

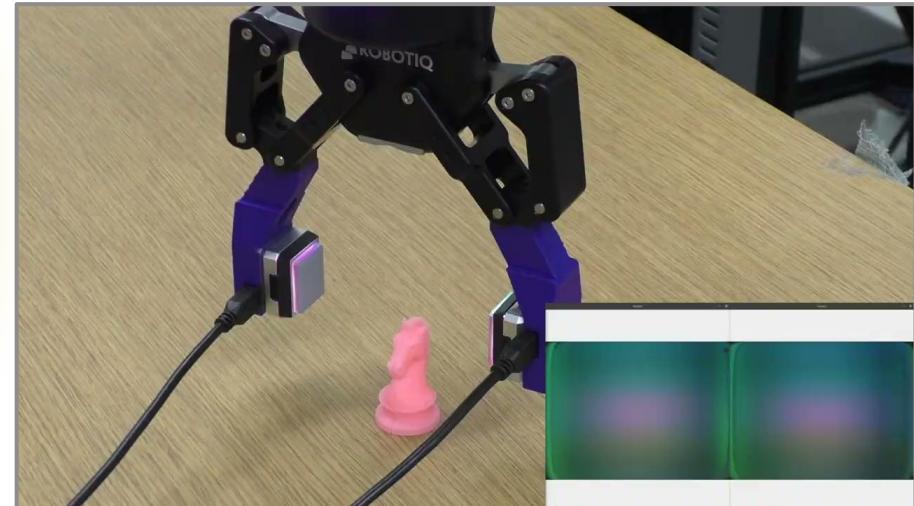
DeepRob

[Student] Lecture 21

By Miles Priebe, Nirmal Raj, and Adam Imdieke

Tactile Perception for Robot Grasping and Manipulation

University of Michigan and University of Minnesota

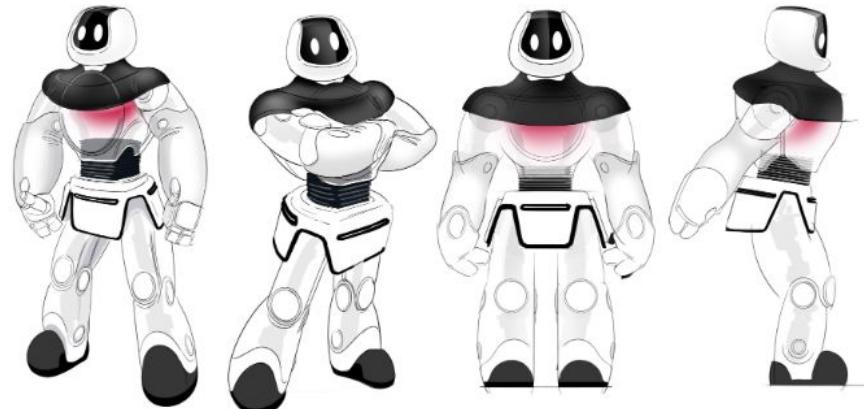


Gelsight grasp demo

Agenda

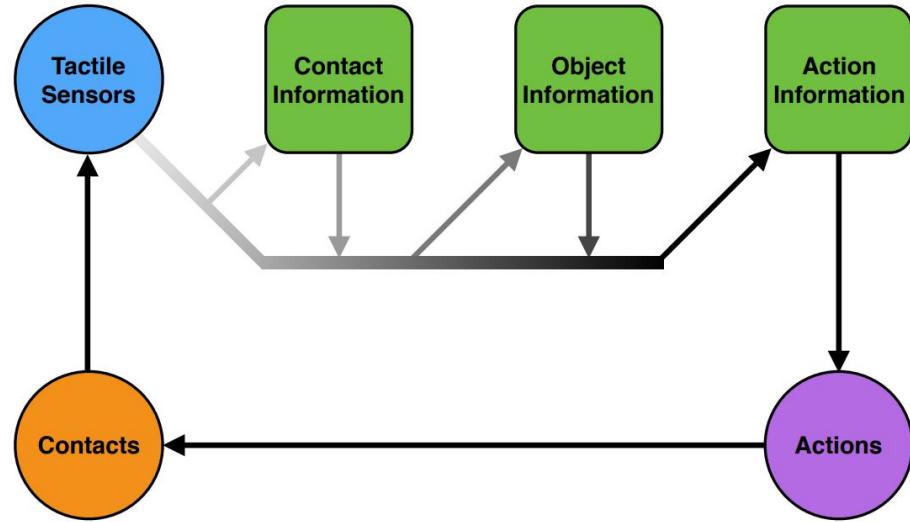
- Tactile perception
- Signal categories
- Types of sensors
- Haptic vs Tactile sensing
- Gelsight
- Tac2Pose
- Tacto
- Tactile sensing for Deep Learning

Punyo



What is Tactile Perception?

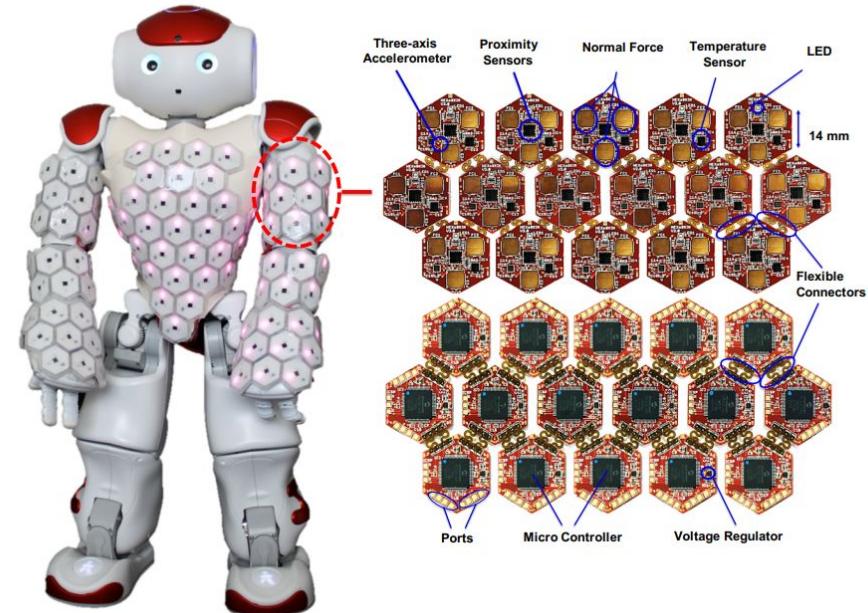
- Key sensor modality for robots
- Provide a rich and diverse set of data signals about...
 - Contact
 - Objects
 - Actions



A Review of Tactile Information: Perception and Action Through Touch, Li et al. , 2020

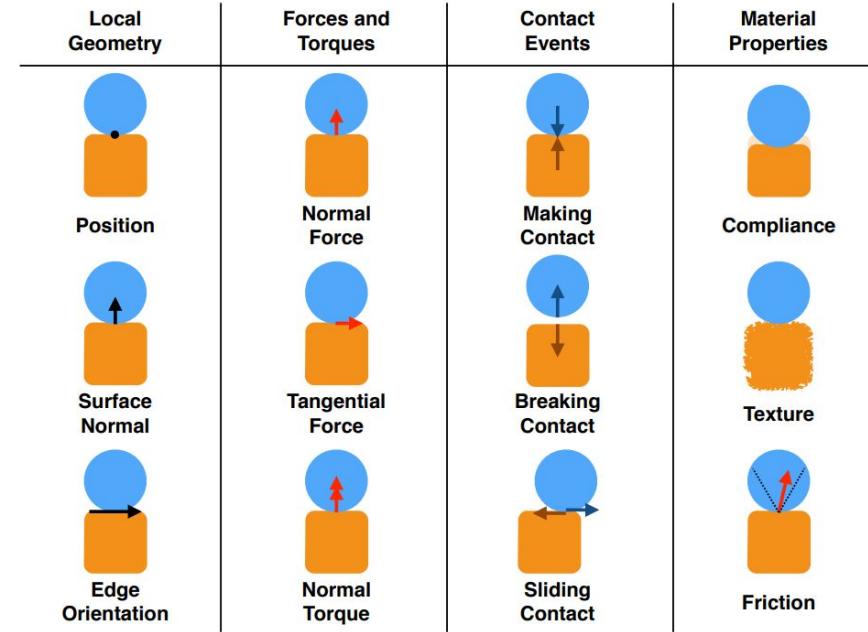
Sensor-Level Signals

- Normal and tangential force
- Vibration
- Thermal
- Pretouch proximity
- Sensor coverage



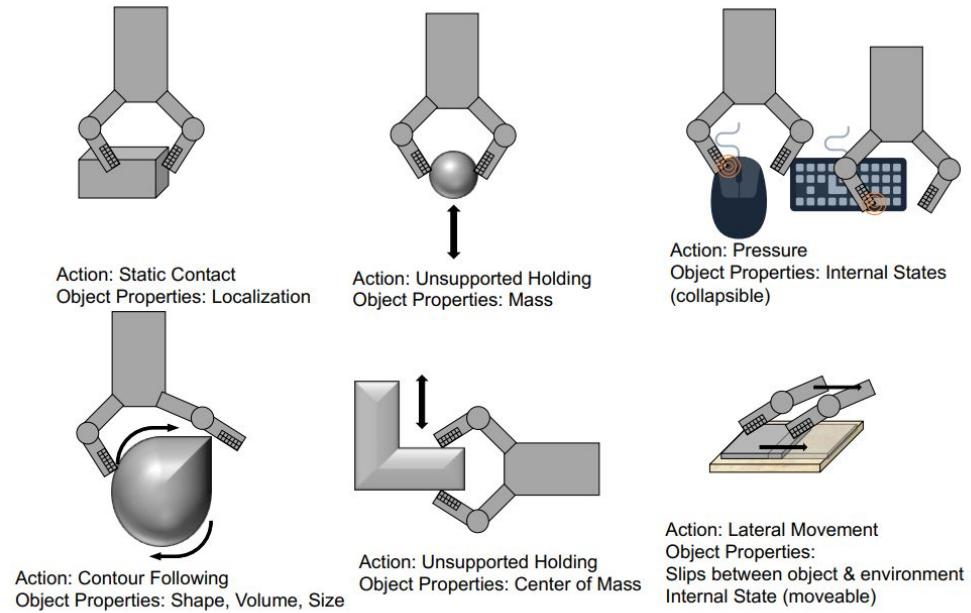
Contact-Level Signals

- Contact geometry
- Force and torque
- Contact events
- Material properties



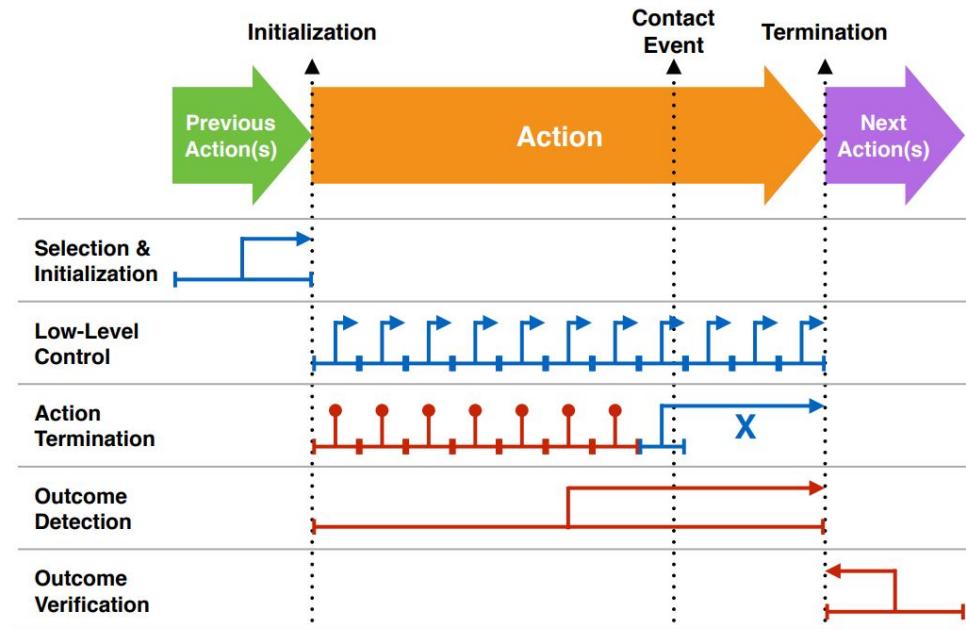
Object-Level Signals

- Object localization
- Shape
- Mass and dynamics
- Contents of containers



Action-Level Signals

- Action selection and initialization
- Tactile feedback for low-level control
- Action termination
- Action outcome detection
- Action outcome verification

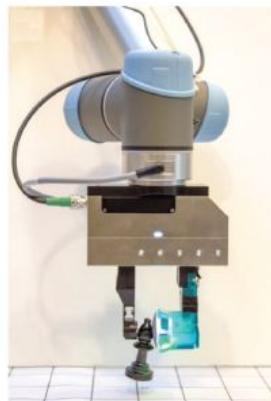


Sensors

Facebook AI Digit



Visuotactile



TRI Punyo SoftBubble

Tactile

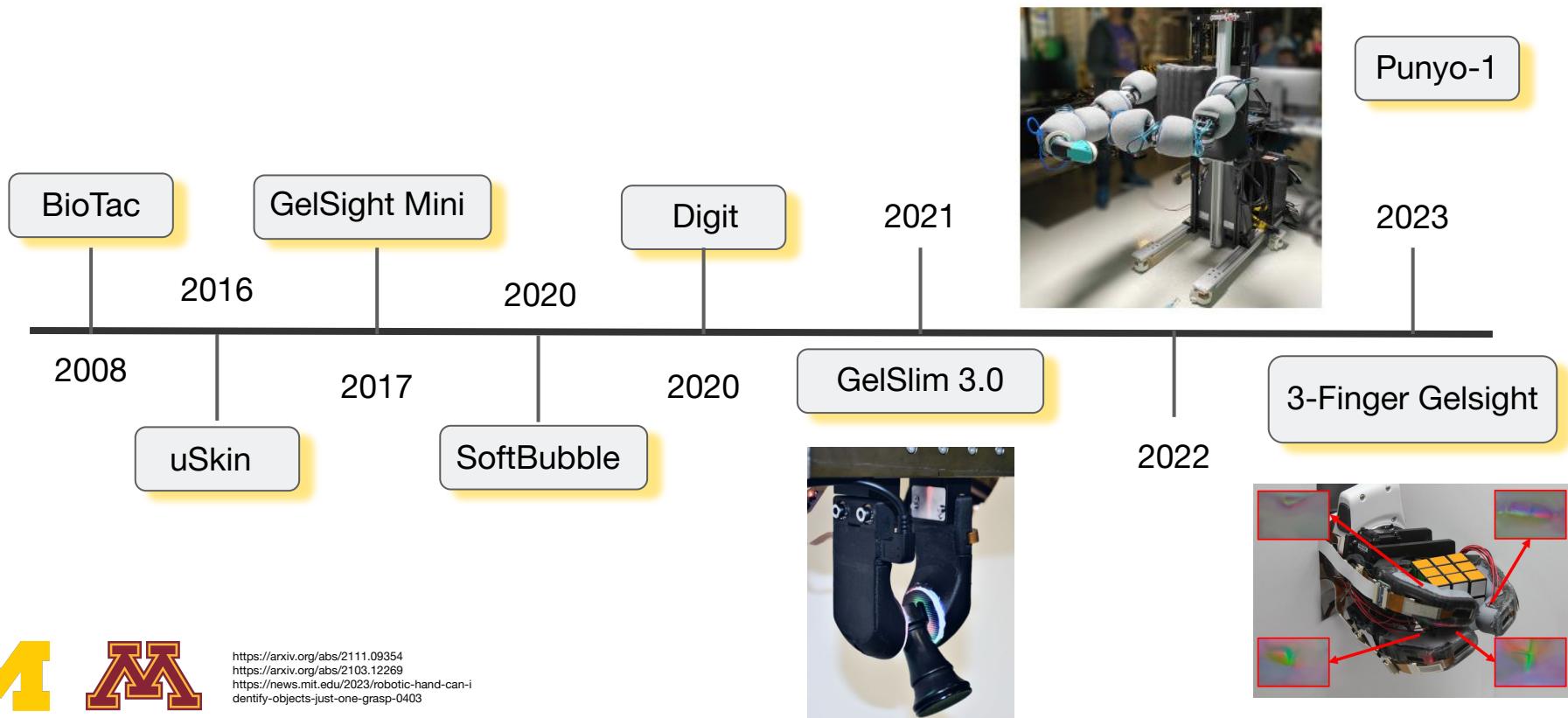


Xela Robotics uSkin

SynTouch BioTac



Tactile Sensing Timeline



Haptic vs. Tactile Sensing

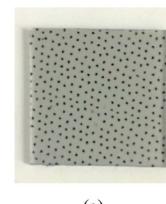
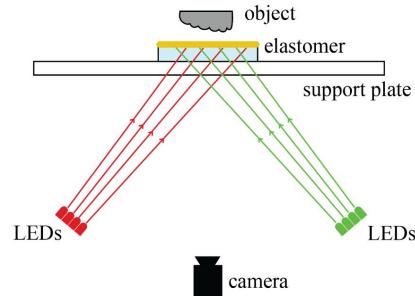
Haptic

- Overall sensory experiences:
 - Tactile
 - Proprioception
 - Kinesthesia

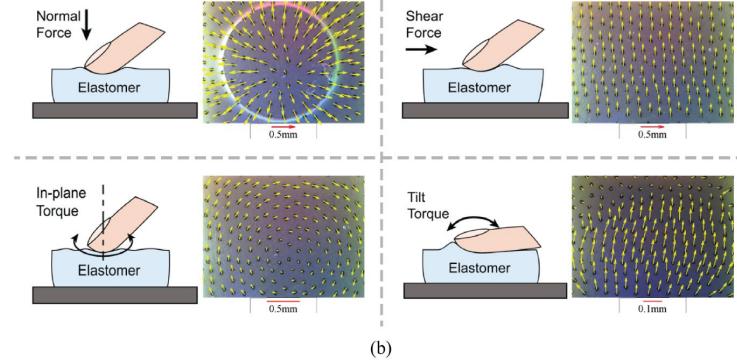
Tactile

- Detection of physical sensations:
 - Pressure
 - Temperature
 - Texture

What is Visuotactile Sensing?

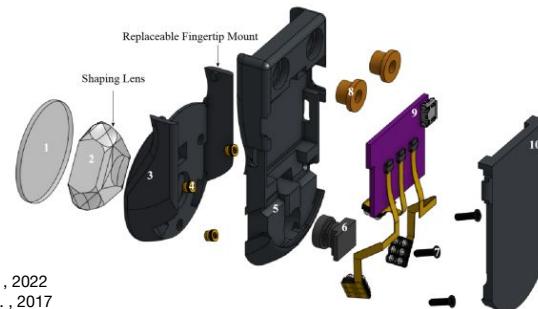
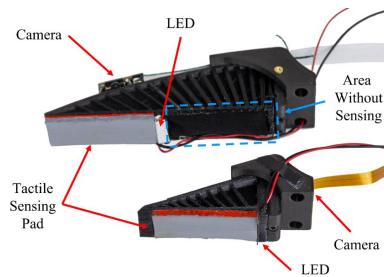
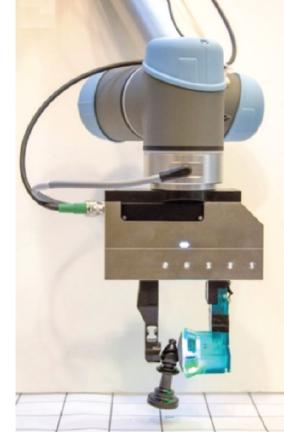


(a)



GelSight Fin Ray: Incorporating Tactile Sensing into a Soft Compliant Robotic Gripper, Liu et al. , 2022
GelSight: High-Resolution Robot Tactile Sensors for Estimating Geometry and Force, Yuan et al. , 2017

Exploring Gelsight Evolution



- 1 Elastomer w/Reflective Skin
- 2 Acrylic Lens
- 3 Fingertip
- 4 Heat Inserts
- 5 Finger-Body
- 6 Camera Module
- 7 Screws
- 8 Mounting Bearing
- 9 Integrated Illumination Controller
- 10 Finger Back

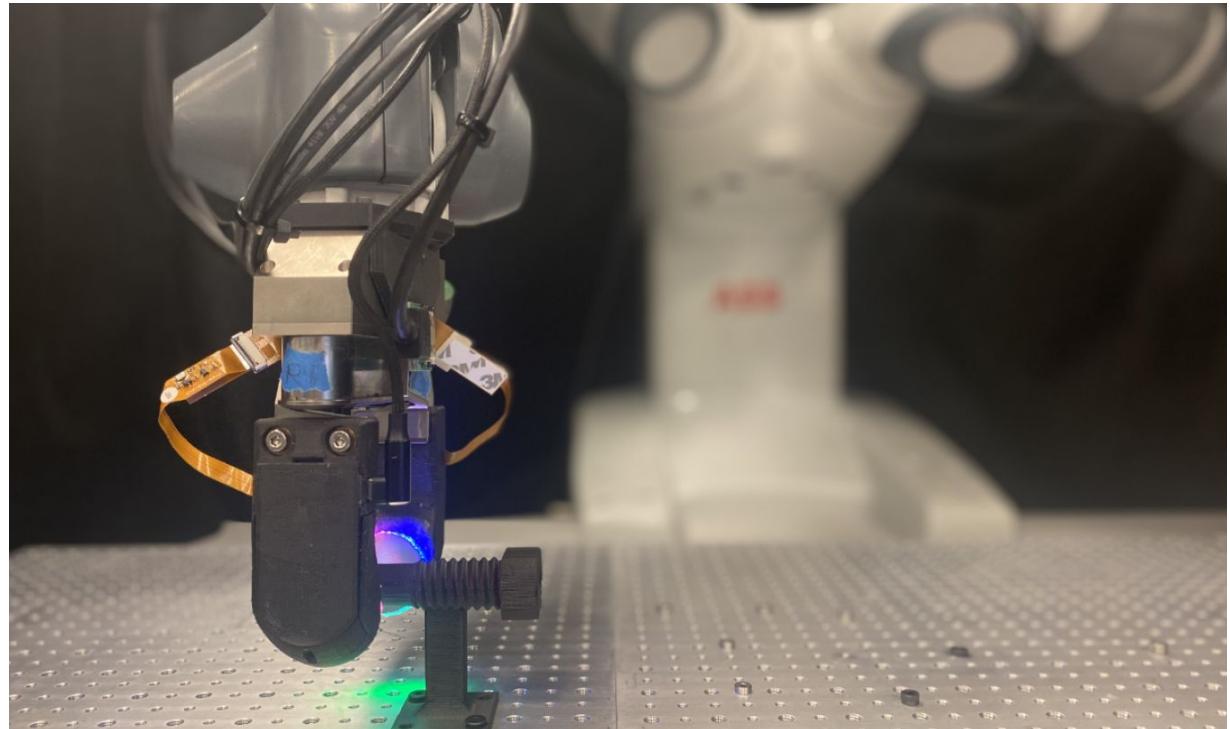


GelSight Fin Ray: Incorporating Tactile Sensing into a Soft Compliant Robotic Gripper, Liu et al. , 2022
 GelSight: High-Resolution Robot Tactile Sensors for Estimating Geometry and Force, Yuan et al. , 2017

Tac2Pose: Tactile Object Pose Estimation from the First Touch.

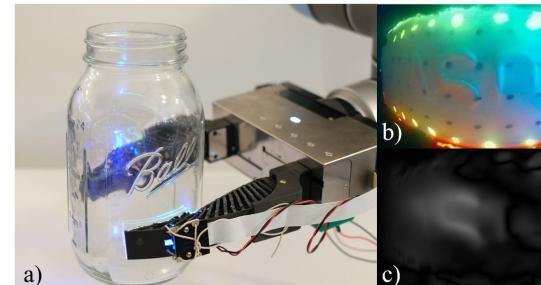
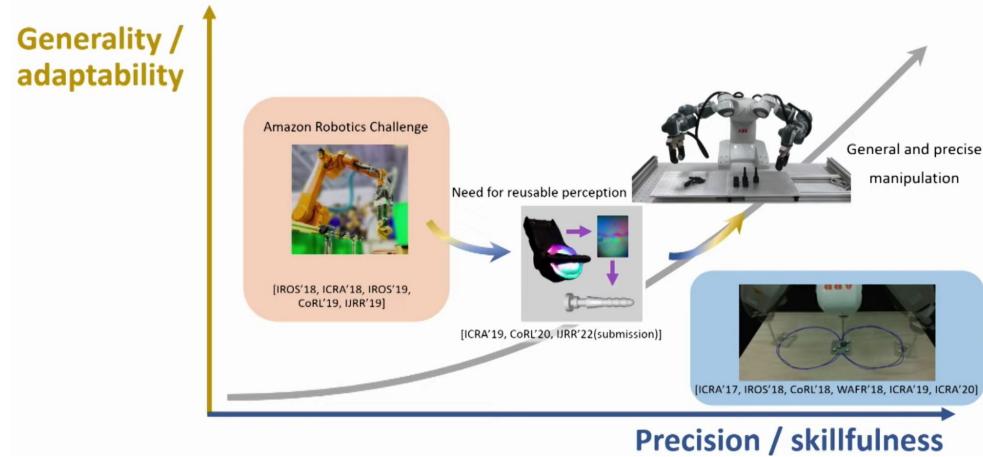
Maria Bauza,
Antonia Bronars, and
Alberto Rodriguez

CORL 2022

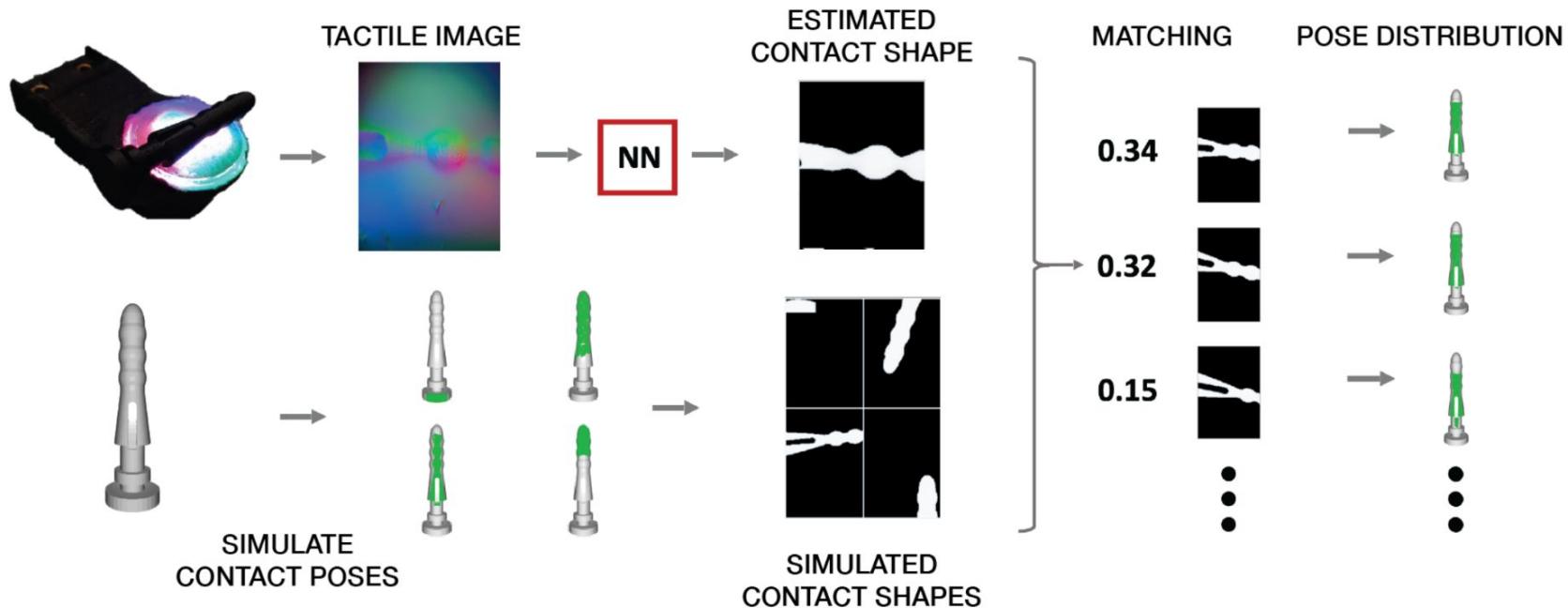


Motivation

- Close the loop
 - Know the pose of the object
 - React to uncertainty
- Industry needs Precision
 - Often Specialized Solutions
- General solutions often lack Precision



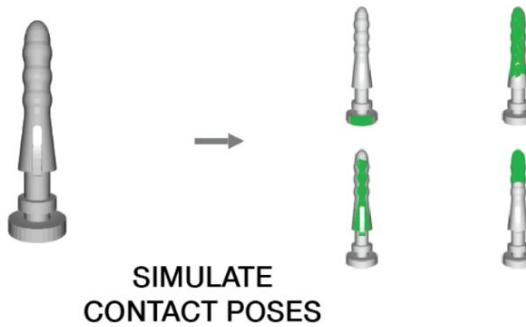
Methods



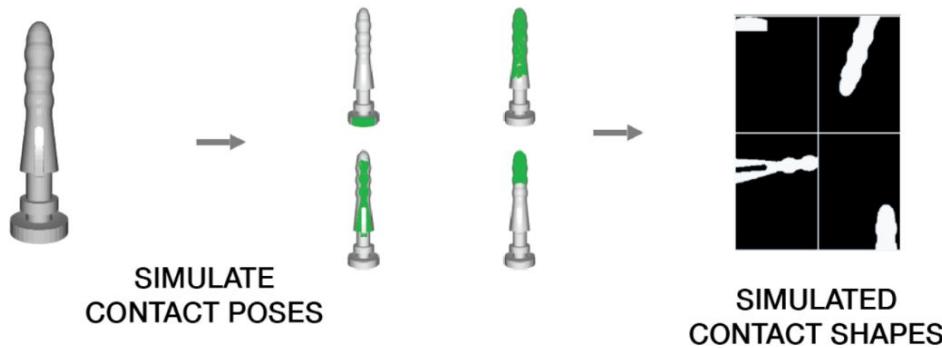
Methods



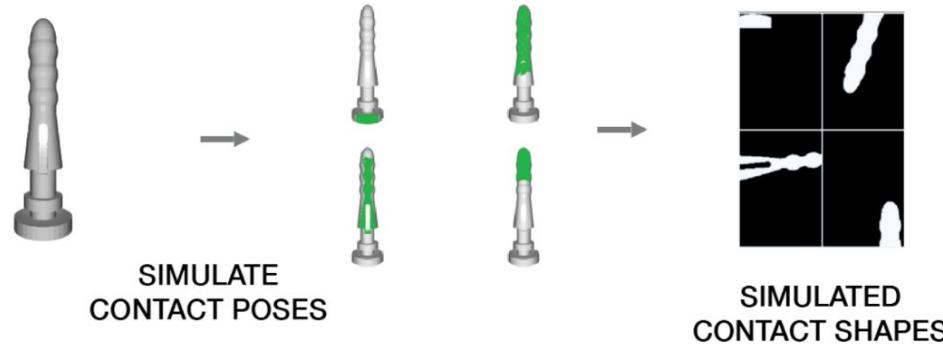
Methods



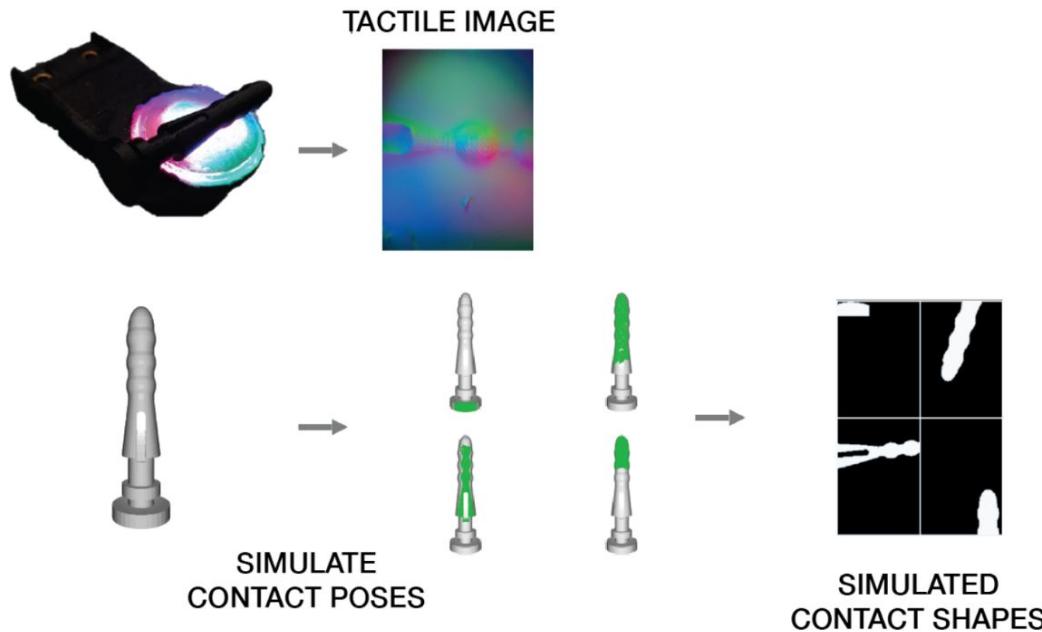
Methods



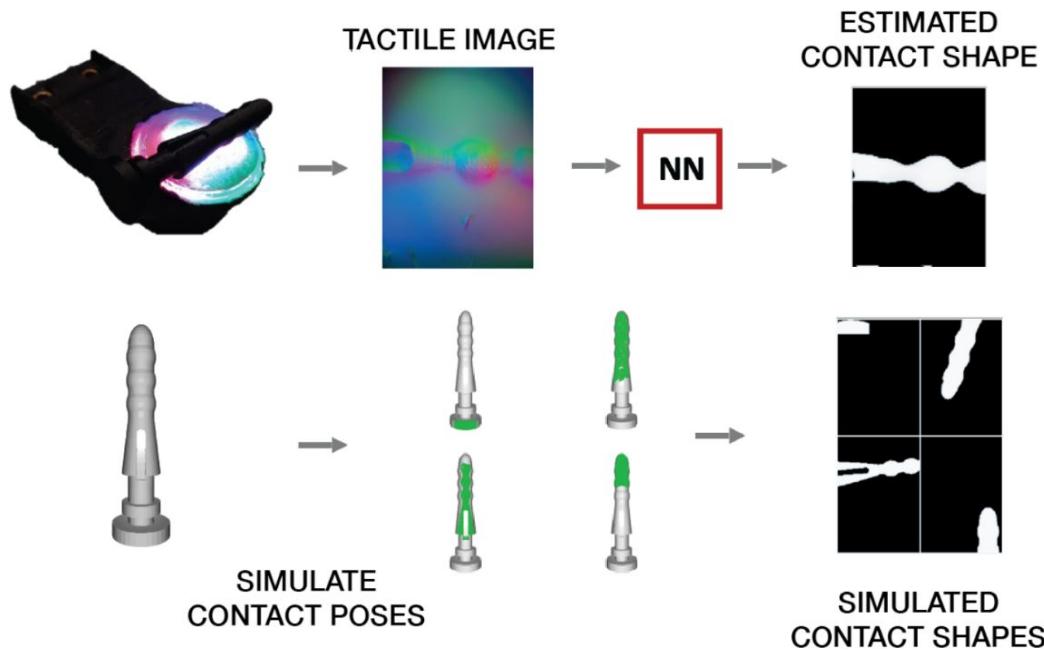
Methods



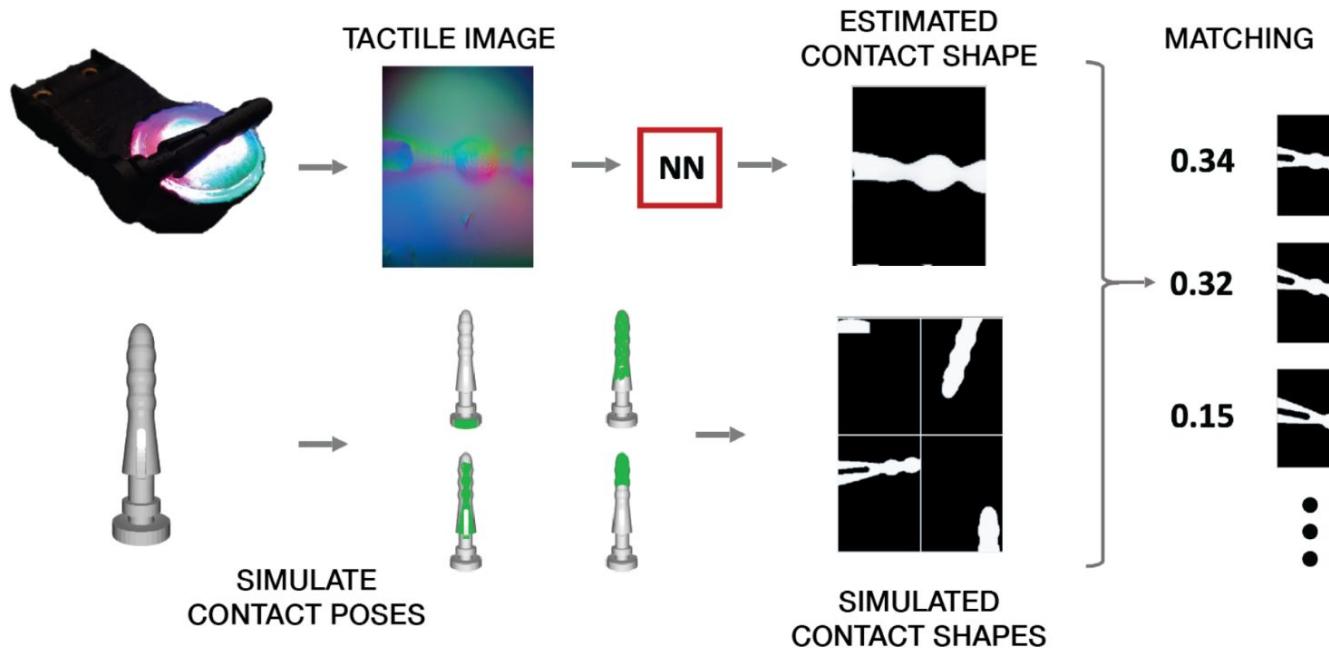
Methods



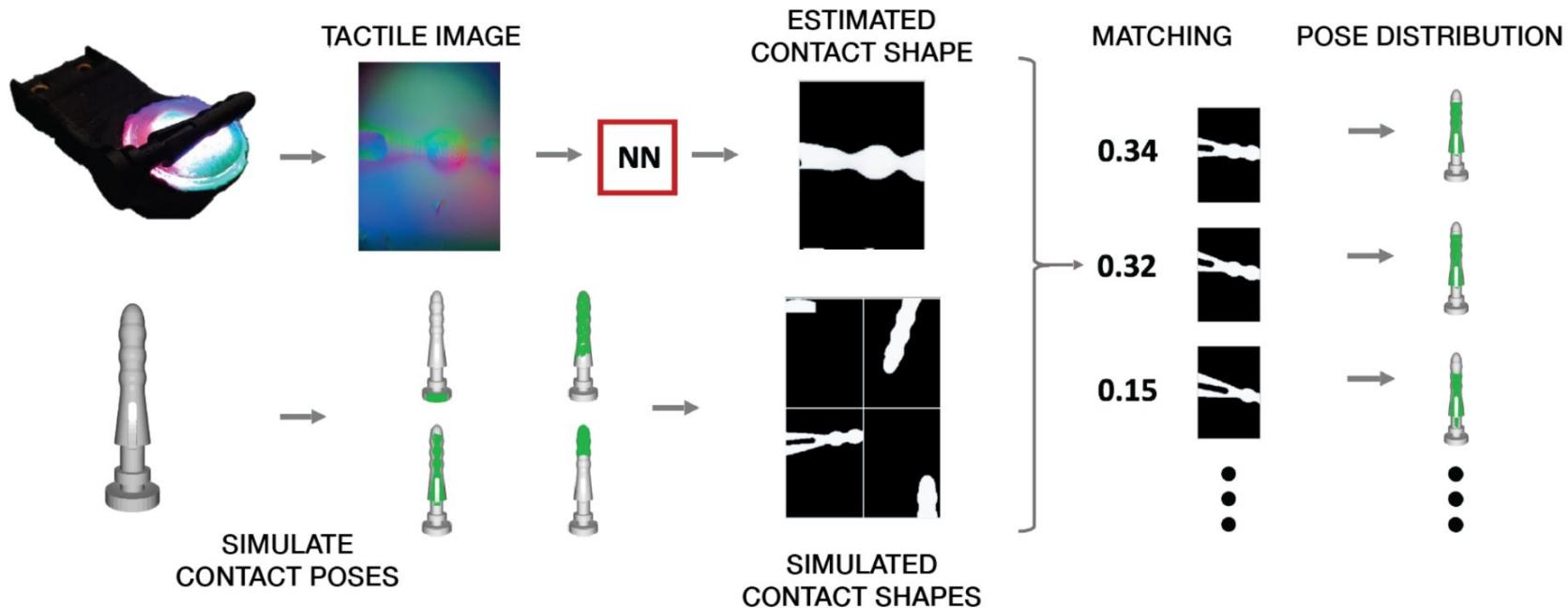
Methods



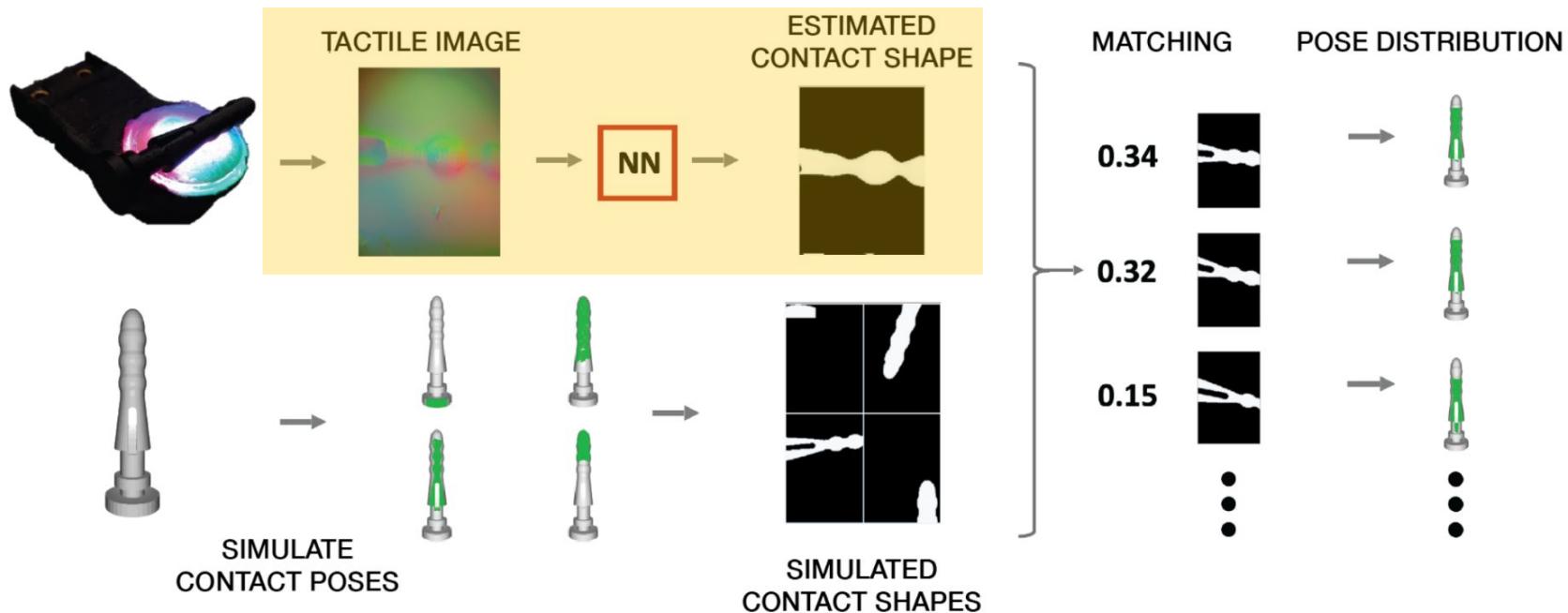
Methods



Methods



Contact Shape Network



Contact Shape Network

Known GelSight Pose

- Real image
- Simulated Binary Contact Shape

General Enough to work across sensors

Based on: [Image-to-Image](#)
[Translation with Conditional](#)
[Adversarial Networks](#)

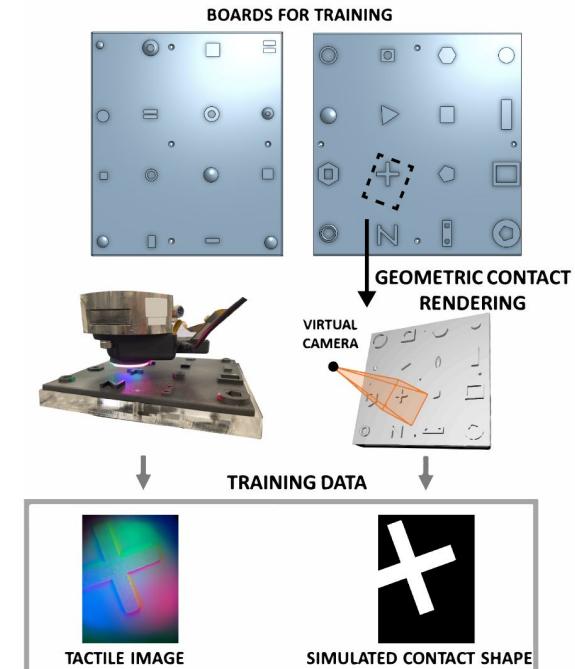
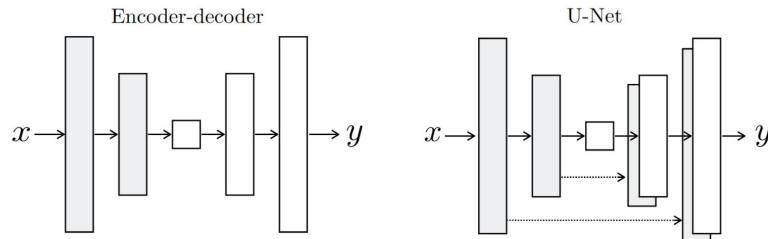


Image-to-Image Translation

- Input: Real image
- Output: Estimated Contact Shape

Trained with ground truth data.



Example: Satellite to Map



Example: Fake shoe to convincing fake shoe

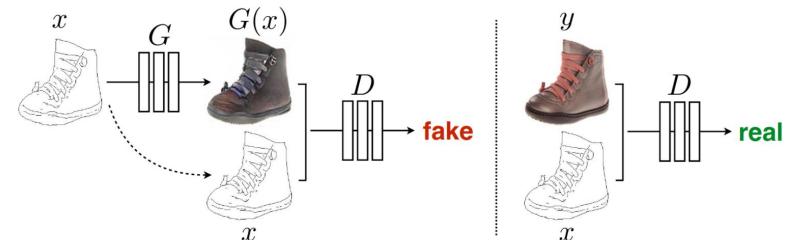
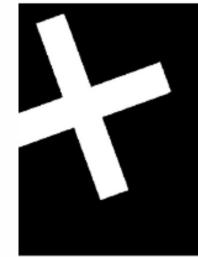


Image-to-Image Translation

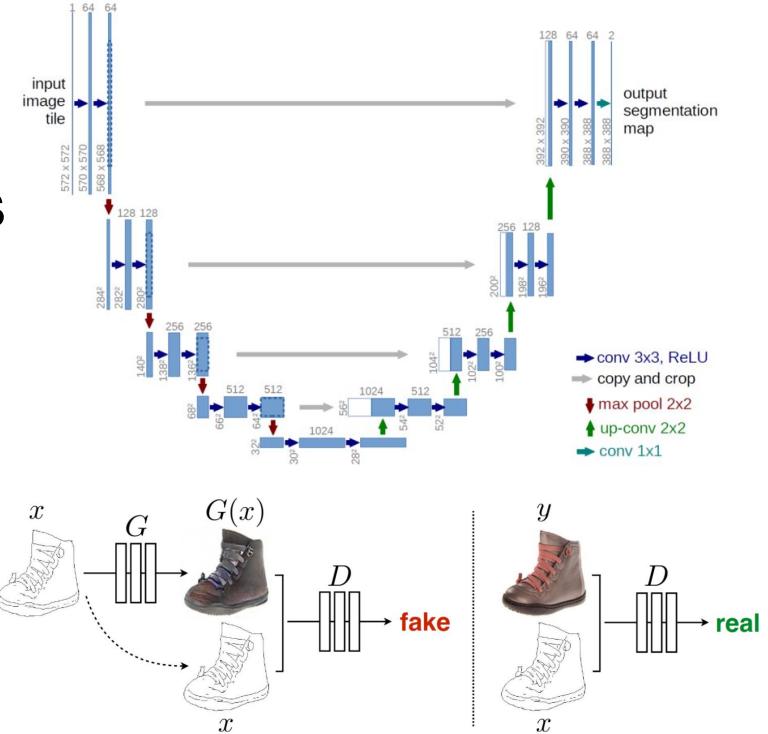
Generator: Creates contact mask
 Discriminator: Identifies fake images



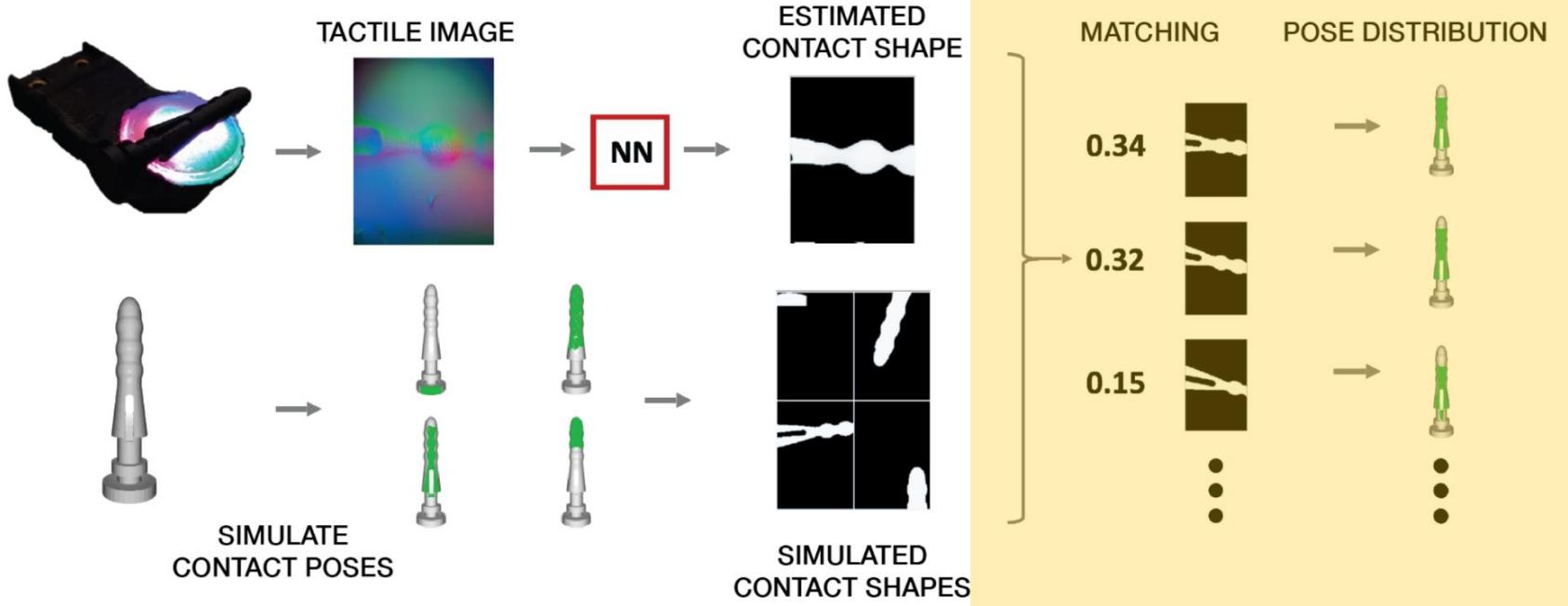
TACTILE IMAGE



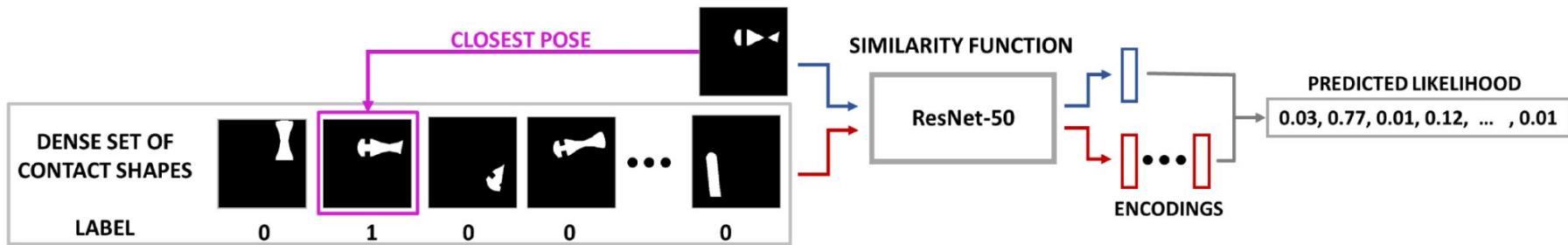
SIMULATED CONTACT SHAPE



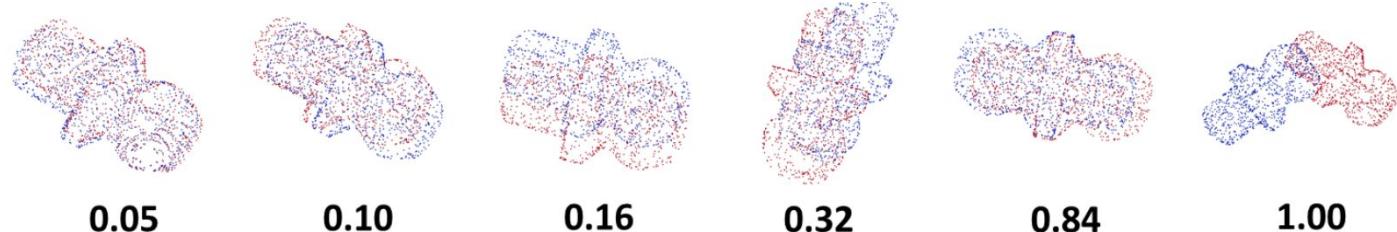
Pose Matching



Pose Matching



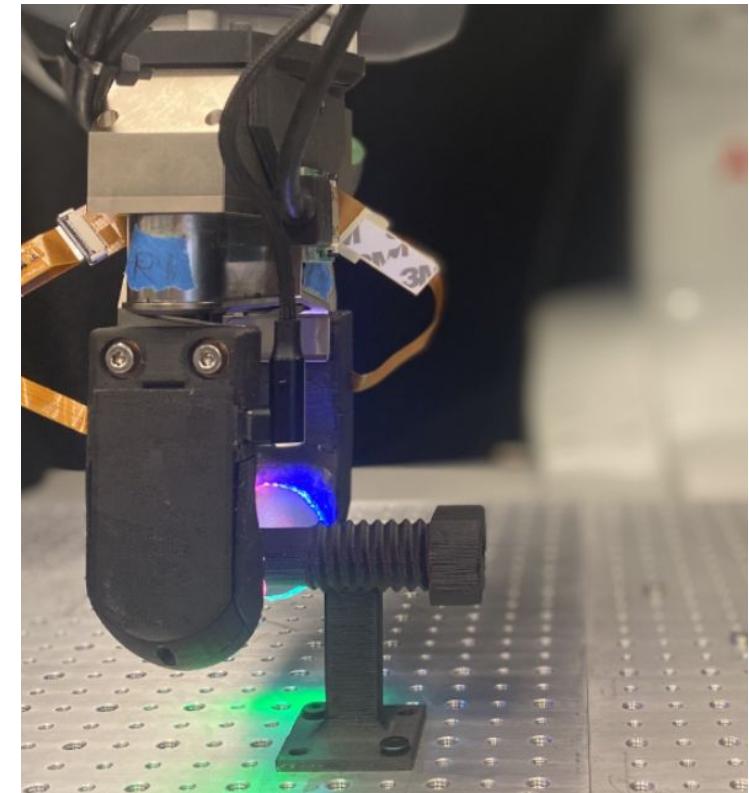
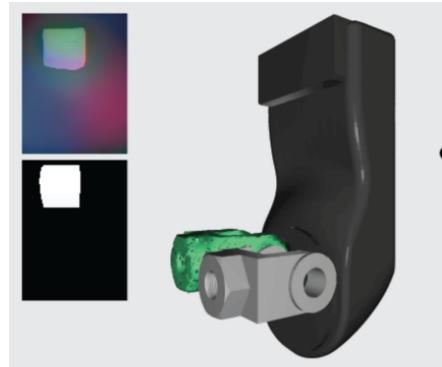
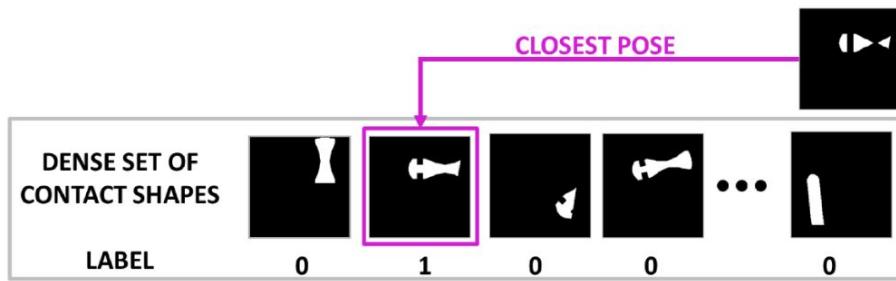
Normalized
Pose Errors:



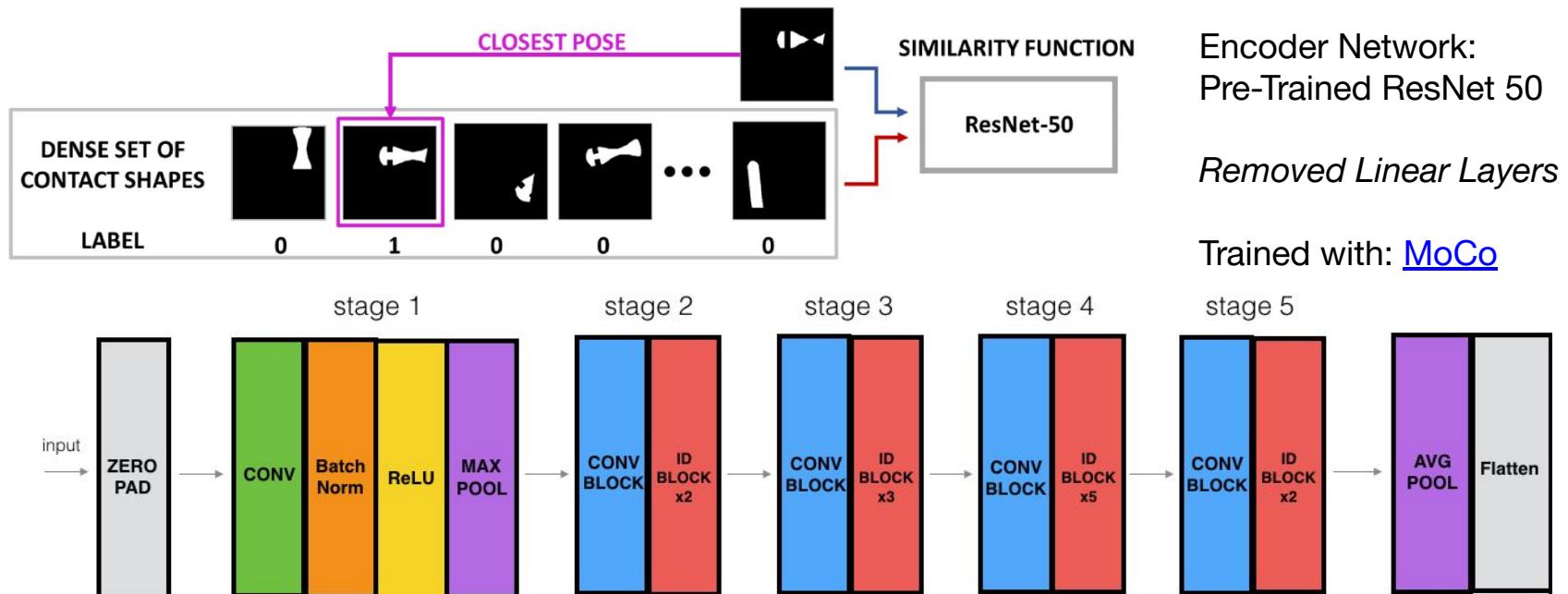
Normalized Pose Error: Original pose error divided by the average error obtained from predicting a random contact pose.



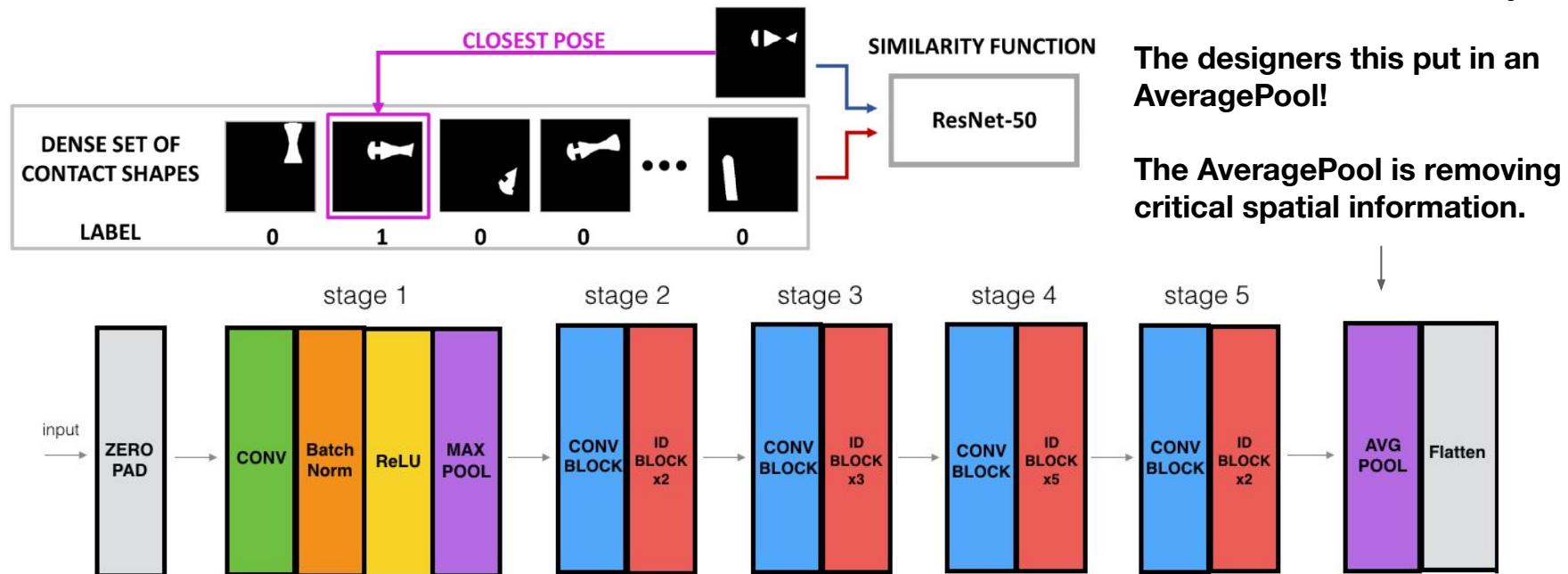
Pose Matching



Pose Matching



Pose Matching



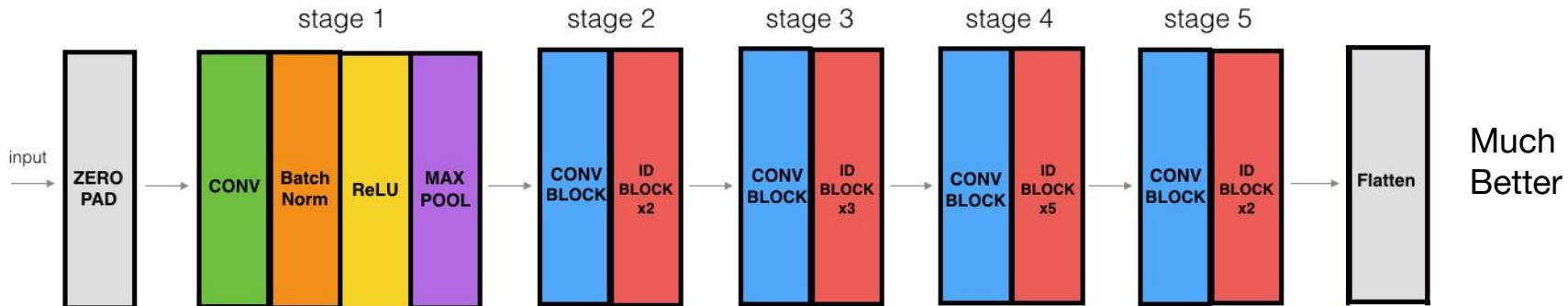
Pose Matching



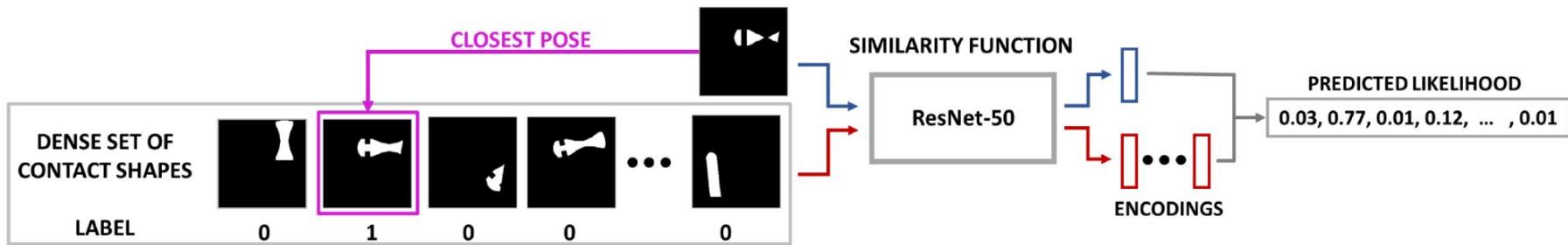
It could never be that easy.

The designers this put in an AveragePool!

The AveragePool is removing critical spatial information.



Pose Matching



Take Largest Probability from SoftMax to get the inferred pose!

Number of Contact Shapes: N
 Encoding Size: S
 Encoded GelSight mask: 1xS
 Encoded simulation mask: NxS
 Dot product distances: 1xN

Probability = SoftMax(Dot product distances)



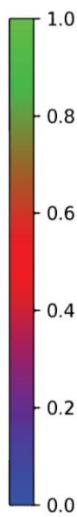
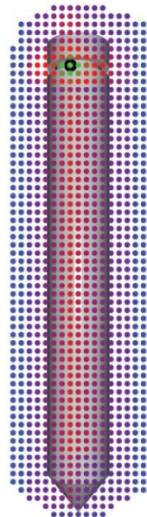
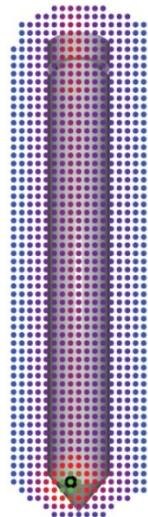
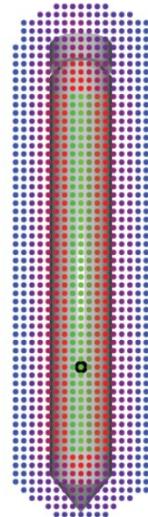
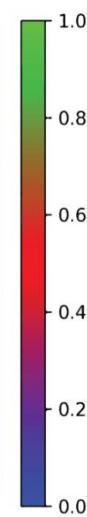
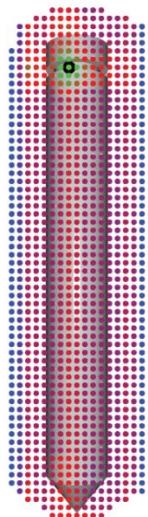
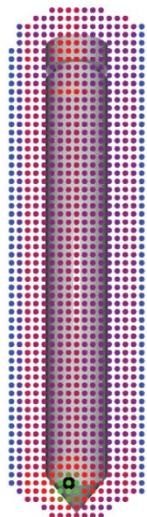
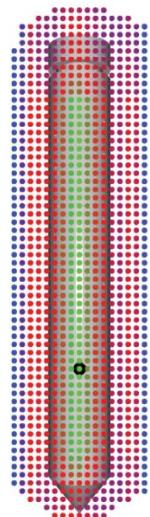
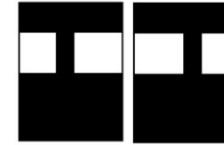
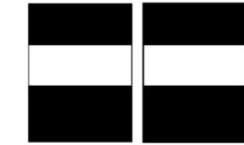
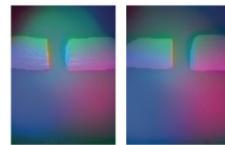
DR

Look! A pencil, how Fun!



M M

Fun is not allowed



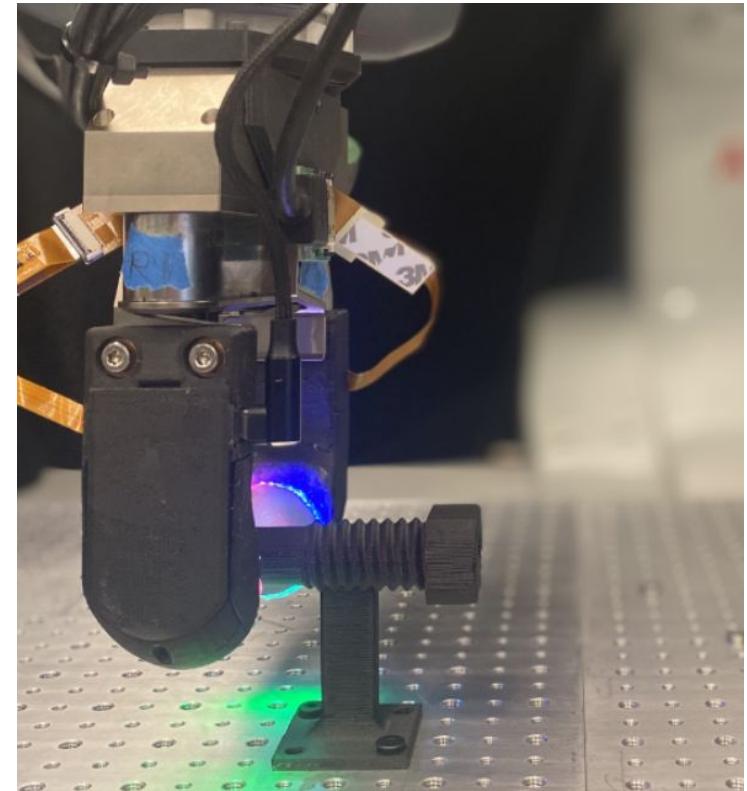
Pose Distributions



These sensors can be small!

Only a few cm² of perception per sensor.

- Unique contact patterns are needed to disambiguate non-unique contact mappings.
- Better to know that you don't know, than to know nothing at all.
 - Regrasp on ambiguous pose distributions.
 - Combine with other modes of sensing (Eg, Visual, Sound, Smell?).



Comparisons to Other Methods

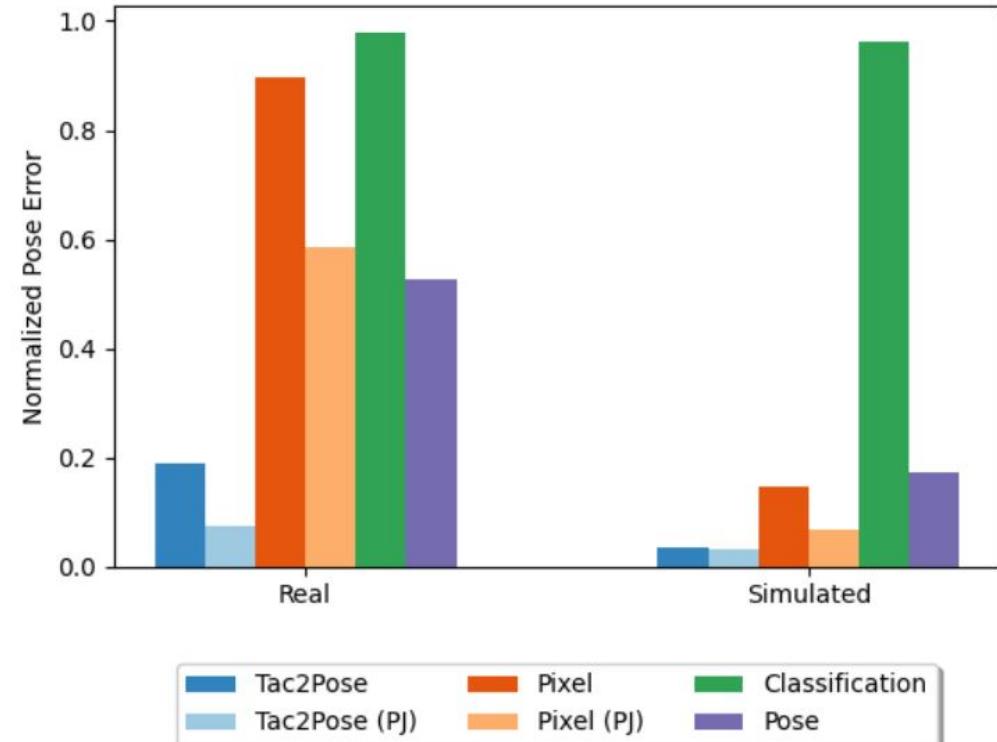
Tac2Pose: Method Described above.

Pixel: No encoder, direct pixel to pixel matching between input contact mask and all simulated contact masks.

Classification: Resnet-50, trained to One-Hot classify each discrete pose.

Pose: Resnet-50, trained to regress each pose.

(PJ): Parallel Jaws, two images.



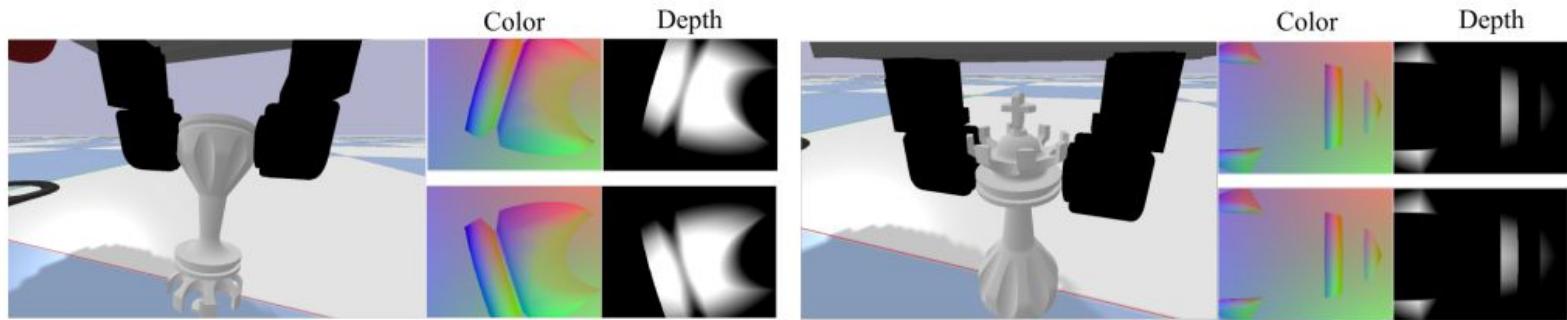
Comparisons to Other Methods

		Tac2Pose		Pixel		Classification	Pose
		SC mm (norm)	PJ mm (norm)	SC mm (norm)	PJ mm (norm)	SC mm (norm)	SC mm (norm)
Long Grease		26.6 (0.76)	3.3 (0.09)	32.8 (0.93)	6.0 (0.17)	33.3 (0.95)	25.3 (0.72)
Snap Ring		1.5 (0.10)	1.4 (0.10)	5.6 (0.39)	2.2 (0.15)	6.0 (0.42)	5.9 (0.41)
Big Head		7.8 (0.20)	6.1 (0.16)	27.6 (0.70)	11.7 (0.30)	35.0 (0.89)	33.8 (0.86)
Cotter		19.0 (0.49)	19.6 (0.51)	31.5 (0.81)	36.7 (0.95)	35.8 (0.93)	38.1 (0.99)
Hanger		6.6 (0.19)	2.6 (0.07)	31.3 (0.90)	20.5 (0.59)	34.2 (0.98)	18.3 (0.53)





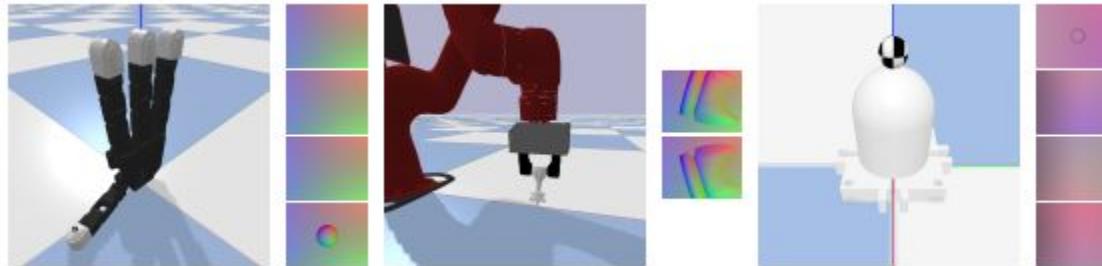
TACTO: A Fast, Flexible, and Open-source Simulator for High-Resolution Vision-based Tactile Sensors



Wang, Shaoxiong, Mike Lambeta, Po-Wei Chou, and Roberto Calandra. *IEEE Robotics and Automation Letters* 7, 2022

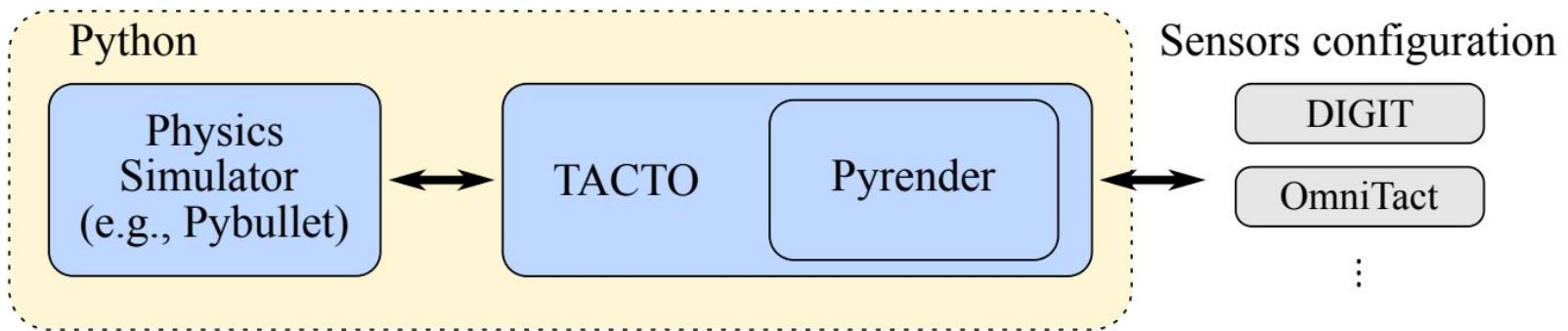


Motivation



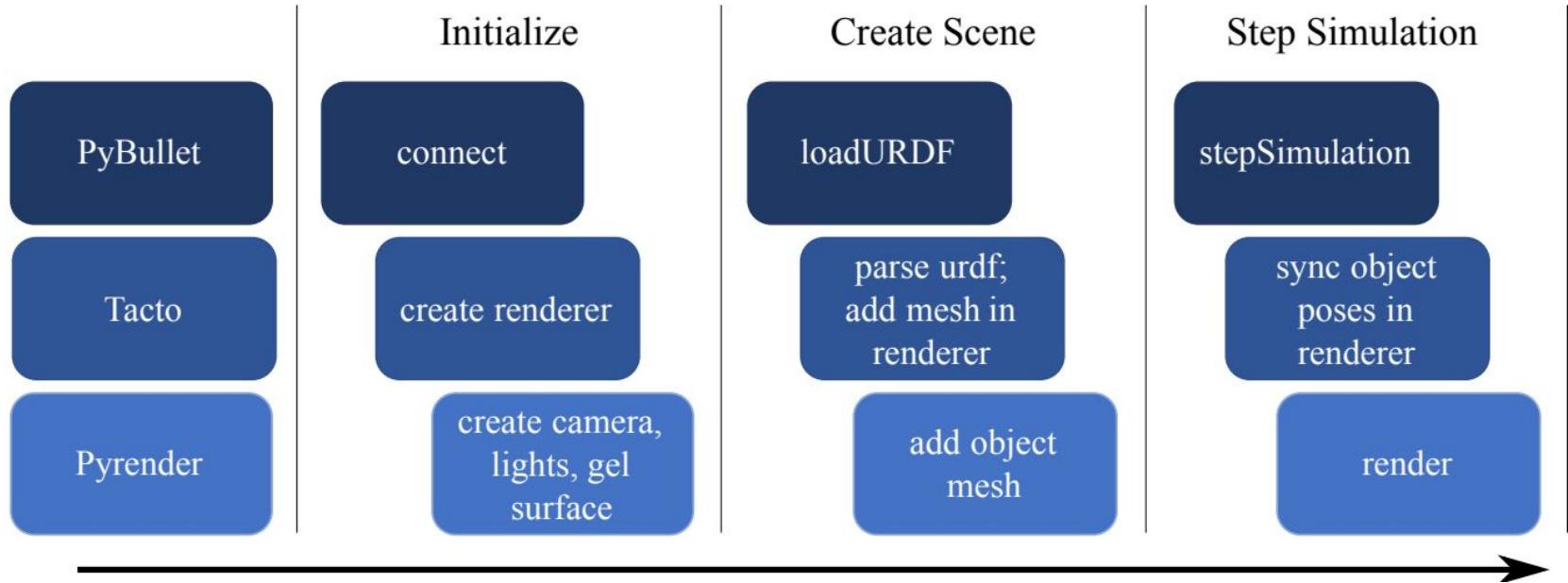
- Simulator for vision based tactile sensors
- Small Sim2Real gap
- Implements OmniTact and DIGIT sensors
- Value for different communities:
 - Hardware designers
 - Robotics
 - Machine learning

Methods



Wang, Shaoxiong, et al. *TACTO: A Fast, Flexible, and Open-Source Simulator for High-Resolution Vision-Based Tactile Sensors*. 2020.

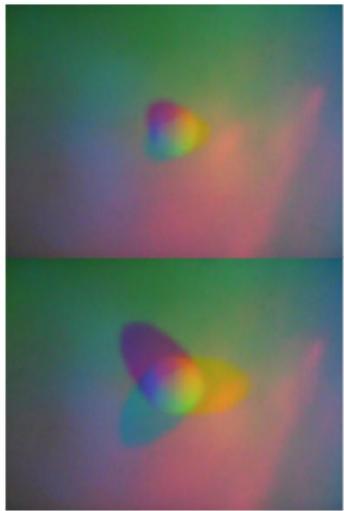
Software Architecture



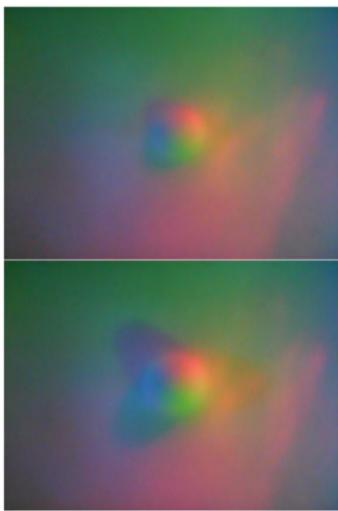
Wang, Shaoxiong, et al. *TACTO: A Fast, Flexible, and Open-Source Simulator for High-Resolution Vision-Based Tactile Sensors*. 2020.

Sim vs Real

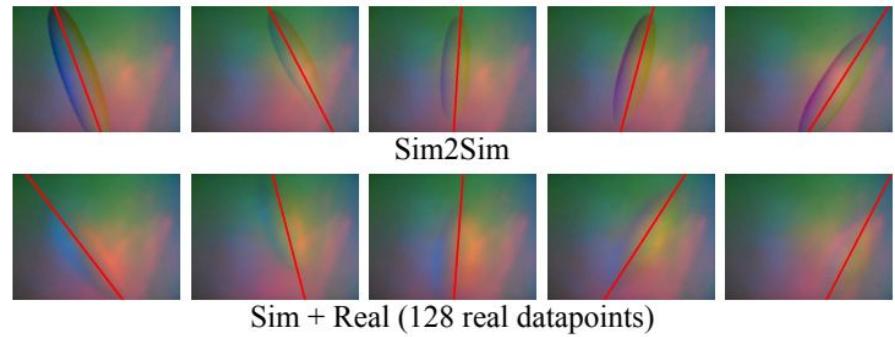
Sim



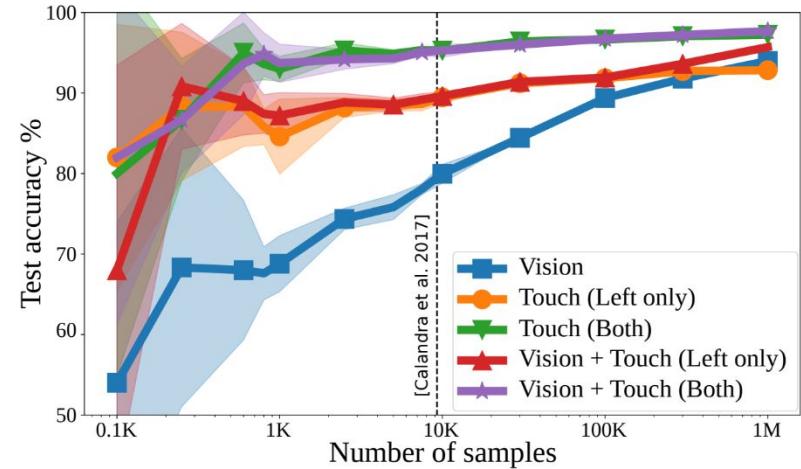
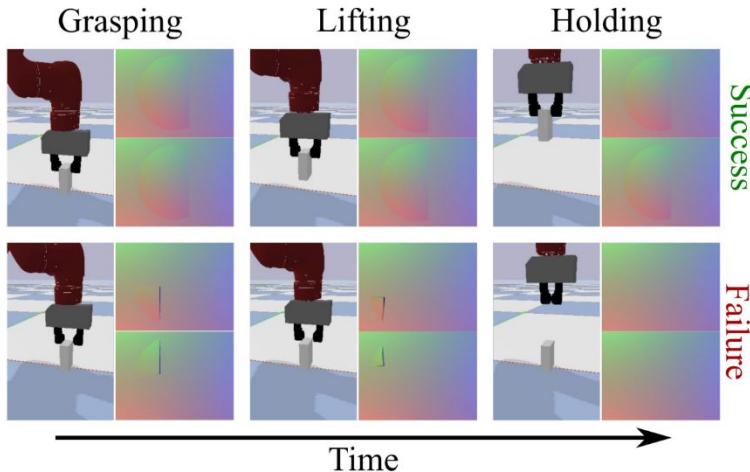
Real



Pose estimation results



Results

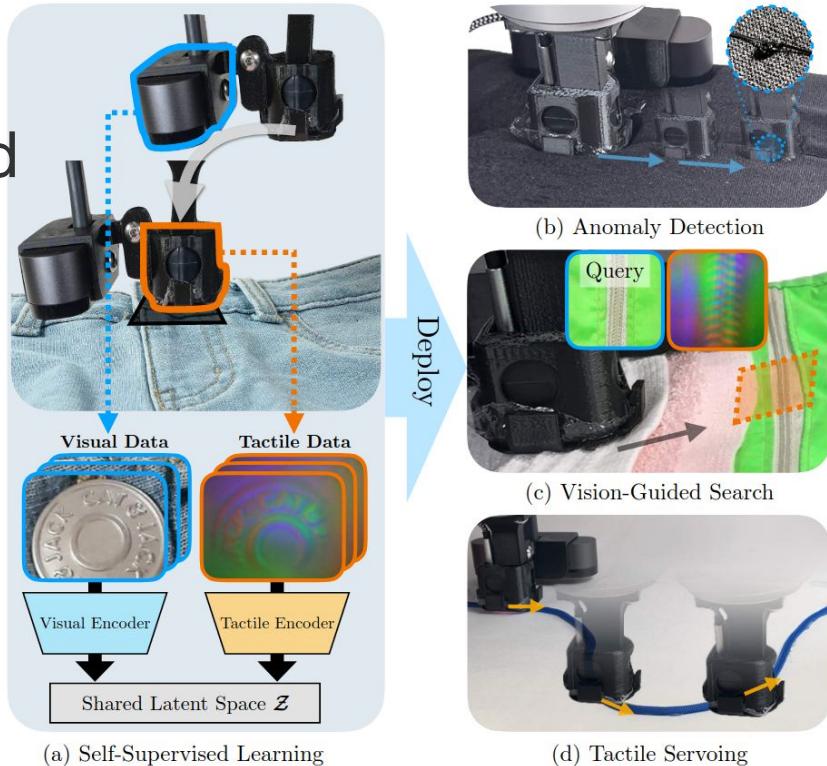


Wang, Shaoxiong, et al. *TACTO: A Fast, Flexible, and Open-Source Simulator for High-Resolution Vision-Based Tactile Sensors*. 2020.

Questions?

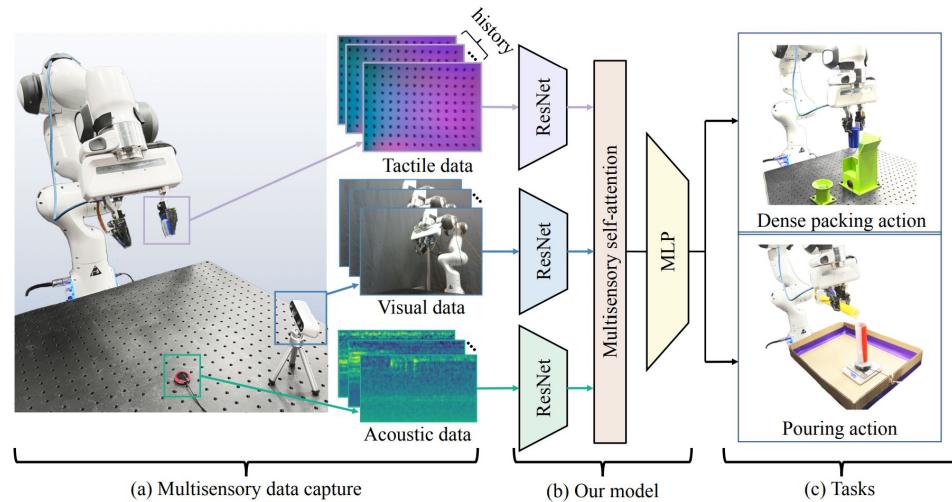
Learning Self-Supervised Representations from Vision and Touch for Active Sliding Perception of Deformable Surfaces

- Align visual and tactile data
 - Train encoders to embed into a shared latent feature space.
 - Uses cross-modal contrastive loss
 - Object agnostic representation.



See, Hear, and Feel: Smart Sensory Fusion for Robotic Manipulation

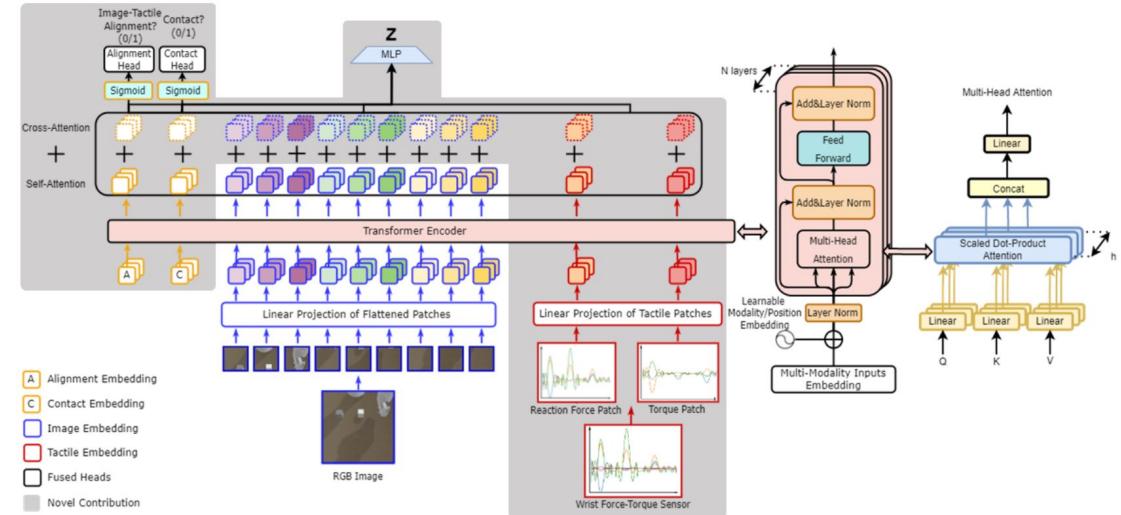
- Explore using multi sensory data for performing Tasks
- Combines vision, tactile, and audio data



Li, Hao, et al. *See, Hear, and Feel: Smart Sensory Fusion for Robotic Manipulation..*
DOI.org (Datacite), <https://doi.org/10.48550/ARXIV.2212.03858>.

Visuo-Tactile Transformers for Manipulation (VTT)

- Modality Patches
- Self and Cross-Modal Attention
- Learned embeddings:
 - Contact
 - Alignment
 - Position/Modality
- Compressed Representation Head
- Combined Reinforcement Learning

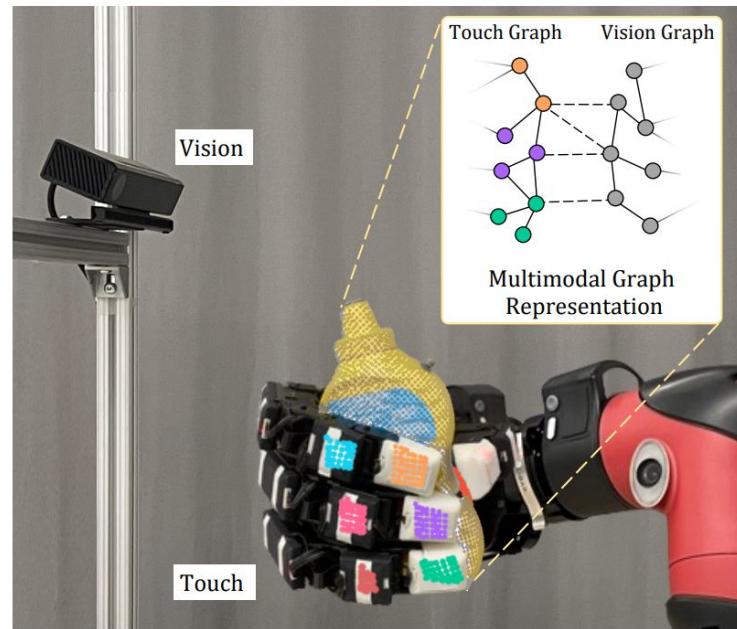


<https://arxiv.org/abs/2210.00121>

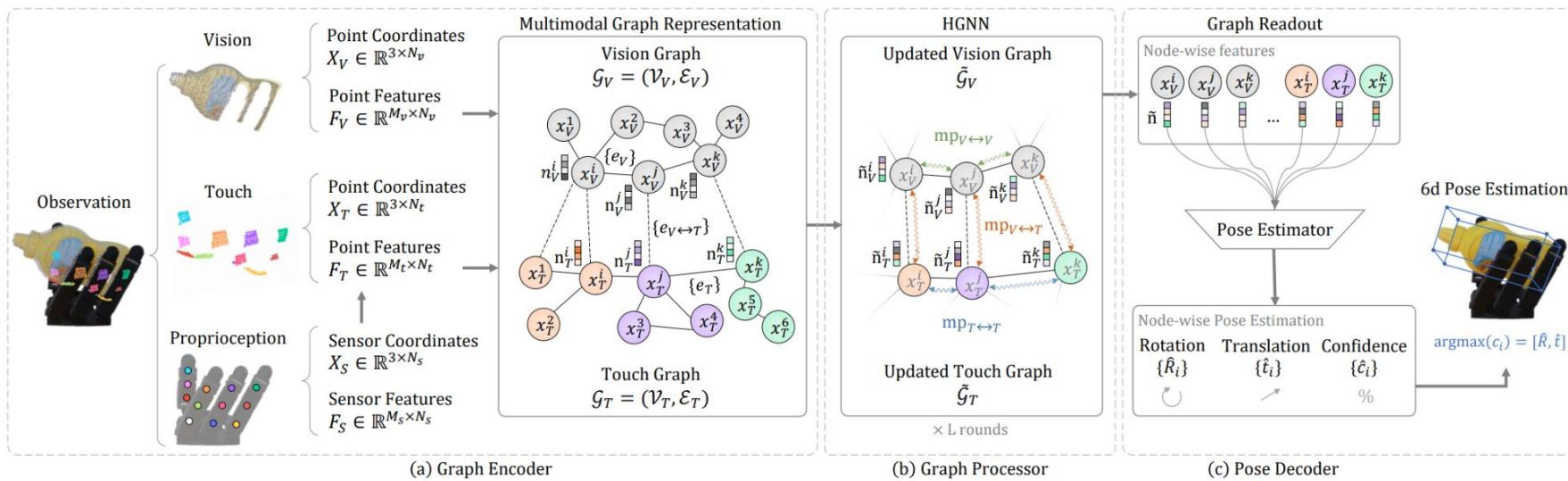
$$\ell_{VTT} = BCE_{logits}(MLP(Al_{head})), Al_{gt}) + BCE_{logits}(MLP(C_{head}), C_{gt})$$

Hierarchical Graph Neural Networks for Proprioceptive 6D Pose Estimation of In-hand objects

- HGNN combines vision and touch
- Geometrically informed 6D object pose estimation
- Multimodal graph message passing
- Proprioceptive information for in-hand object representation



Architecture



Node-wise pose estimation loss

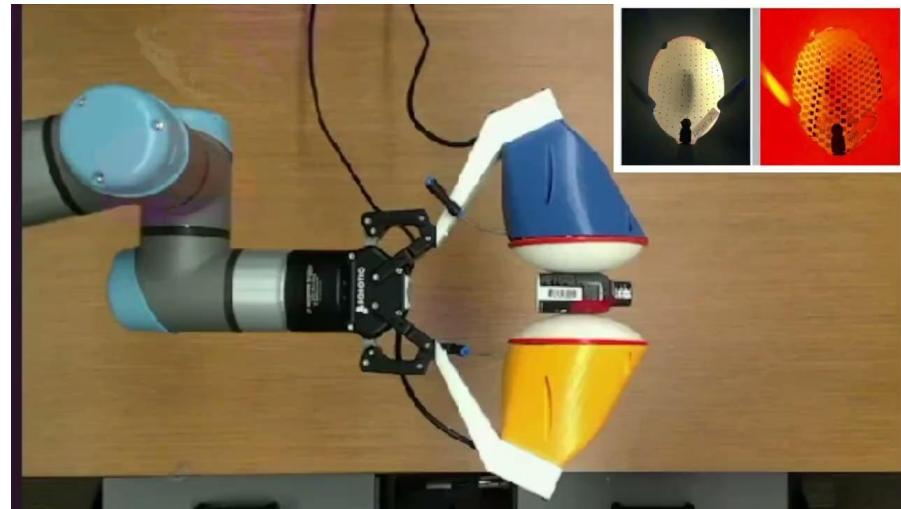
$$L_i^{\mathbf{n}} = \frac{1}{P} \sum_{p=1 \dots P} \|(R_{gt}x_p + t_{gt}) - (\hat{R}_i x_p + \hat{t}_i)\| \longrightarrow L = \frac{1}{K} \sum_{i=1 \dots K} (L_i^{\mathbf{n}} \hat{c}_i - \lambda \log(\hat{c}_i))$$

Total loss



Recap

- Tactile perception
- Signal categories
- Types of sensors
- Haptic vs Tactile sensing
- Gelsight
- Tac2Pose
- Tacto
- Tactile sensing for Deep Learning



Questions?