NRI: INT: COLLAB: Integrated Modeling and Learning for Robust Grasping and Dexterous Manipulation with Adaptive Hands

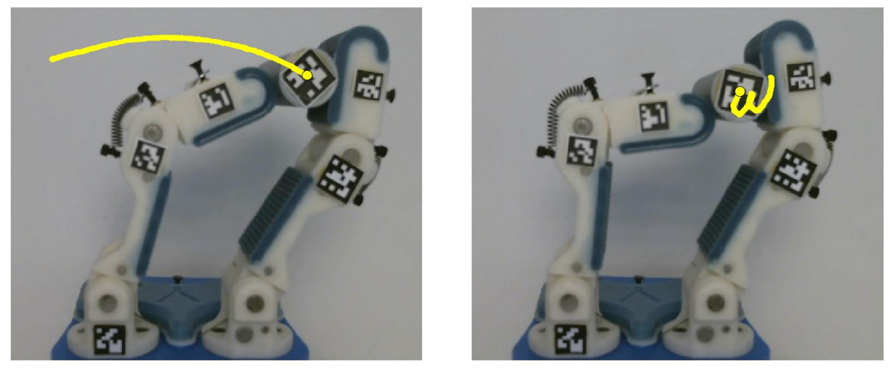
Kostas Bekris[1], Abdeslam Boularias[1] and Aaron Dollar[2]

[1]Department of Computer Science, Rutgers University, New-Brunswick, NJ [2]School of Engineering, Yale university, New-Haven, CT

Objective

Underactuated hands:
- Able to passively adapt to objects of uncertain size and shape.
- Provide good grasping performance without sensing and with open-loop control.
- Enable low cost and compact design.

Challenge: Analytical models are difficult to compute accurately.



This project aims for dexterous within-hand manipulation through advanced machine learning and planning tools.

Path planning for within-hand manipulation over learned safe states [1]

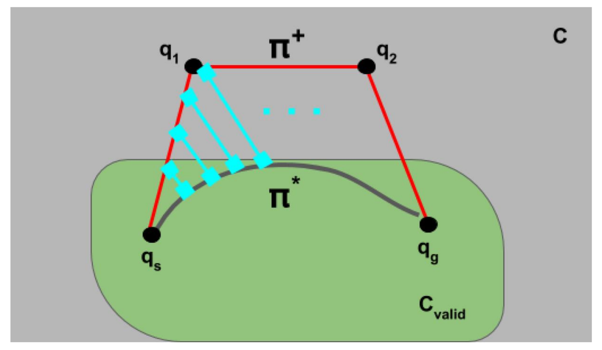
We proposed a framework for tracking a desired path of an object held by an adaptive hand. Given a reference path π^+, the objective is to plan a path so as to find a path π^* such that

$$\pi^* = \underset{\pi}{\operatorname{argmin}}\, diff(\pi, \pi^+)$$

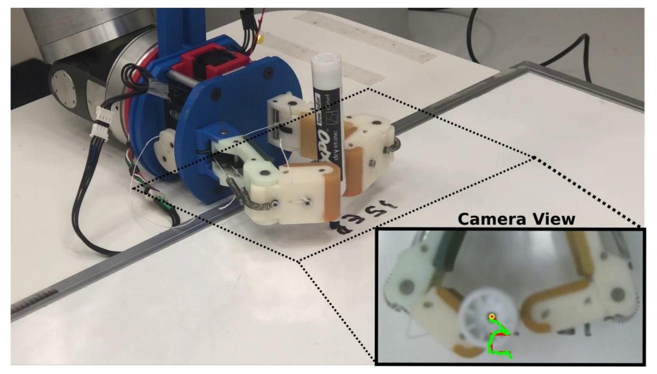
where $diff(\pi, \pi^+)$ is some similarity measure.

- **Classification**: Data-driven classification process to estimate the probability of failure for given states.
- **Curve similarity**: Dynamic Time Warping (DTW) measures the path difference and minimizes the area between planned and reference curves.
- **Planning through informed search**:
  - Compared A* and I-SST.
  - Evaluation function $f(q) = g(q) + h(q)$.
  - Cost $g(q)$ is the DTW of the traversed section.
  - Heuristic cost $h(q)$ is

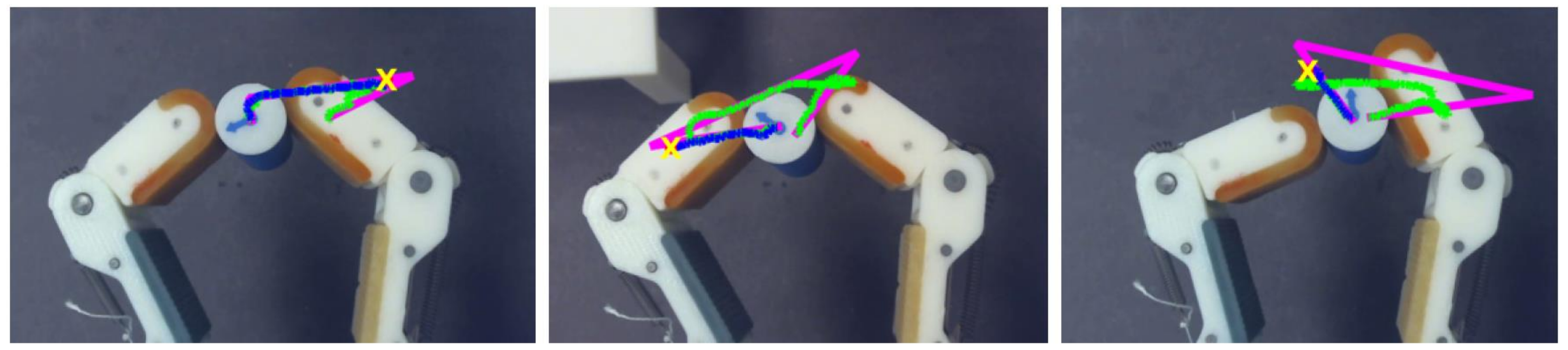
$$h(q) = \frac{1}{2}\sum_{k=0}^{m}(\|q - q^+\|_2 - \delta k)$$



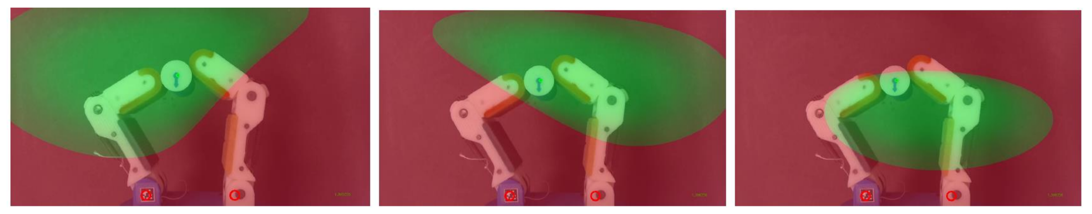
A reference path and a path tracking it while remaining in the valid region.



Two fingered adaptive hand (Model T42) writing "ISER".



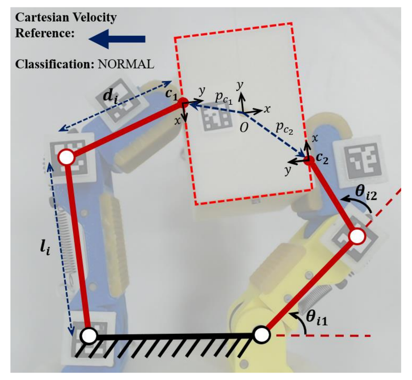
Random paths to track (pink), executed trajectories with naïve planning (blue) and executed trajectories with I-SST (green). The object drops with naïve executions (yellow crosses) while I-SST completes the trajectory successfully.



The classifier output for the exploration direction that caused dropping the object (green – normal, red – drop)

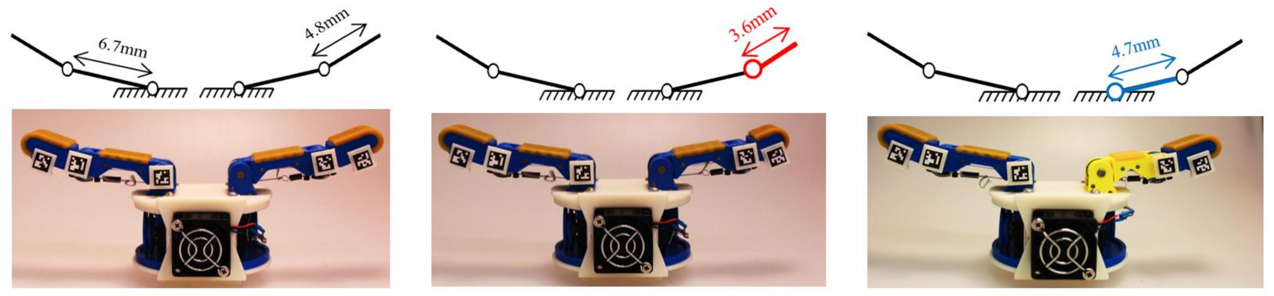
Learning from transferable mechanics models [2]

- **Previous work:**
  - Ability to predict modes (normal, drop, stuck, and sliding) with 94% percent accuracy.
  - However, this model was gripper specific and could not be transferred.
- **In this work:**
  - Identified a gripper agnostic feature set (including Jacobian, Grasp Matrix, and contact curvatures).
  - Enables to predict modes of grippers with different physical dimensions.



Features extracted from vision to construct the finger Jacobian and the grasp matrix.

- **Results**:
  - A classifier was trained on one T42.
  - Predicted modes with around 84% accuracy when tested with two different grippers.

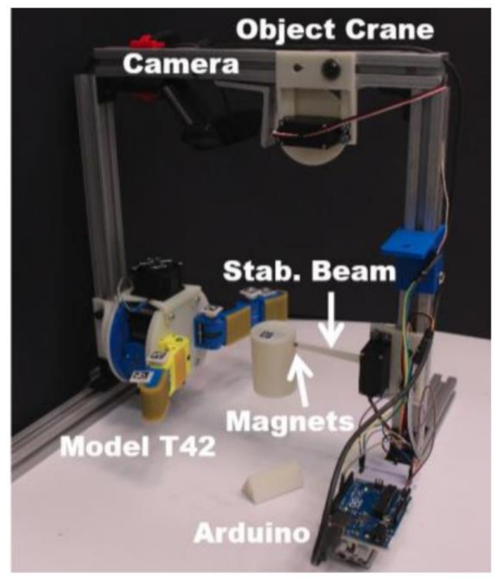


Number	Feature Set	Notation
1-2	Min/Max SVD Grasp Matrix	g_{min}, g_{max}
3-4	Left/Right Finger Manip. Measure	j_l, j_r
5-6	Left/Right Penalized Manip. Measure	j_l', j_r'
7-8	Left/Right Finger Pad Curvature	k_{lf}, k_{rf}
9-10	Left/Right Object Curvature	k_{lO}, k_{rO}
11-12	X/Y Cartesian Velocity Reference	$v_x,\ v_y$

Features collected

	Random Forests	SVM - Linear	SVM – Radial
All Features	84.6 %	79.5 %	82.8 %
6 Most Imp.	82.7 %	81.8 %	81.9 %

Classification results

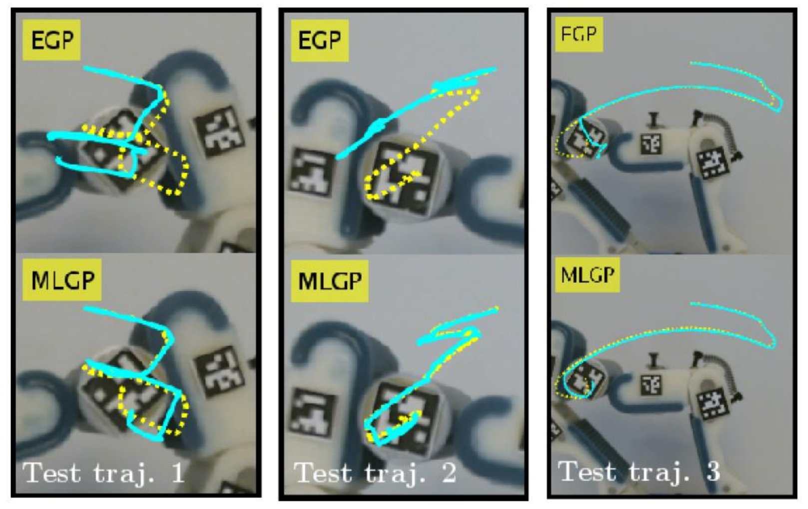


Automated data collection

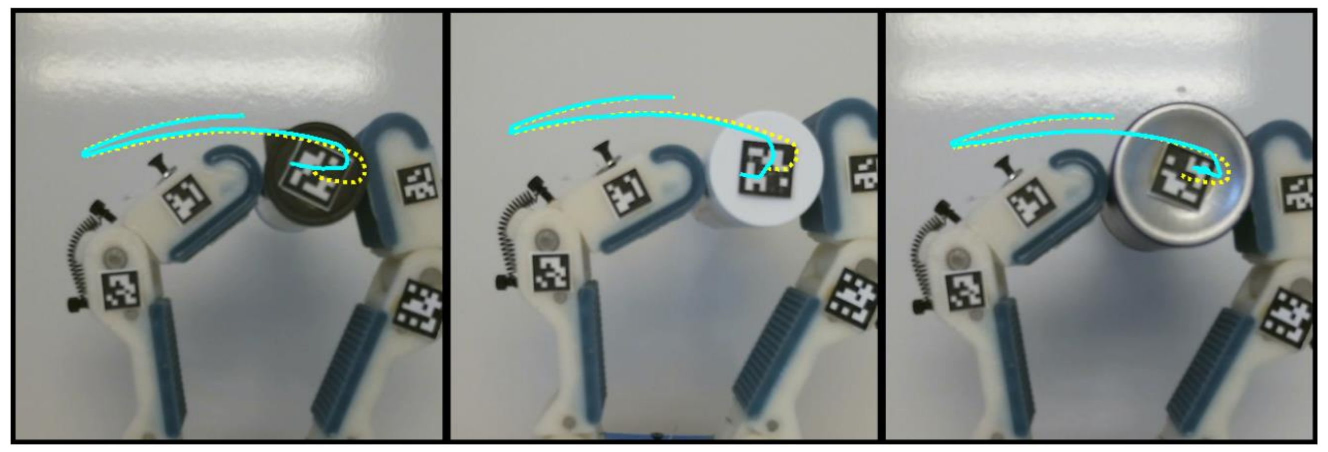
Learning the dynamics of an adaptive hand [3]

We learn a stochastic model of the hand automatically from data with minimum user effort. The focus is on identifying the dominant, sensable features required to express the hand's dynamics, thereby enabling the learning of a probabilistic transition model from recorded trajectories.

- **What are the underlying features that sufficiently describe the configuration of the hand?** Object position along with the actuator loads.
- **Manifold Learning Gaussian Process (MLGP):** Diffusion maps are used for efficient local regression.
- **Failure avoidance**: Sparsity analysis identifies failure regions in the observable state space.
- **Generalization**: Ability to generalize to unknown new objects of varying sizes.

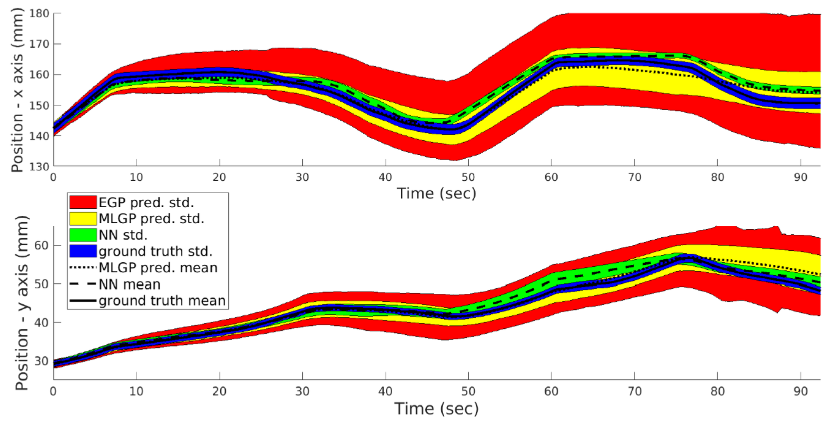


Recorded and predicted paths using object position and actuator loads while comparing EGP and MLGP.



Generalization to novel objects of different diameters.

Closed loop tracking of a rectangle with the transition model.



Distribution propagation while sampling from the GP distribution.

Group

Rutgers University	Yale University
Avishai Sintov – Post-doc	Kaiyu Hang – Post-doc
Andrew Kimmel – PhD student	Berk Calli – Post-doc (now at WPI)
Bowen Wen – PhD student	Andrew Morgan – PhD student
Juntao Tan – MSc student	Walter Bircher – PhD student

RUTGERS UNIVERSITY | NEW BRUNSWICK

Yale University

[1] B. Calli, A. Kimmel, K. Hang, K. Bekris, and A. Dollar, "Path planning for within-hand manipulation over learned representations of safe states," in Int. Symp. on Exp. Rob., Buenos Aires, Argentina, 2018.
[2] A. Morgan, W. Bircher, B. Calli and A. Dollar, "Learning from transferable mechanics models: generalizable online mode detection in underactuated dexterous manipulation", submitted to ICRA, Sep. 2018.
[3] A. Sintov, A. Morgan, A. Kimmel, A. Dollar, K. Bekris and A. Boularias, "Learning the dynamics of an underactuated adaptive hand", submitted to the IEEE Robotics & Automation Letters and ICRA, Sep. 2018.

Award ID#: 1734492