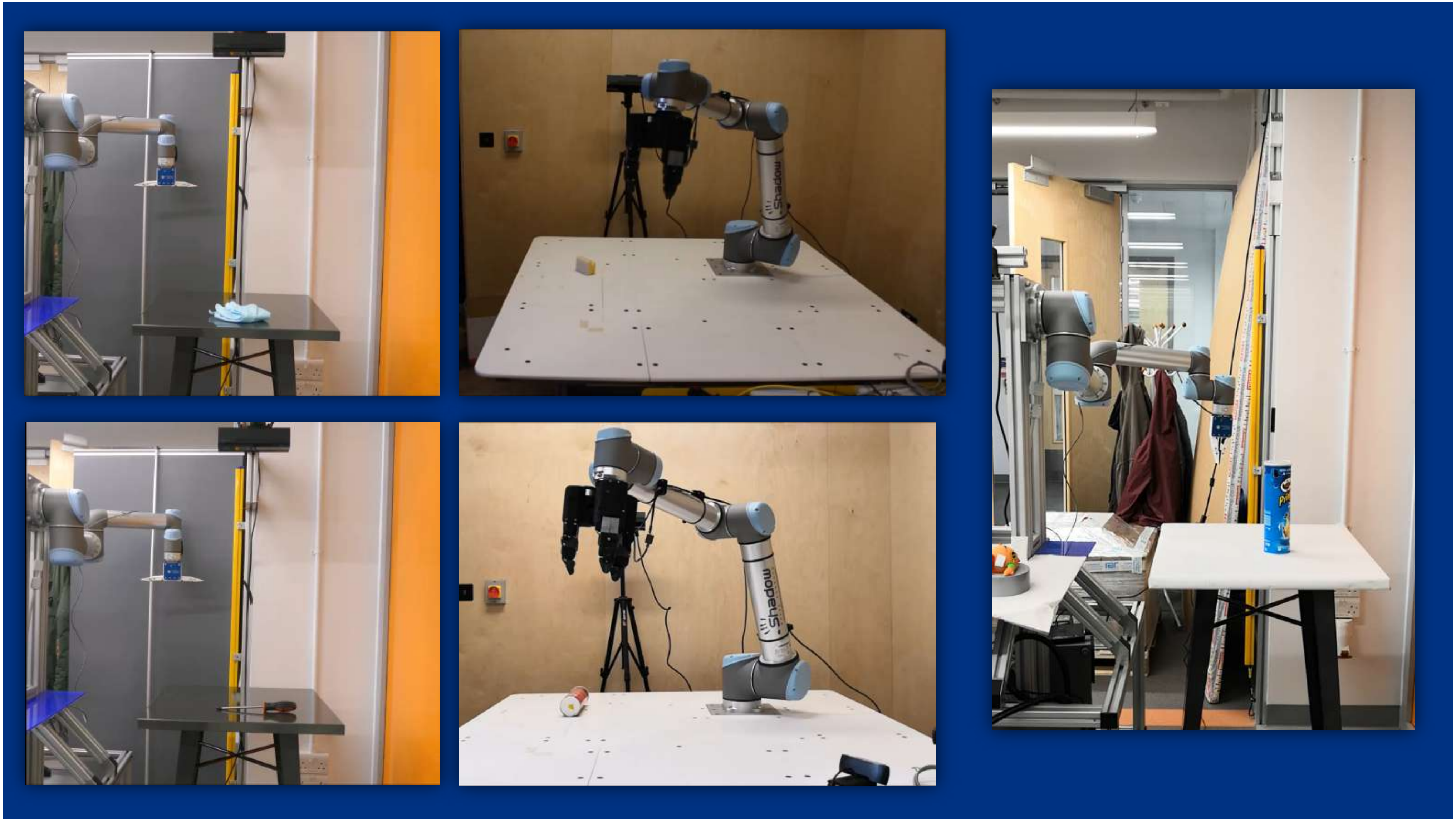
- 2 methods
  - Pick&Place (Baseline)
  - Forearm Push + Pick&Place (planner selects push or pick)
- 3 runs for each num. object (varied 3 to 10)
- Results
  - New approach completes task %27.9 faster on average
  - Planner often executes a big push early
- Take Home Story
  - Robot links are under-utilized. Contact other than end-effector is avoided in robotics (motion planning!)
  - Embracing contact with links enables new opportunities in non-prehensile manipulation



Robust and fast generation of top and side grasps for unknown objects

Brice Denoun[1,2], Beatriz Leon[2], Claudio Zito[3], Rustam Stolkin[3], Lorenzo Jamone[1] and Miles Hansard[1]

[1]Queen Mary University of London, United Kingdom
[2]The Shadow Robot Company, United Kingdom
[3]University of Birmingham, United Kingdom


Shadow
Shadow

Queen Mary
University of London

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Claudio Zito, Maxime Adjigble, Brice D. Denoun,
Lorenzo Jamone, Miles Hansard and Rustam Stolkin

Metrics and Benchmarks for Remote Shared Controllers in Industrial Applications

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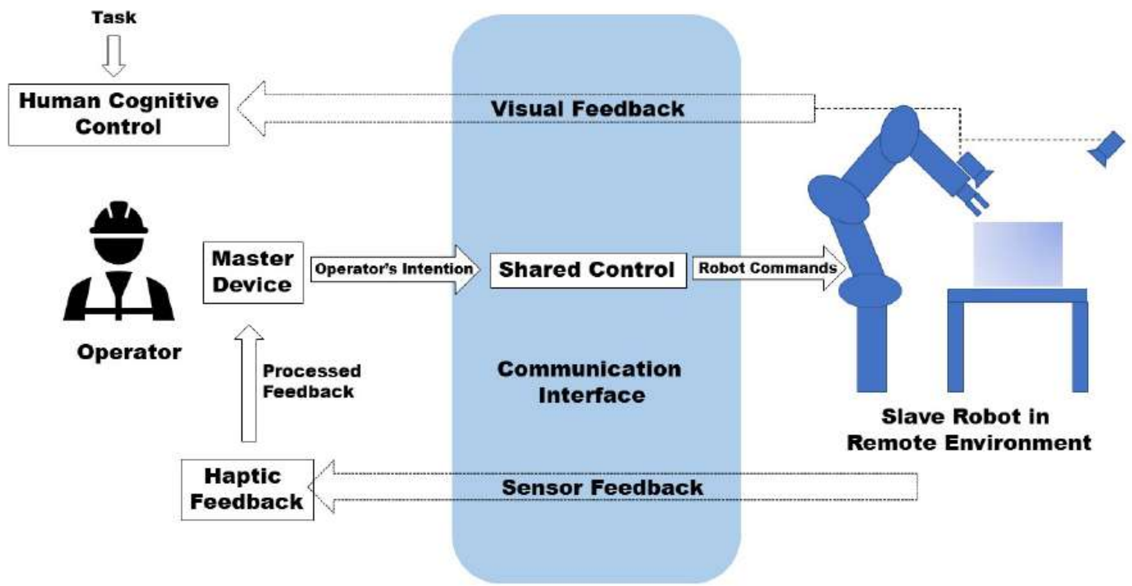
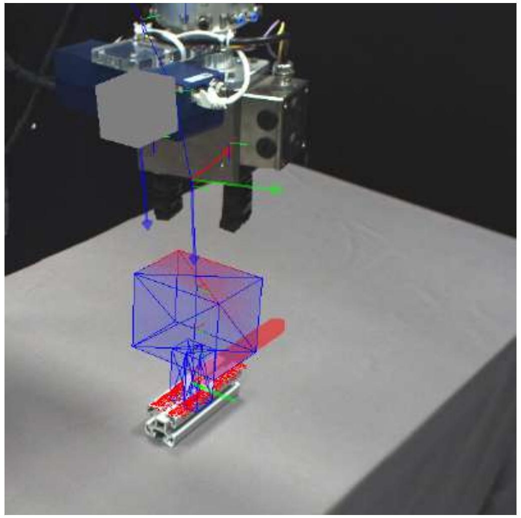
Framework


Task
Human Cognitive Control
Visual Feedback
Operator
Master Device
Operator's Intention
Shared Control
Robot Commands
Processed Feedback
Communication Interface
Slave Robot in Remote Environment
Haptic Feedback
Sensor Feedback



Metrics & Benchmarks

Metrics

I. Task efficiency:
   - the efficiency of the human-robot team to perform the task
   - measured as task success rate.

II. Task effort:
   - the required time to complete the task.

III. Robot demand attention
   - User's cognitive burden on operate the robot

Benchmark

I. Grasp Efficiency:
   - Primitive shapes
   - Evaluate controllability & Grasp Stability

II. Pick & Place:
   - Industrial dataset
   - Evaluate on a single object & clutter scenes

III. Assembly:
   - Peg-in-the-hole problem
   - Evaluate efficiency beyond grasping