SCHEDULE

8:55 – 9:05	**Introduction** Rob Platt and Peter Whitney Northeastern
9:05 – 9:30	**Keynote Speaker: Hierarchical Contact Tuning in Soft Robotic Grippers** Kaitlyn Becker MIT
9:30 – 9:45	**Bidirectional Human-Robot Feedback and Physical Effects of Assisted Manipulation with a Robotic Hand Orthosis for Stroke** Ava Chen Columbia
9:45 – 10:00	**Self-assembling Soft Modular Robots for Manipulation** Luyang Zhao Dartmouth
10:00 – 10:15	**Augmented Tactile Sensing During Training Allows for Efficient Learning and Cheap Deployment** Ludovico Papavassiliou Harvard
10:15 – 10:30	**GROUNDING LANGUAGE PLANS IN DEMONSTRATIONS THROUGH COUNTERFACTUAL PERTURBATIONS** Felix Yanwei Wang MIT
10:30 – 10:37	**Sponsor Talk: Be a Part of the Future of Robotic Manipulation!** Lael Odhner AI Institute
10:37 – 11:10	**Coffee Break with Poster Session/Demos**
11:10 – 11:25	**Towards a Dynamic Table Tennis Playing Robot** David Nguyen MIT
11:25 – 11:40	**Design of a Dexterous Gripper with Multimodal Tactile Sensing** Andrew SaLoutos MIT
11:40 – 11:55	**A Fractal Suction-based Robotic Gripper for Versatile Grasping** Jakub Kowalewski

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11:55 – 12:10	**Force Control of Series Elastic Pneumatic Underactuated Gripper** Chunpeng Wang Northeastern
12:10 – 12:25	**Equivariant Diffusion Policy** Dian Wang Northeastern
12:25 – 12:32	**Sponsor Talk, Amazon** Amazon
12:32 – 1:35	**Lunch with Poster Session/Demos**
1:35 – 2:00	**Keynote** Kostas Bekris Rutgers
2:00 – 2:15	**On Bringing Robots Home** Nur Muhammad “Mahi” Shafiullah NYU
2:15 – 2:30	**PolyTask: Learning Unified Policies through Behavior Distillation** Siddhant Haldar NYU
2:30 – 2:45	**Resolution Complete In-Place Object Retrieval given Known Object Models** Daniel Nakhimovich Rutgers
2:45 – 3:00	**Plan-Guided Reinforcement Learning for Whole-Body Manipulation** Aykut Onol TRI
3:00 – 3:30	Coffee Break with Poster Session/Demos
3:30 – 3:45	**Effect of Gripper Load Distribution on Human Package Opening Demonstrations** Natalija Beslic UMass
3:45 – 4:00	**Towards an Efficient Synthetic Image Data Pipeline for Training Vision-Based Robot Systems** Peter Gavriel UML

NYU

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Siddhant Haldar
NYU

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Peter Gavriel
UML

4:00 – 4:15	**Collaborative Open-source Manipulation Performance Assessment for Robotics Enhancement (COMPARE) Ecosystem** Adam Norton UML
4:15 – 4:30	**Leveraging Dexterous Picking Skills for Complex Multi-Object Scenes** Mihir Pradeep Deshmukh WPI
4:30 – 4:45	**Not Twisting Your Arm: Combining Grasping and Rotation in a Single Robot Hand Mechanism** Vatsal Patel Yale
4:45 – 5:00	**Direct Self-Identification of Inverse Jacobians for Dexterous Manipulation Through Particle Filtering** Joshua T. Grace Yale
5:00 – 5:10	**Closing Remarks**

9:30 – 9:45

Bidirectional Human-Robot Feedback and Physical Effects of Assisted Manipulation with a Robotic Hand Orthosis for Stroke

Ava Chen
Columbia

Strokes happen a lot, makes it hard to do precise manipulation

- rehab is focusing on active coordination, not just passive.
- Hard to do (opening harder than closing)

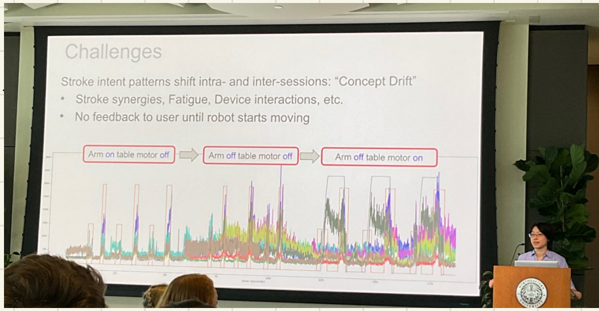
* working on device to help w/ opening hands

Brain sends signals to arm to actuate, hand "amplifies" these signals.

- recording EMG is hard

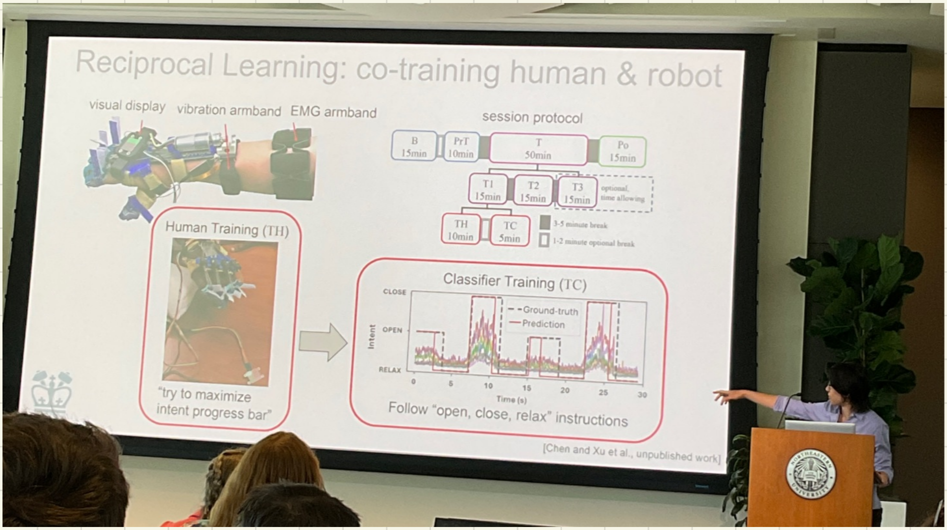
- Want robot to help you open hand
  - need to figure out when you want to do that

- intent detection is hard



semi-supervised learning

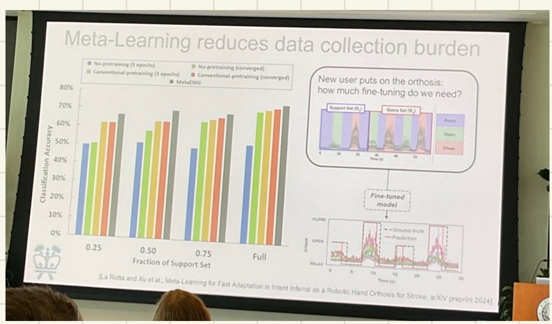
- make models for different intents, pool them together for final intent inference.

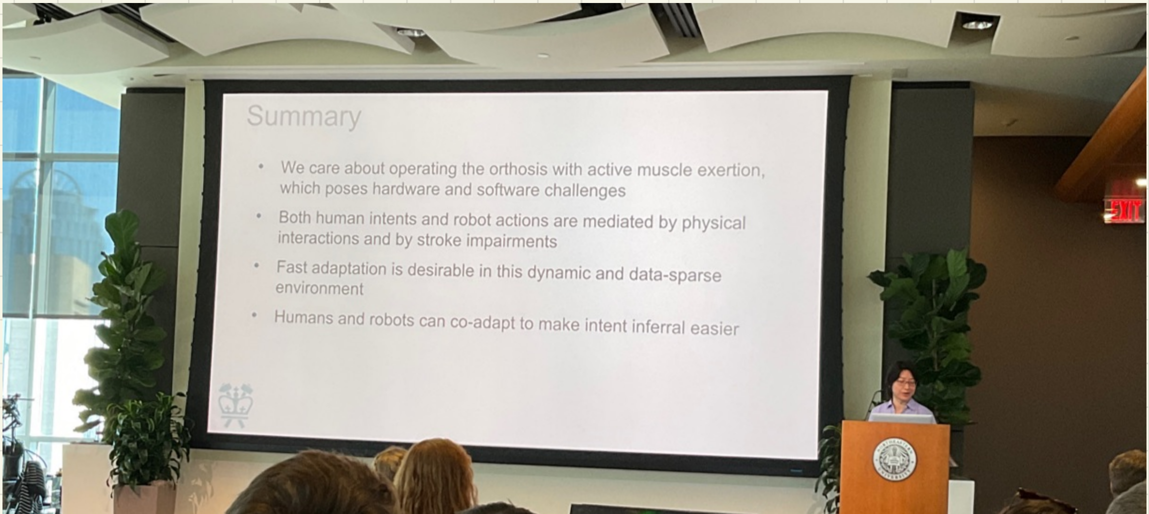


Humans are not static generators of data (they change).

Meta learning for fast-adaptation w/ small training data on new users

- How much finetuning is needed?

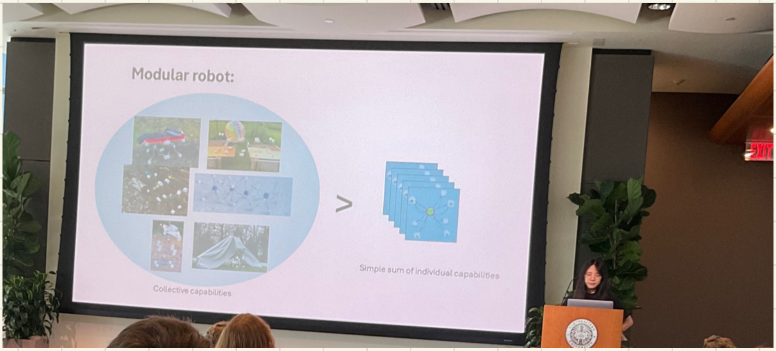




9:45 – 10:00	**Self-assembling Soft Modular Robots for Manipulation** Luyang Zhao Dartmouth

- Ants can assemble and collectively do tasks
  - form rafts, walk together to carry heavy things
- Can we make robots that can collaboratively manipulate / locomote?

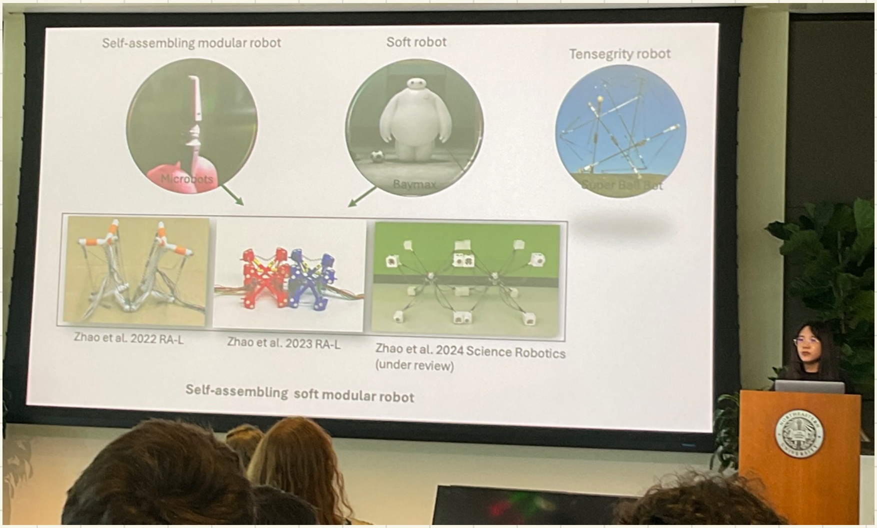
  → concept of modular robots



- Soft robots are good b/c
  - simple mechanical design
  - safe operation in precense of humans / objects
  - resistance to mechanical impact
  - compliance to adapt to uneven terrain

Inspiration:

assistive tool for generating gaits w/ human constraints



Applications
1) transfer objects
2) non-prehensile manipulation
3) gripper integration (arm + drone)
4) module ~~base~~ d arm
5) module rescue (drone des form top state estimation)

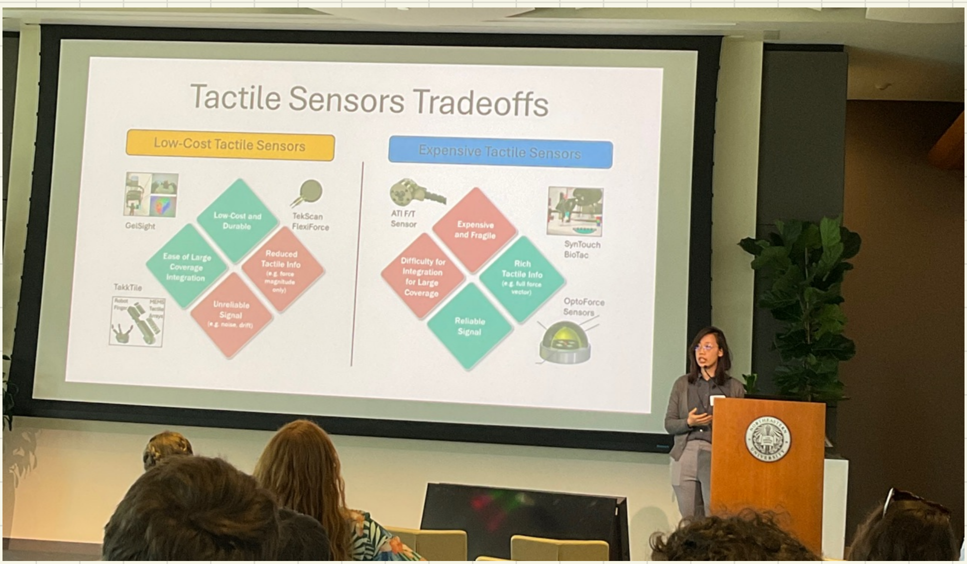
- New talk

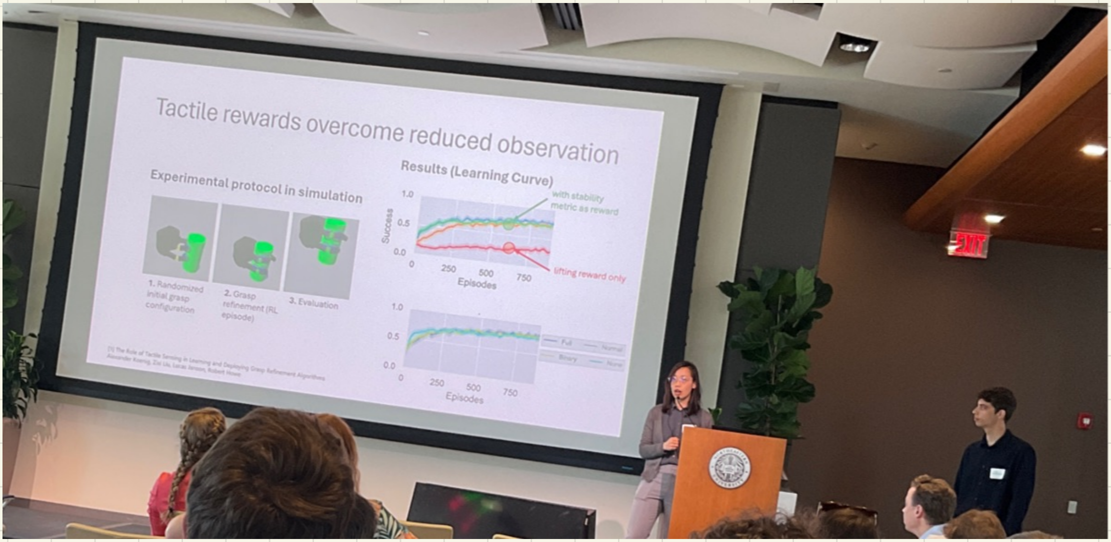
10:00 – 10:15
Augmented Tactile Sensing During Training Allows for Efficient Learning and Cheap Deployment
Ludovico Papavassiliou
Harvard

- automated grasping is hard
- RL has been popular in grasping

parts of RL:
- state (proprioceptive + tactile)
- action (hand motion)
- reward (grasp quality metrics, binary grasp success)

tactile data is useful for state + reward

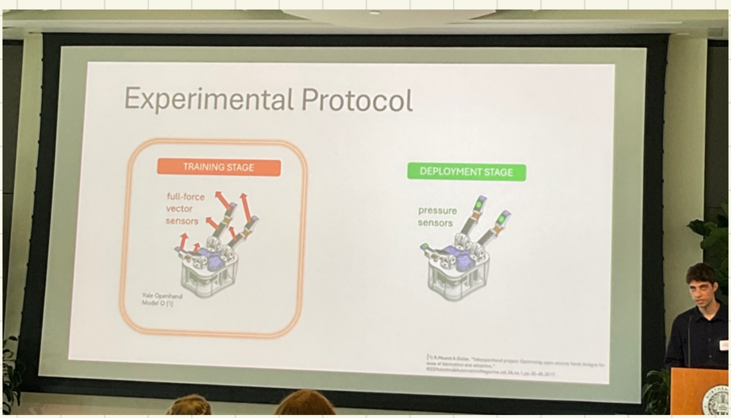


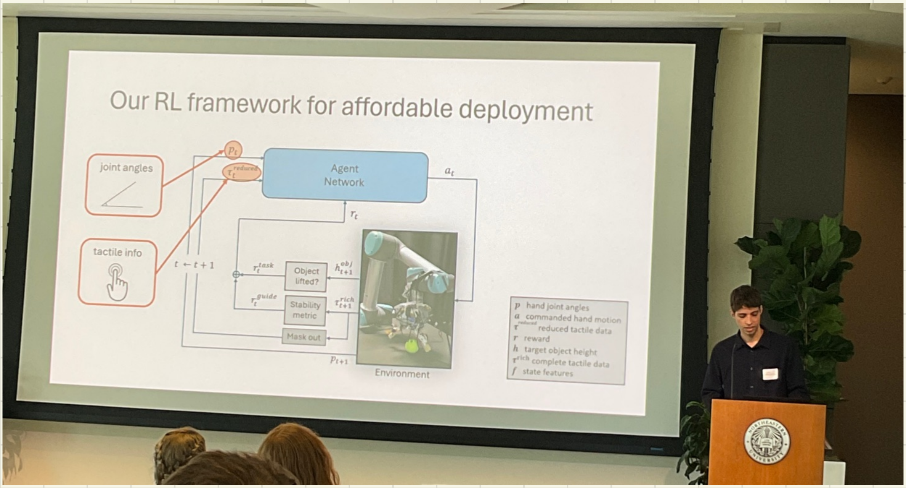


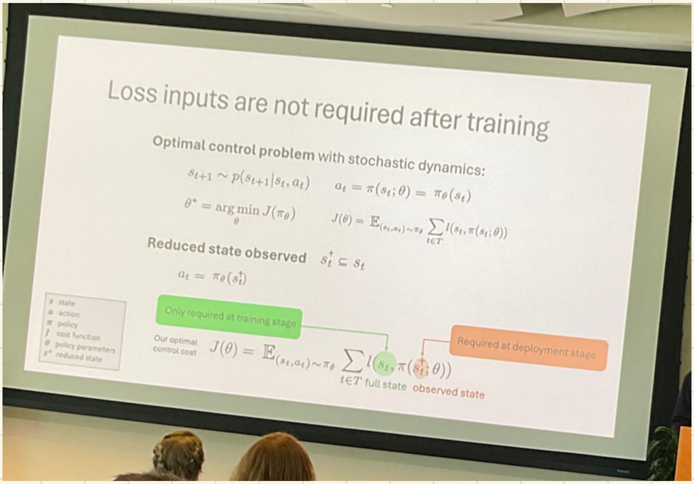
• tactile data in reward is v/ useful
• " " in state is not that helpful

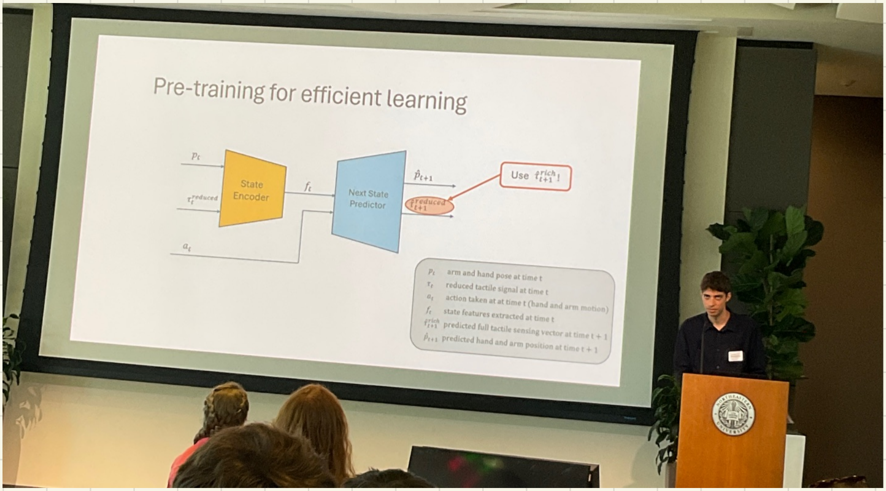
=> tactile data is useful for training but maybe not needed at inference!

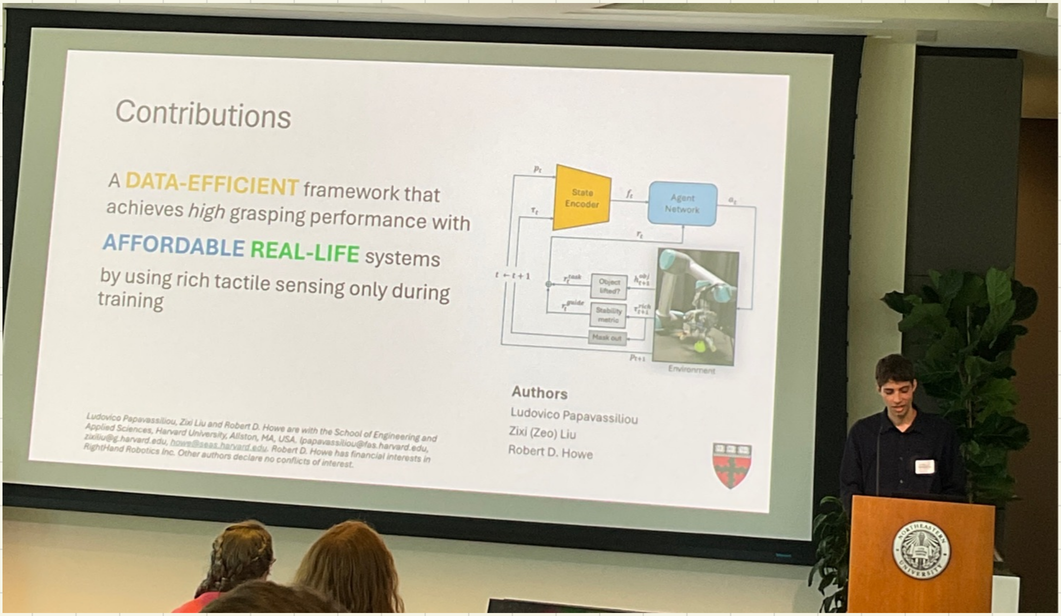
Different training / inference platform




Our RL framework for affordable deployment
joint angles
tactile info
p_t
$\tau_t^{reduced}$
Agent Network
a_t
r_t
$t \leftarrow t+1$
r_t^{task}
Object lifted?
h_{t+1}^{obj}
r_t^{guide}
Stability metric
τ_{t+1}^{rich}
Mask out
p_{t+1}
Environment
p hand joint angles
a commanded hand motion
$\tau^{reduced}$ reduced tactile data
r reward
h target object height
τ^{rich} complete tactile data
f state features


Loss inputs are not required after training
Optimal control problem with stochastic dynamics:
$s_{t+1} \sim p(s_{t+1}|s_t, a_t)$ $a_t = \pi(s_t;\theta) = \pi_\theta(s_t)$
$\theta^* = \arg\min_\theta J(\pi_\theta)$ $J(\theta) = \mathbb{E}_{(s_t,a_t)\sim\pi_\theta} \sum_{t\in T} l(s_t, \pi(s_t;\theta))$
Reduced state observed $s_t^\dagger \subseteq s_t$
$a_t = \pi_\theta(s_t^\dagger)$
s state
a action
π policy
J cost function
θ policy parameters
$s^\dagger$ reduced state
Only required at training stage
Required at deployment stage
Our optimal control cost
$J(\theta) = \mathbb{E}_{(s_t,a_t)\sim\pi_\theta} \sum_{t\in T} l(s_t, \pi(s_t^\dagger;\theta))$
full state
observed state


Pre-training for efficient learning
p_t
$\tau_t^{reduced}$
a_t
State Encoder
f_t
Next State Predictor
$\hat{p}_{t+1}$
$\hat{\tau}_{t+1}^{reduced}$
Use $\hat{\tau}_{t+1}^{rich}$!
p_t arm and hand pose at time t
τ_t reduced tactile signal at time t
a_t action taken at at time t (hand and arm motion)
f_t state features extracted at time t
$\hat{\tau}_{t+1}^{rich}$ predicted full tactile sensing vector at time t + 1
$\hat{p}_{t+1}$ predicted hand and arm position at time t + 1



Q: what if hand kinematic is different from training vs. test? rather than just low-fidelity tactile data?

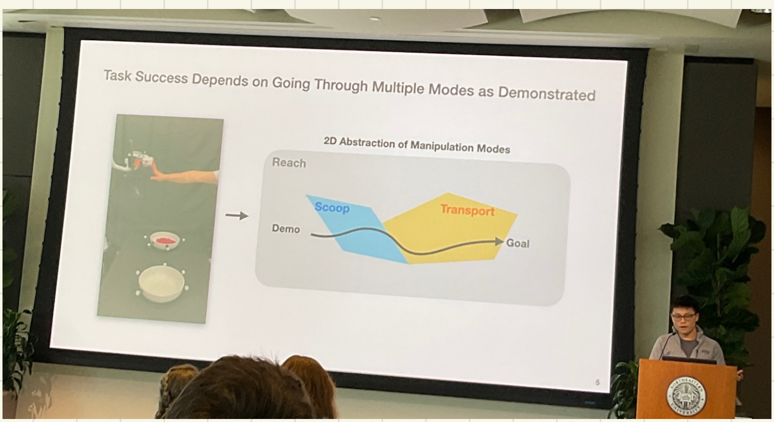
10:15 – 10:30

GROUNDING LANGUAGE PLANS IN DEMONSTRATIONS THROUGH COUNTERFACTUAL PERTURBATIONS

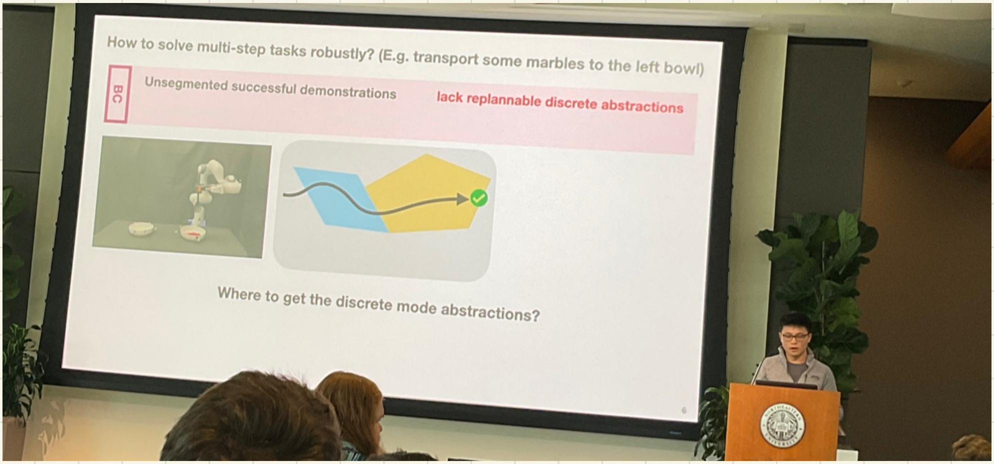
Felix Yanwei Wang
MIT

standard

his question

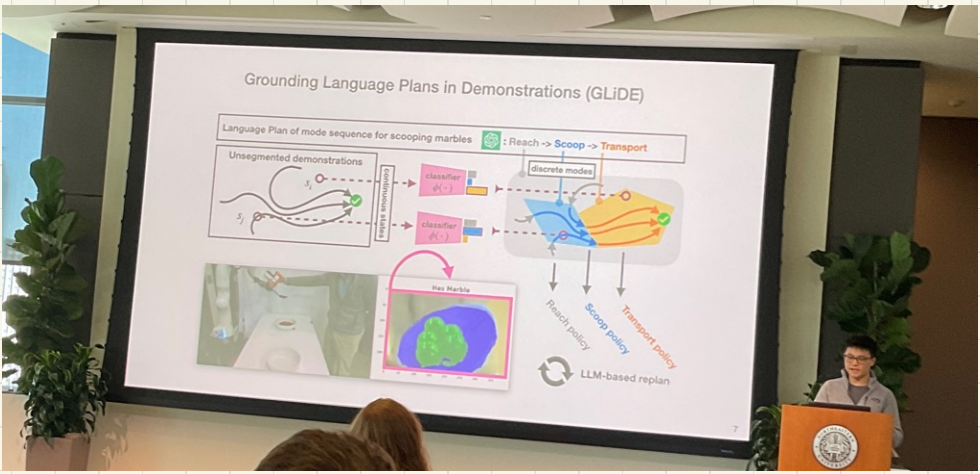


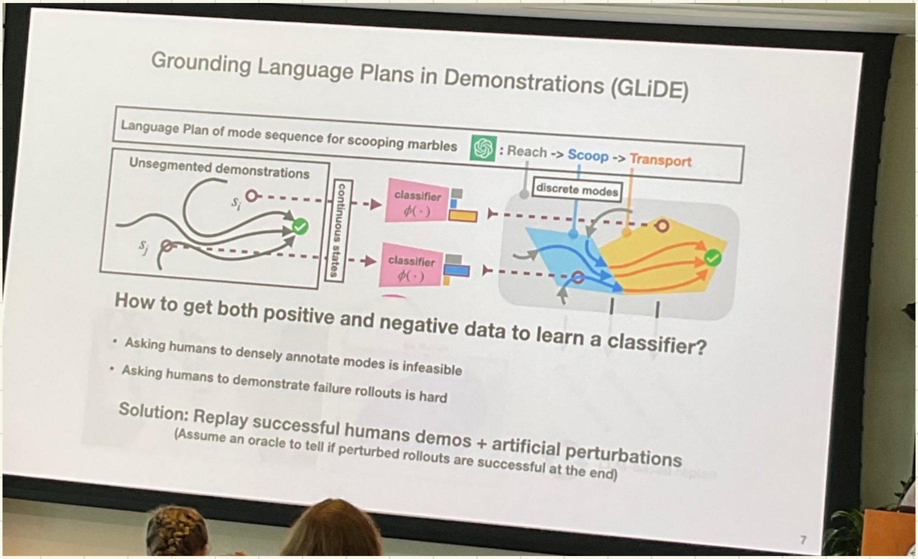
- Perturbation in reaching is recoverable
- " " transport can result in task failure.



How to avoid prebuilt skills/symbols?

idea: ↓





Q: # of modes is known beforehand?
or are modes learned?

10:30 – 10:37

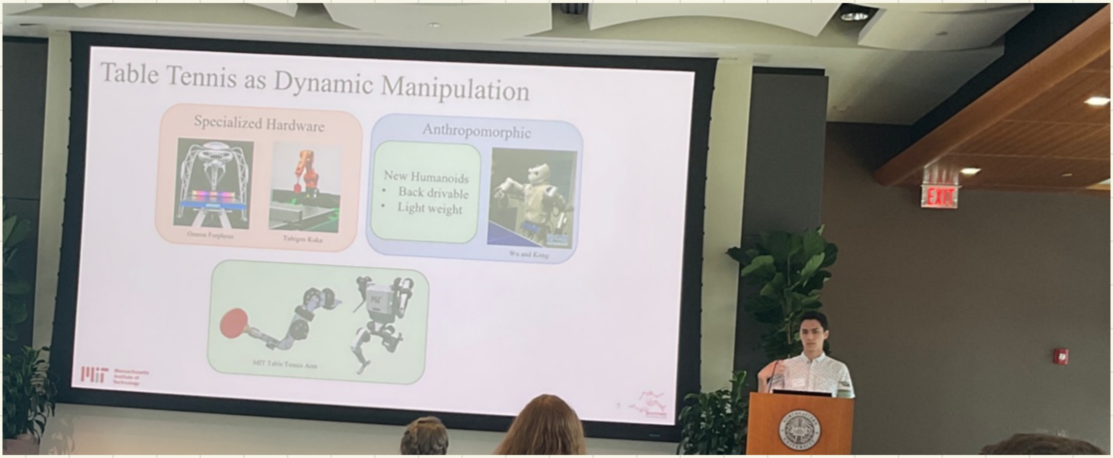
Sponsor Talk: Be a Part of the Future of Robotic Manipulation!

Lael Odhner

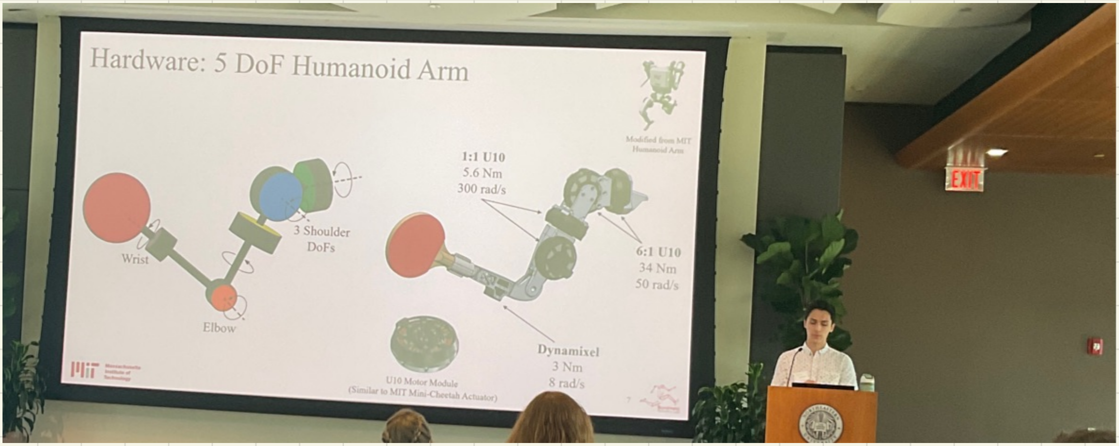
AI Institute

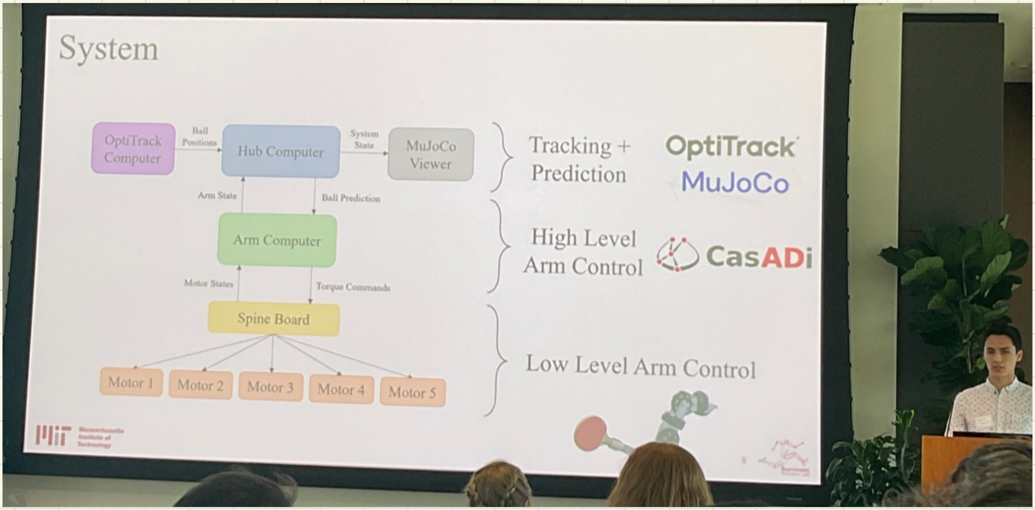
11:10 – 11:25	**Towards a Dynamic Table Tennis Playing Robot** David Nguyen MIT	

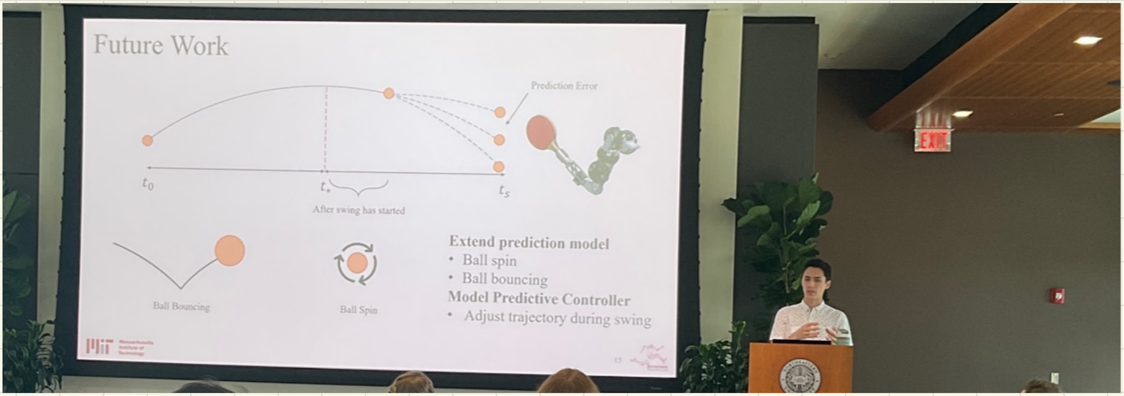
Interest in Dynamic manipulation



Goal: Dynamic side of ping pong
- spin, spiking, etc.




System
OptiTrack Computer
Ball Positions
Hub Computer
System State
MuJoCo Viewer
Arm State
Ball Prediction
Arm Computer
Motor States
Torque Commands
Spine Board
Motor 1
Motor 2
Motor 3
Motor 4
Motor 5
Tracking + Prediction
OptiTrack
MuJoCo
High Level Arm Control
CasADi
Low Level Arm Control
Massachusetts Institute of Technology

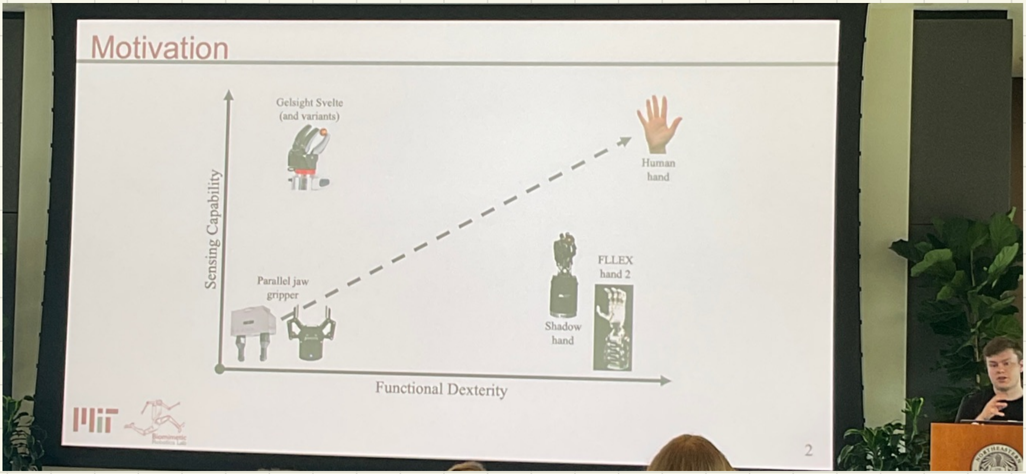

Future Work
Prediction Error
t_0
t_*
t_s
After swing has started
Ball Bouncing
Ball Spin
Extend prediction model
• Ball spin
• Ball bouncing
Model Predictive Controller
• Adjust trajectory during swing
EXIT

11:25 – 11:40

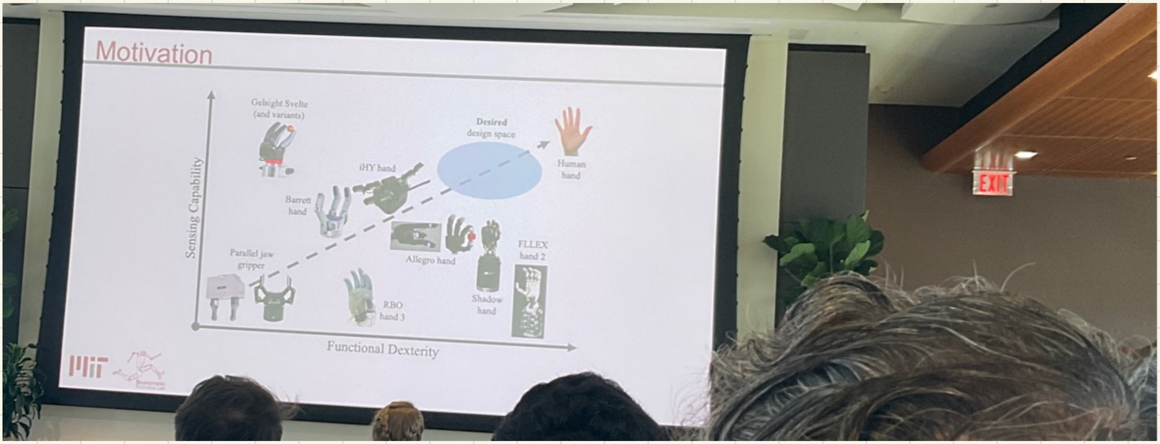
Design of a Dexterous Gripper with Multimodal Tactile Sensing

Andrew SaLoutos

MIT

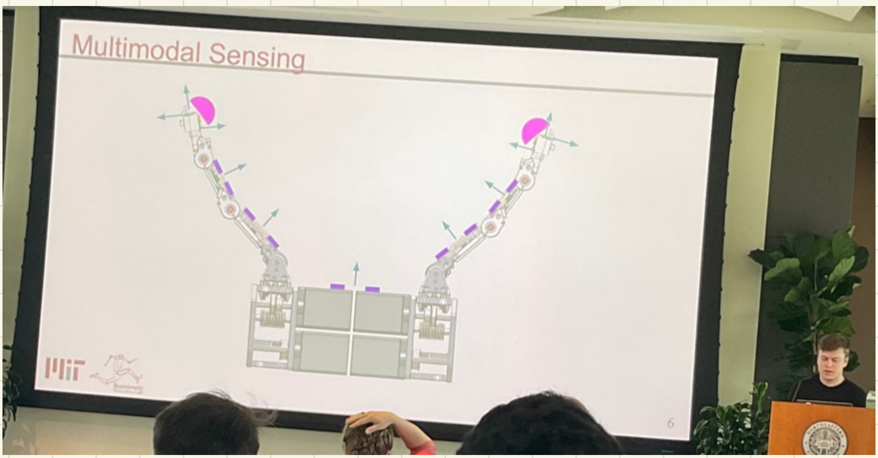


↕ Design space for grippers



Actuated fingers

2 fingers, 4 DoF each
wrist-roll actuator

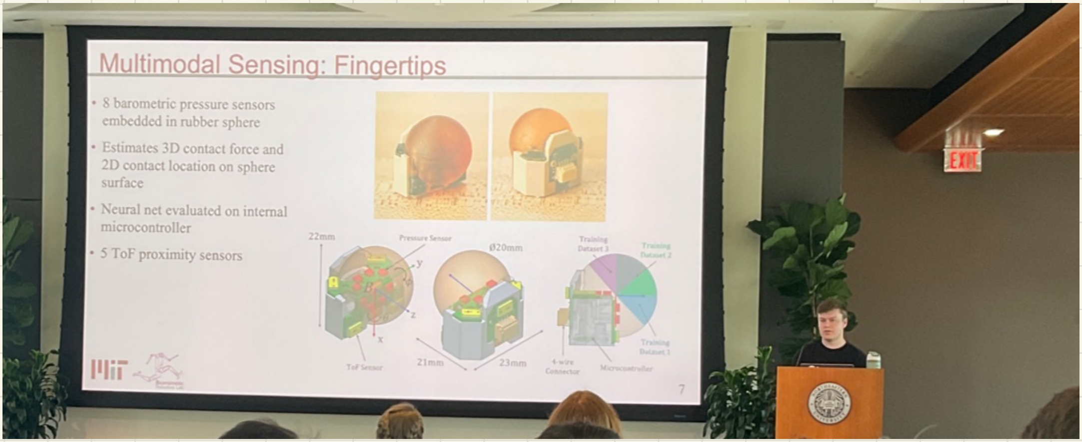


control PCB on top of gripper

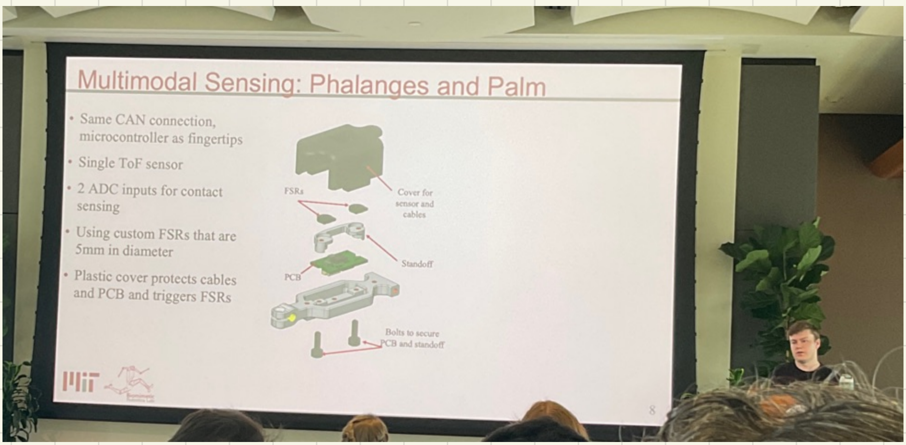
proximity sensors!

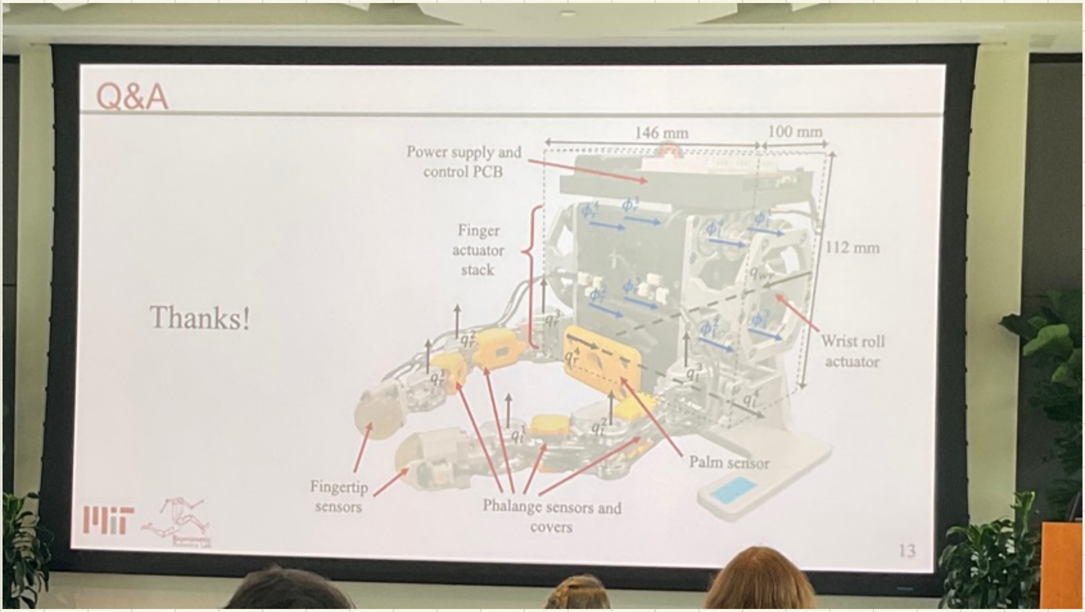
2D contact location
3D force

100-200 Hz on sensor data



Previous work





11:40 – 11:55

A Fractal Suction-based Robotic Gripper for Versatile Grasping

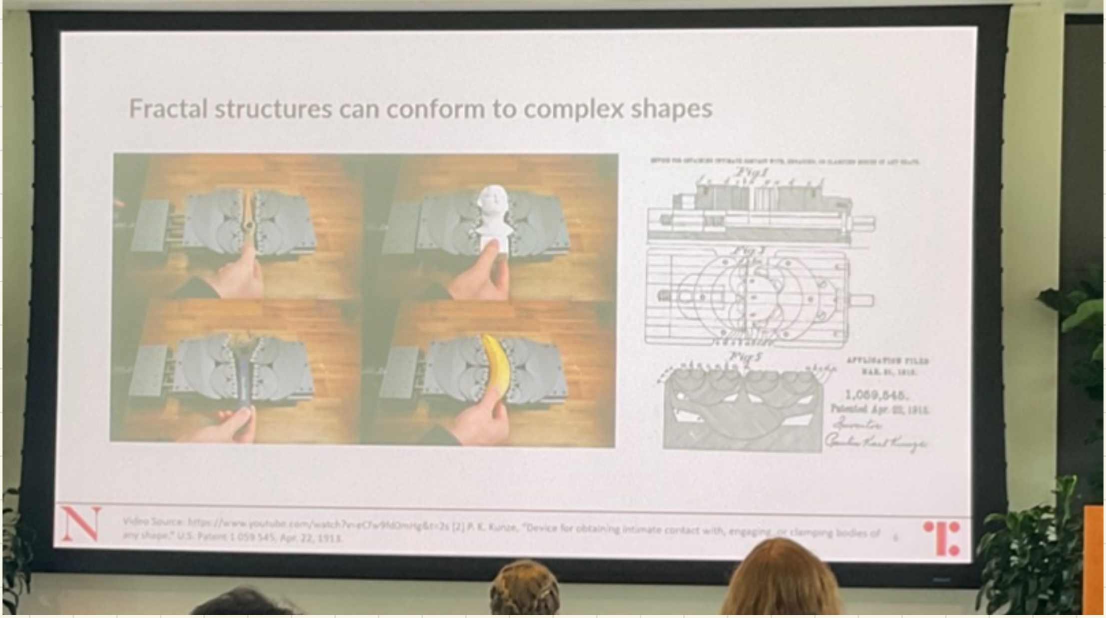
Jakub Kowalewski

Northeastern

- suction cups are popular
  - good for smooth and flat surfaces
  - pick up things bigger than it

Not good for
  - non-convex regions
  - sensitive to approach angle.

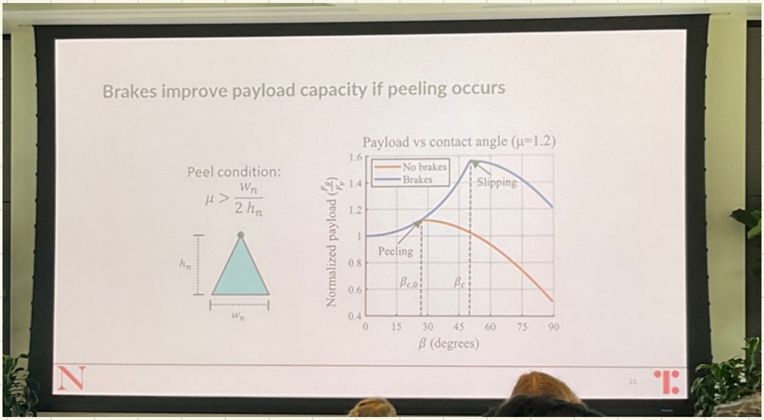
How to solve this?

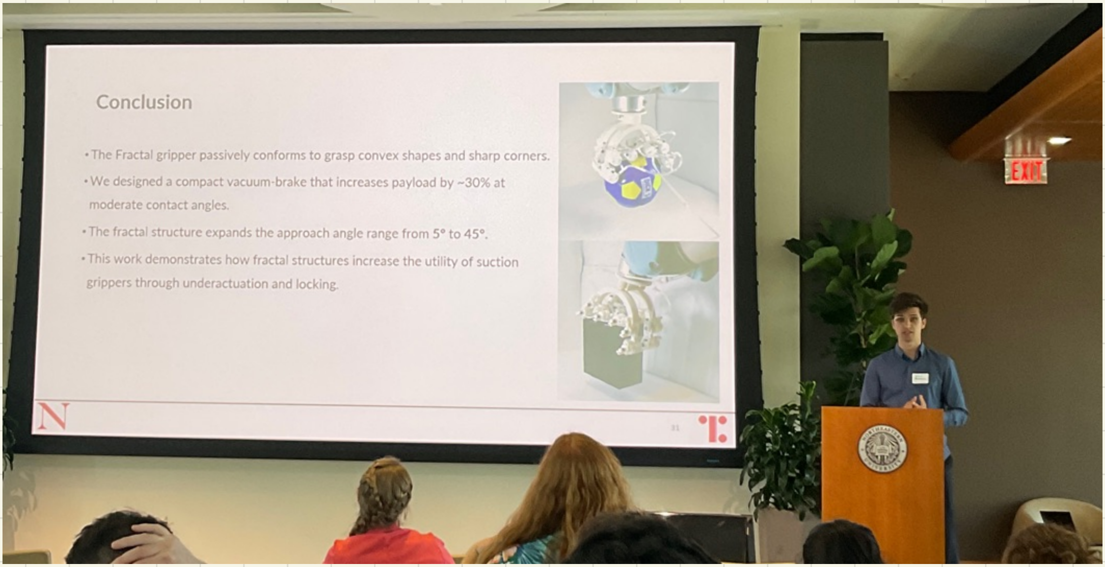


what fractal design is best for conforming to surfaces? → design experiments

when do brakes help w/ payload capacity?

peeling: suction looses contact w/ surface!



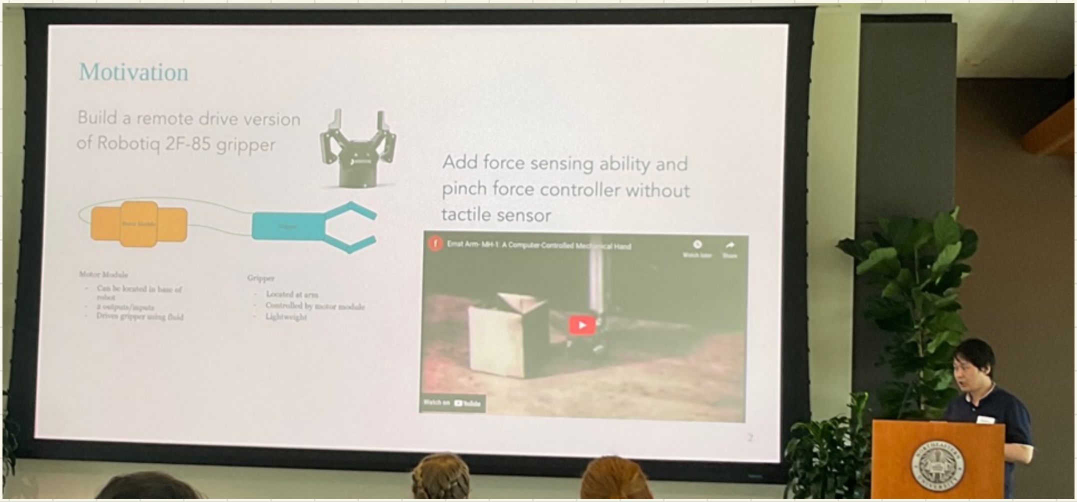


11:55 – 12:10

Force Control of Series Elastic Pneumatic Underactuated Gripper

Chunpeng Wang

Northeastern



Keynote

1:35 – 2:00 Kostas Bekris
Rutgers

Some key ingredients for robotic manipulation

For amazon picking challenge (circa 2015)

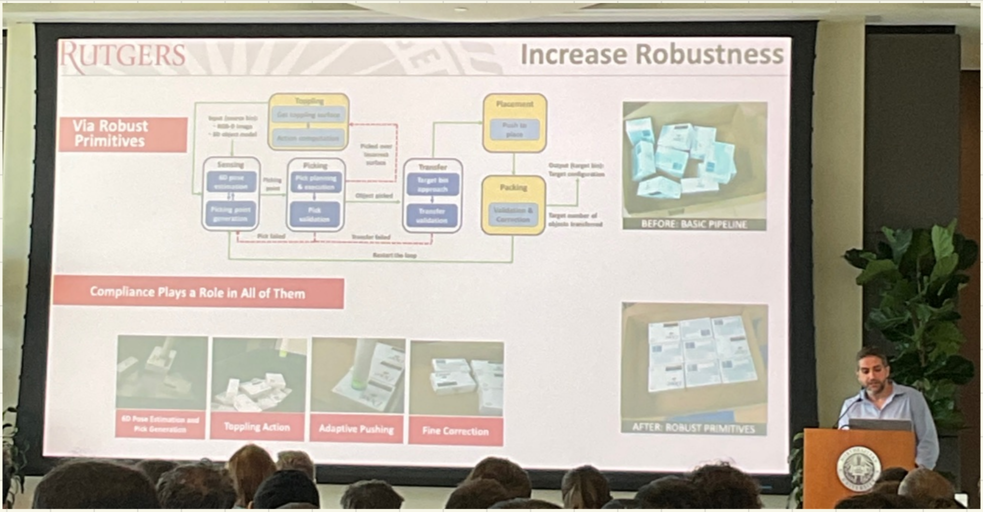
- sense-plan-act

what can go wrong

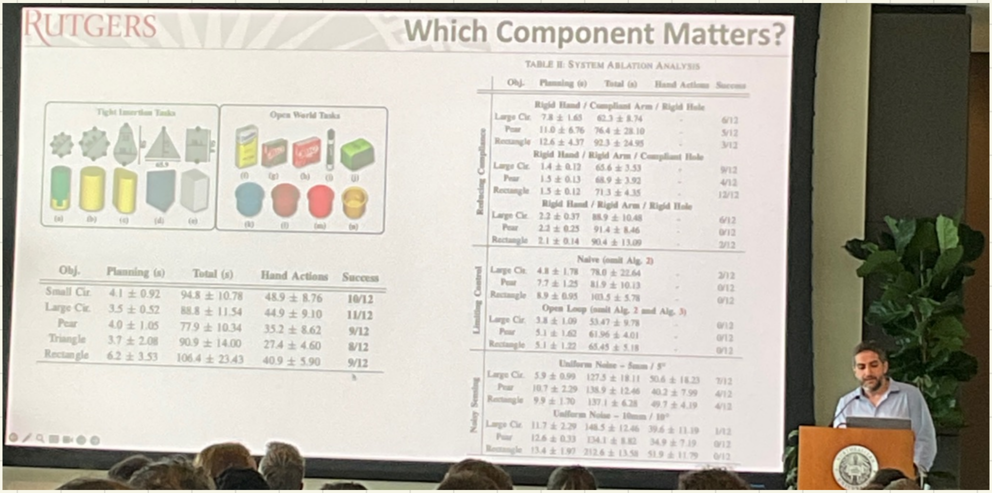
- sensing, acting wrong
- planner doesn't find feasible solution

Some key ingredients

- move beyond "still" perception-action settings
- embodiment matters
  - simplify problem via hardware when possible
- "pick-and-dr

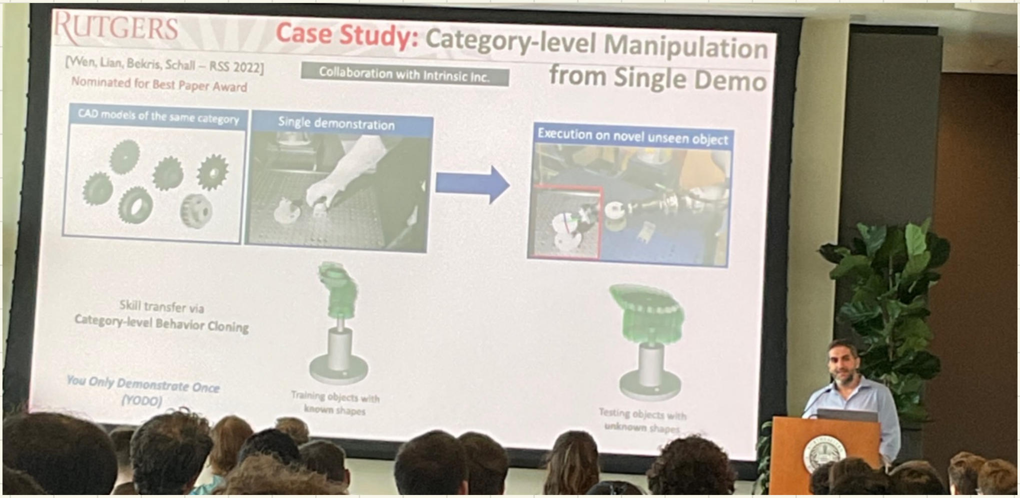


what compont matter most in succesfull manipulation for peg-and-hole?



BundleTrack
FoundationPose

category-level behavioral cloning



You only demonstrate once (~~X~~ODO)

2:00 – 2:15	**On Bringing Robots Home** Nur Muhammad "Mahi" Shafiullah NYU

2:15 – 2:30	**PolyTask: Learning Unified Policies through Behavior Distillation** Siddhant Haldar NYU

*Regularized Optimal Transport (ROT)

2:30 – 2:45	**Resolution Complete In-Place Object Retrieval given Known Object Models** Daniel Nakhimovich Rutgers

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