Integrated Modeling and Learning for Robust Grasping and Dexterous Manipulation with Adaptive Hands

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Yale University

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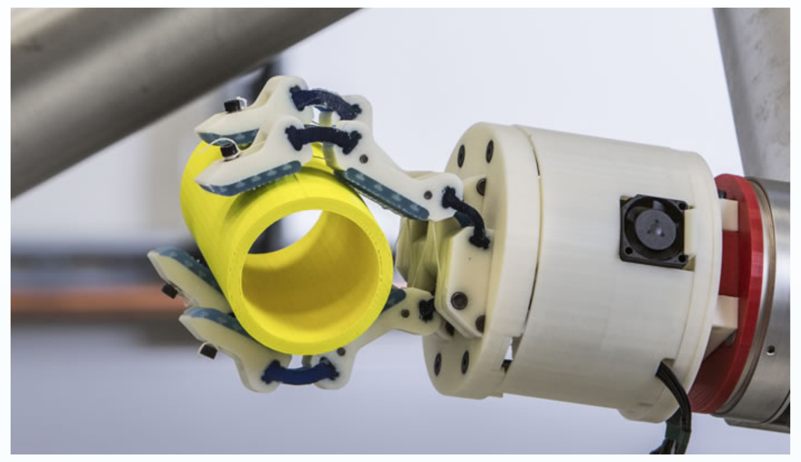
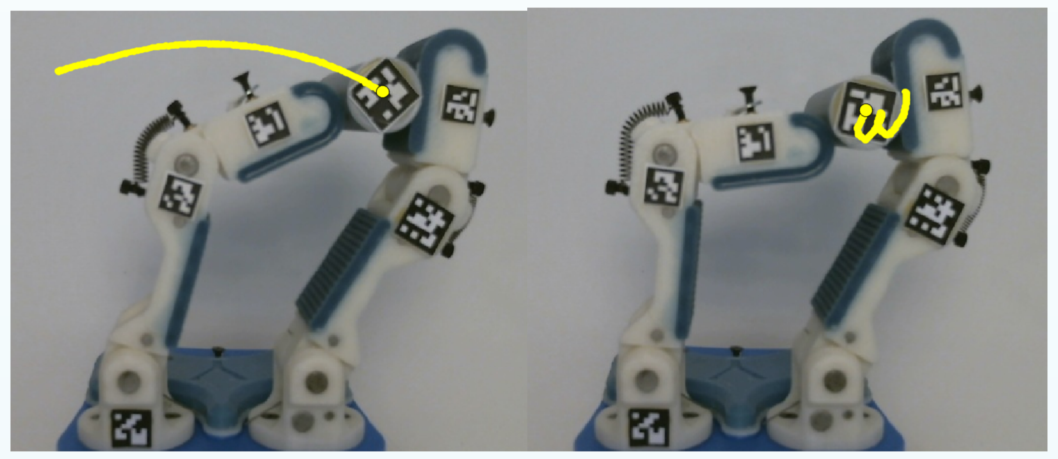
Yale OpenHand Project

https://www.eng.yale.edu/grablab/openhand/



Why Underactuated Adaptive Hands?

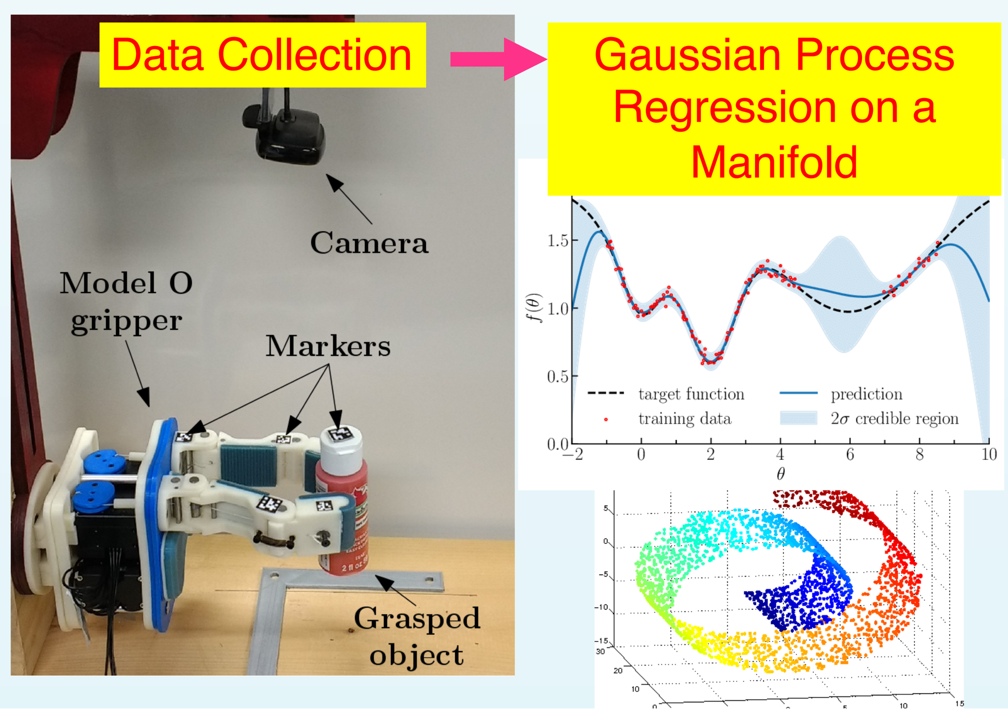
- Able to passively adapt to objects of uncertain size and shape.
- Provide good grasping performance without sensing and with open-loop control.
- Enable a low cost and compact design.

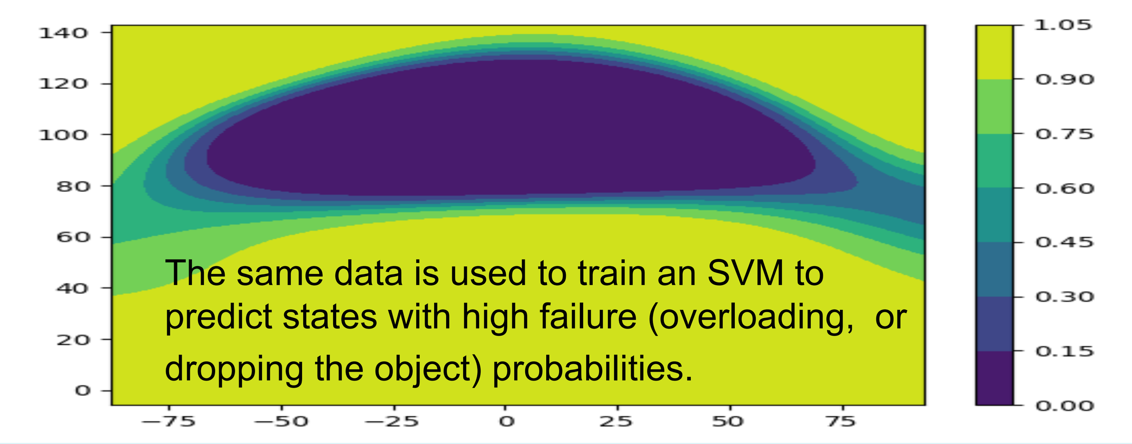


However, under-actuated hands

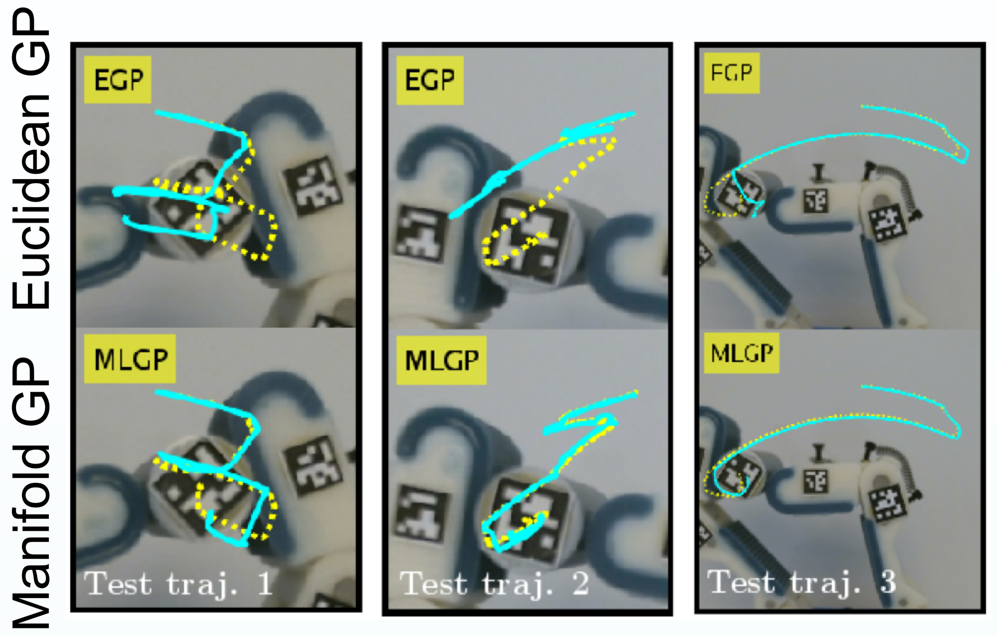
- are difficult to model analytically and to control,
- and have a high uncertainty due to the use of soft materials and low-cost manufacturing.

Learning a State Transition Model

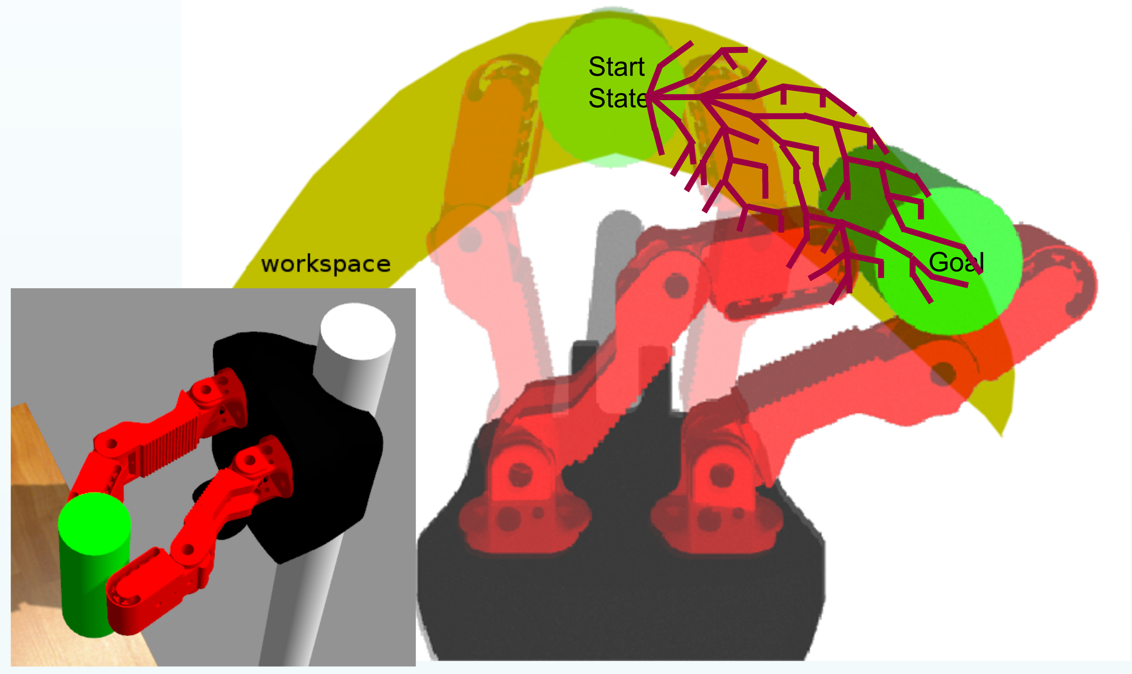




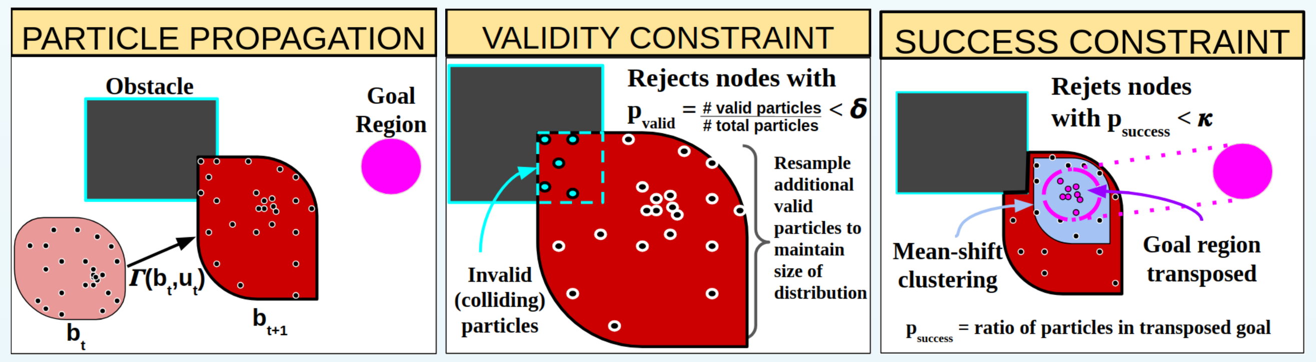
Path Tracking Experiments

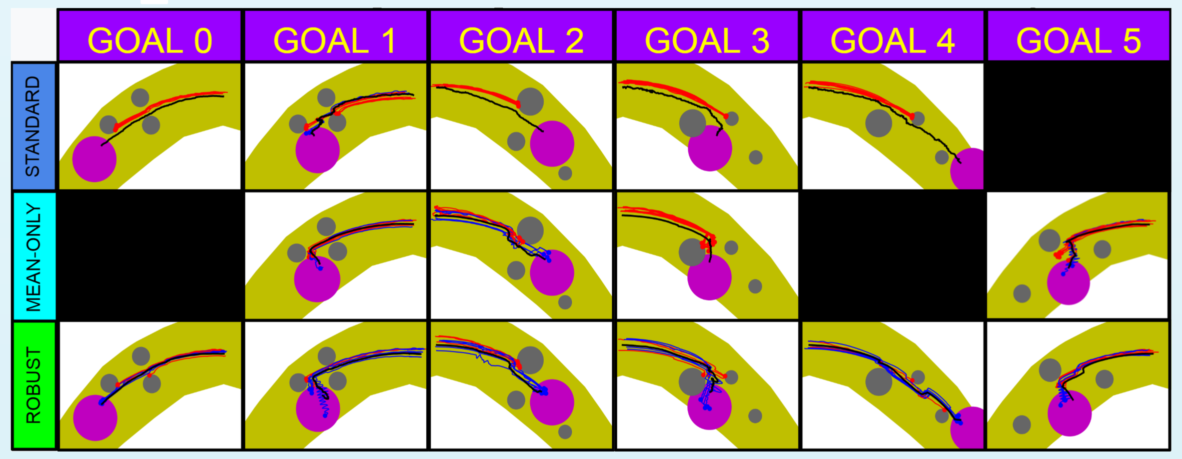


Robust Belief-Space Planning Using Learned Transition Model



Planning tree constructed using the transition function given by a neural network



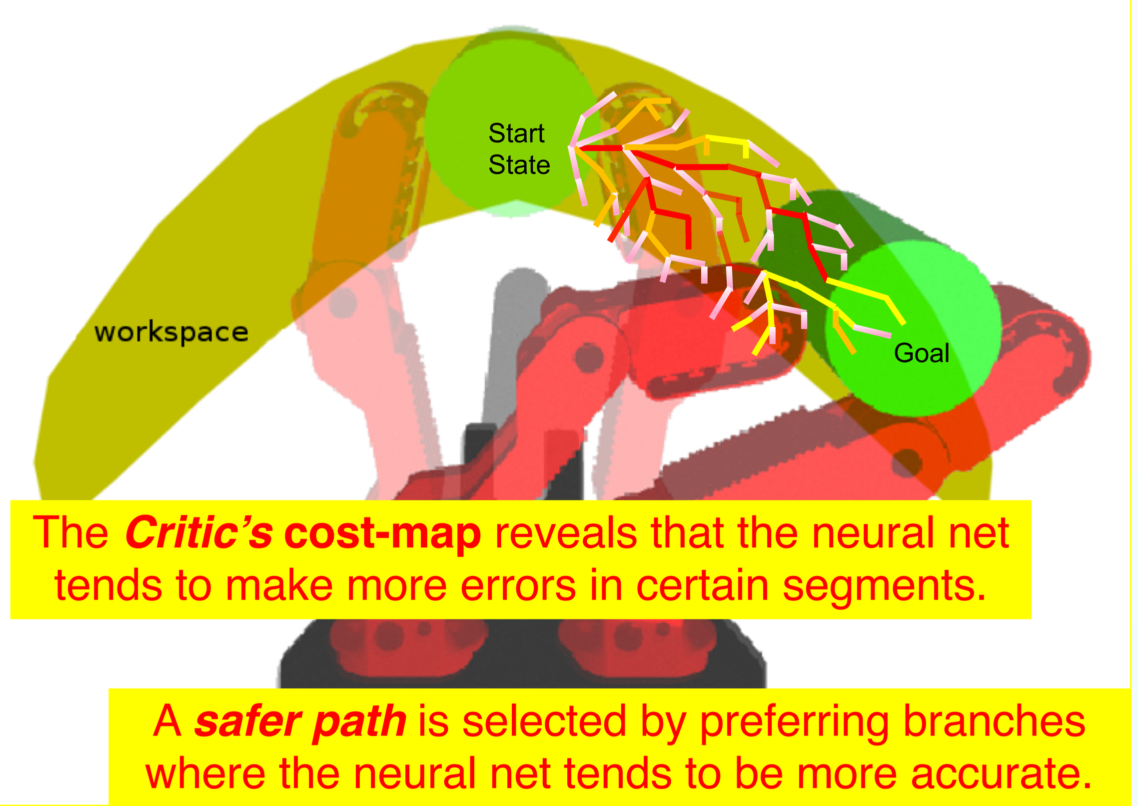


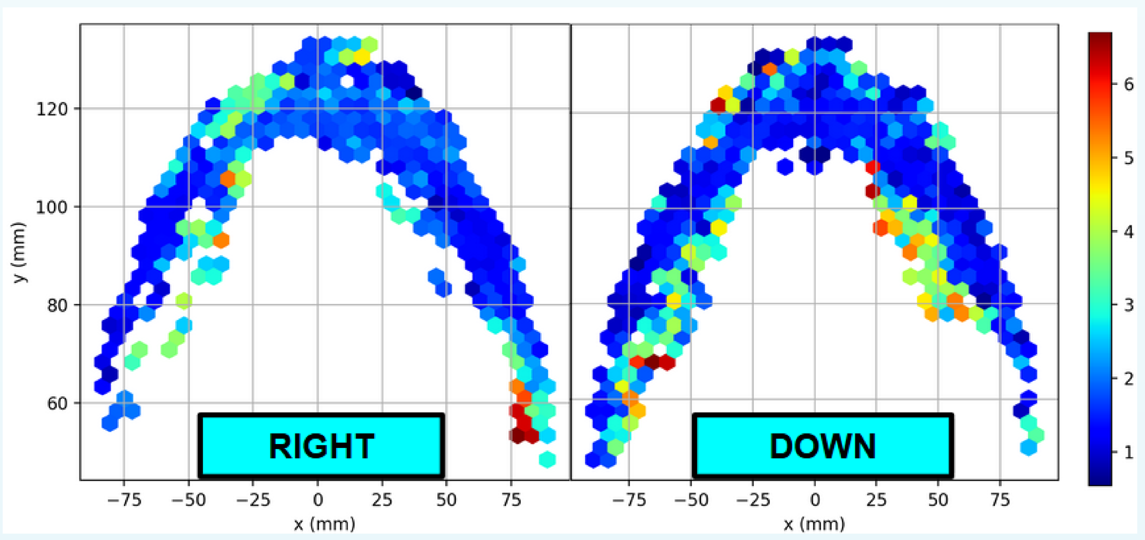
Planning Experiments

	STANDARD	MEAN-ONLY	ROBUST
Initial Solution Time [s]	15.6	550.6	615.9
Initial Solution Path Length [mm]	51.28	55.98	67.01
Final Solution Path Length [mm]	49.73	50.12	65.42
Planning Solved Rate	83.3	58.3	91.7
Reached Goal Success Rate	0.04	0.25	.62
Validity Rate	0.06	.78	.73

Motion Planning with Competency-Aware Transition Models

A second neural network, called the ***critic network,*** is trained to predict where the transition neural network makes more mistakes.

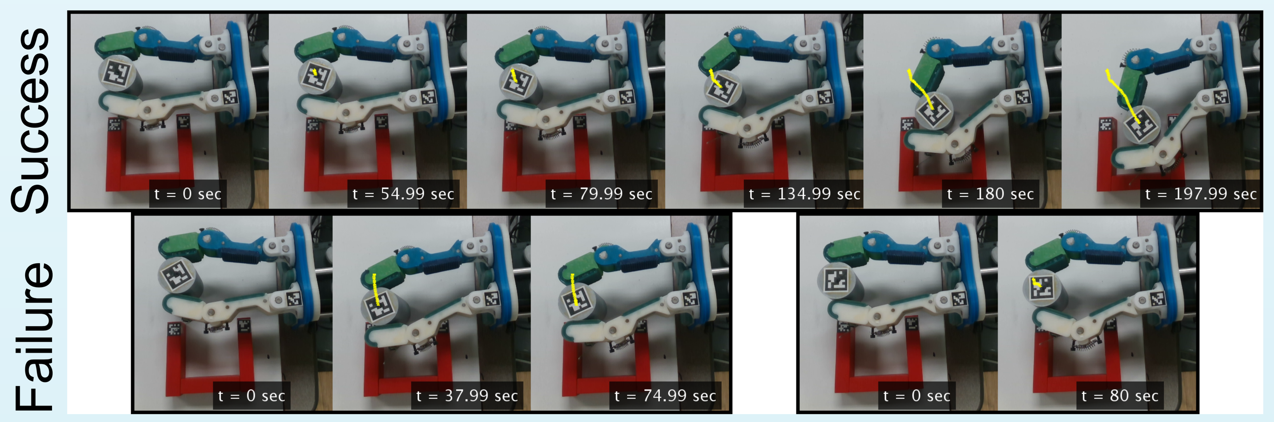




Heatmap illustrations of the critic values projected on the x−y plane with regards to different action directions.

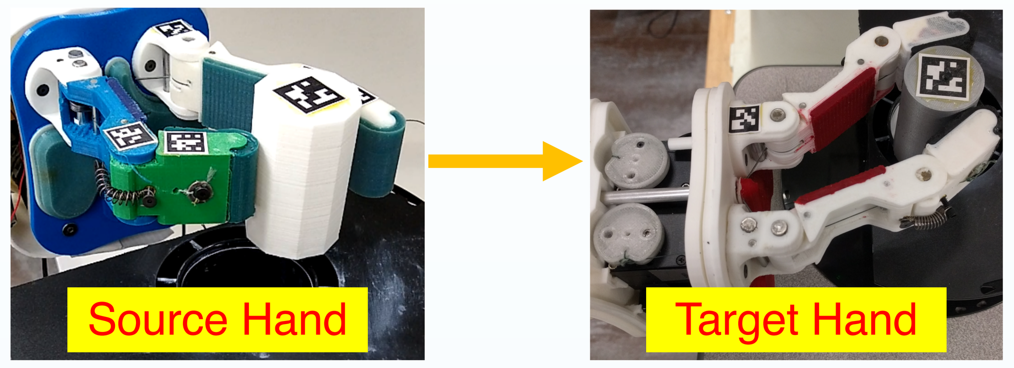
Motion Planning with Obstacle Avoidance Experiments

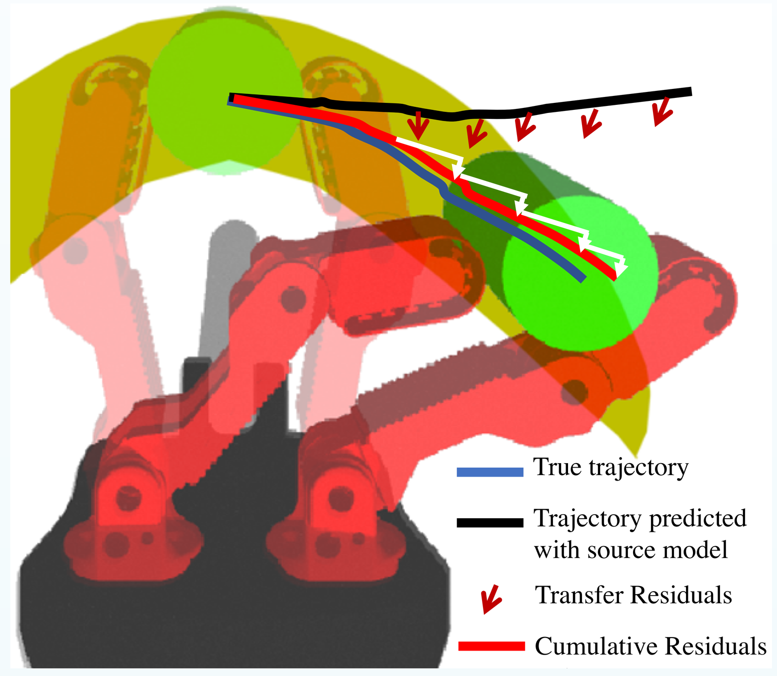
Goal	1		2		3		4		5	
	STA.	H-CRITIC	STA.	H-CRITIC	STA.	H-CRITIC	STA.	H-CRITIC	STA.	H-CRITIC
path length (mm)	111	87.42	206	91.33	169	175	97.5	93.3	83	64.9
rollout suc. rate (%)	0	20	50	80	0	100	0	90	100	100
RMSE (mm)	NA	2.27	3.61	2.16	NA	5.06	NA	2.57	1.45	1.21



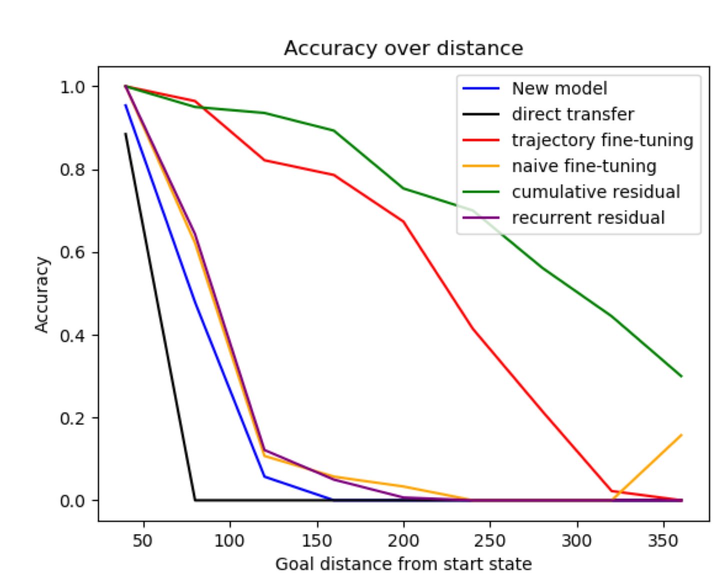
Learning to Transfer Dynamic Models of Underactuated Soft Robotic Hands

Instead of learning a new model for every new hand from scratch (12 more hours of data collection), we record only a small number of new trajectories and learn to transfer the original transition model.





Errors of predicted future states accumulate over time. The proposed ***cumulative residuals*** approach solves this issue by bounding the *Lyapunov exponent* of the transferred mode.



Publications

- Liam Schramm, Avishai Sintov and Abdeslam Boularias. "*Learning to Transfer Dynamic Models of Underactuated Soft Robotic Hands*". In ICRA 2020.
- Avishai Sintov, Andrew Kimmel, Kostas E. Bekris and Abdeslam Boularias. "*Motion Planning with Competency-Aware Transition Models for Underactuated Adaptive Hands*". In ICRA 2020.
- Andrew Kimmel, Avishai Sintov, Juntao Tan, Bowen Wen, Abdeslam Boularias and Kostas E. Bekris. "*Belief-Space Planning using Learned Models with Application to Underactuated Hands*". In ISRR 2019.
- Avishai Sintov, Andrew Morgan, Andrew Kimmel, Aaron Dollar, Kostas Bekris, Abdeslam Boularias. "*Learning a State Transition Model of an Underactuated Adaptive Hand*". In ICRA-RAL 2019.