

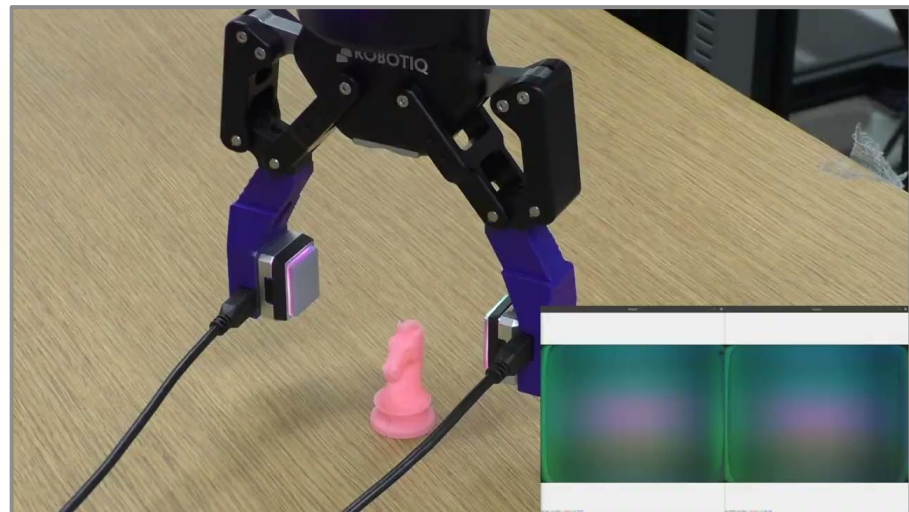
# DeepRob

[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

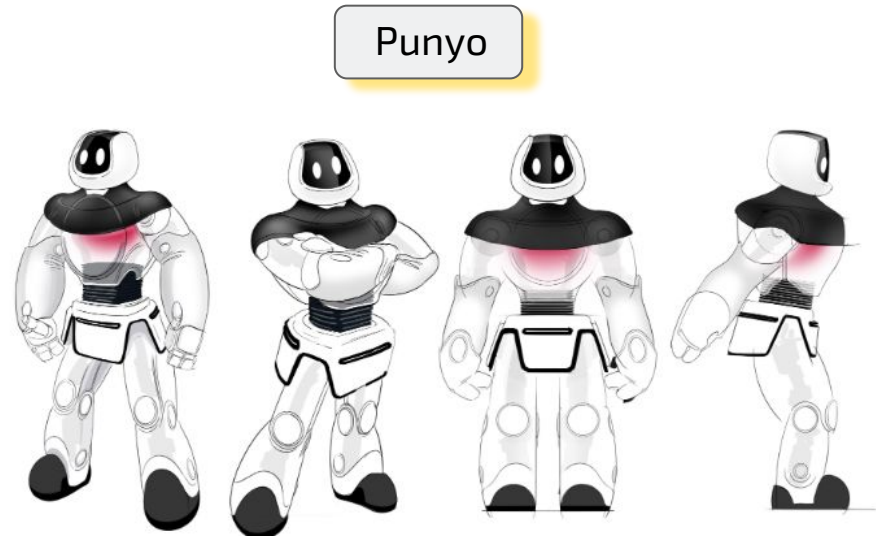


Gelsight grasp demo

# Agenda

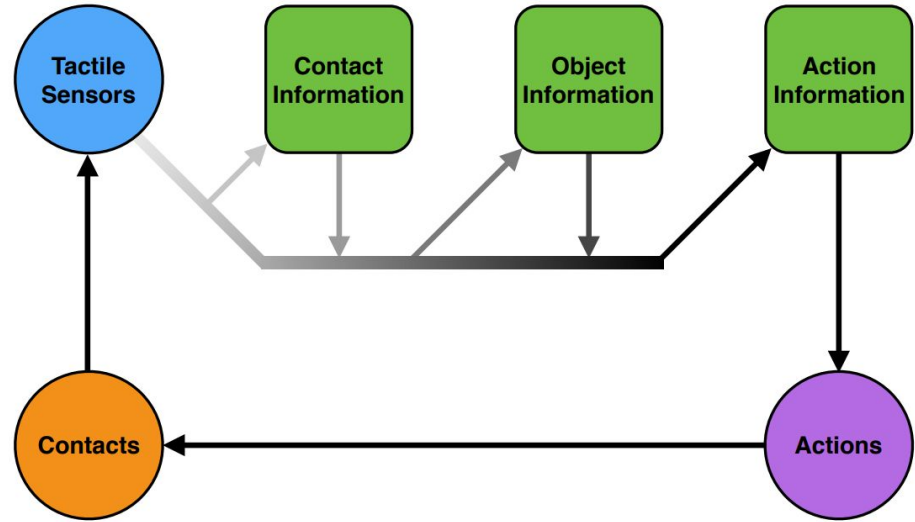
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- Tactile perception
- Signal categories
- Types of sensors
- Haptic vs Tactile sensing
- Gelsight
- Tac2Pose
- Tacto
- Tactile sensing for Deep Learning



# What is Tactile Perception?

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

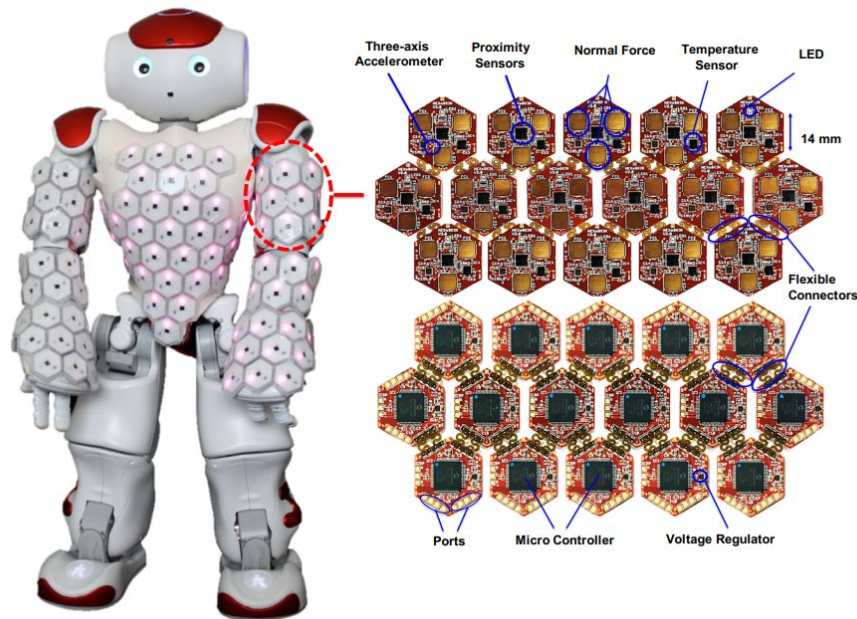


A Review of Tactile Information: Perception and Action Through Touch, Li et al. , 2020



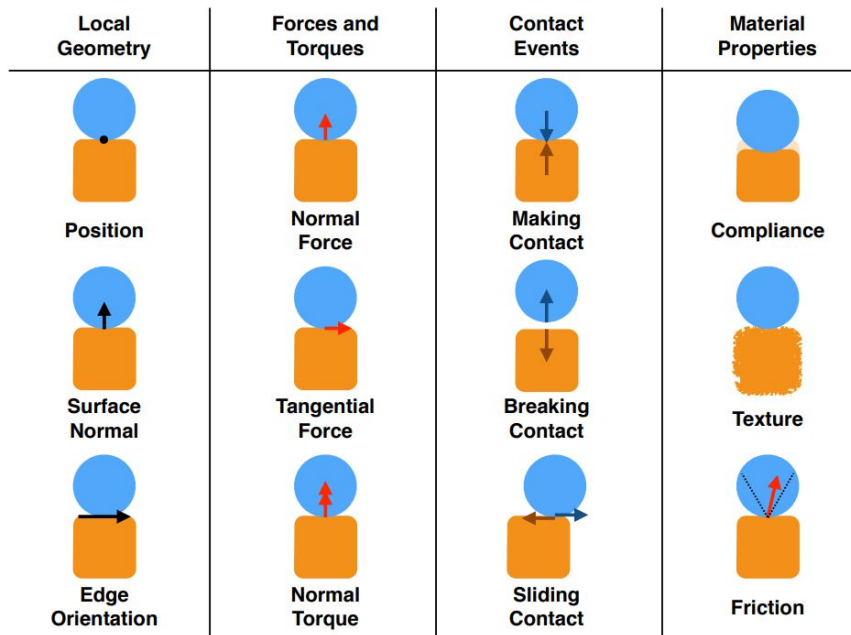
# Sensor-Level Signals

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



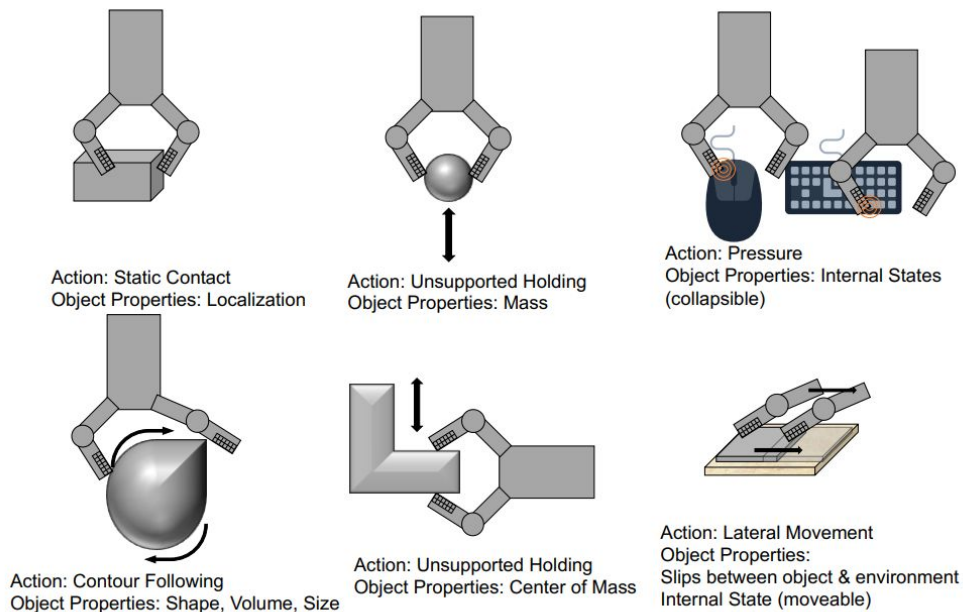
# Contact-Level Signals

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



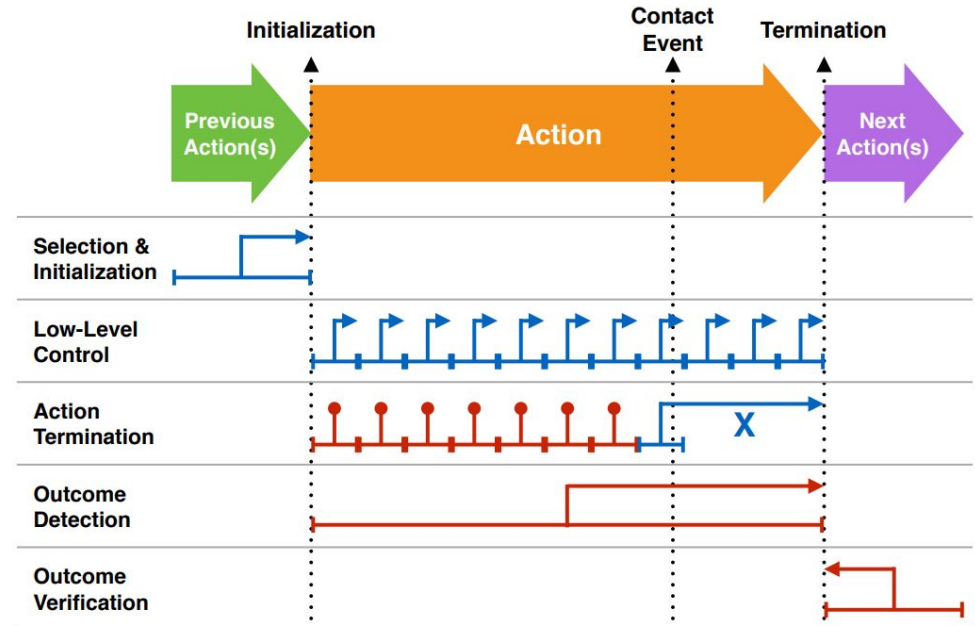
# Object-Level Signals

- 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

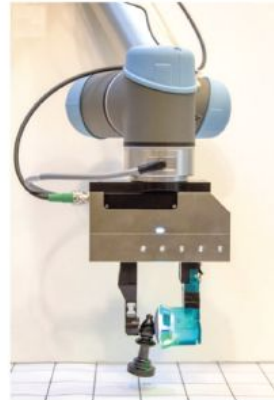


# Sensors

Facebook AI Digit



Visuotactile



GelSight Mini

Tactile



Xela Robotics uSkin

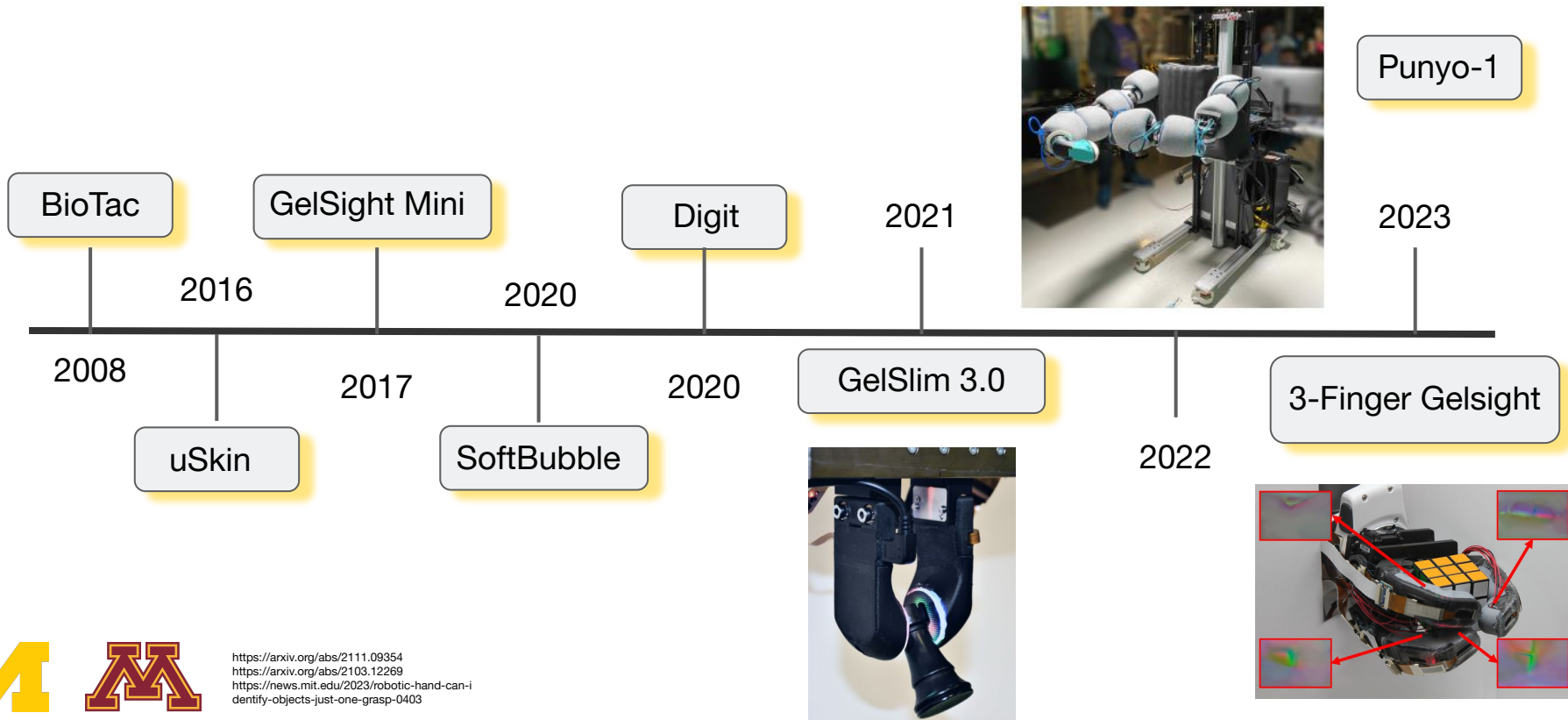
SynTouch BioTac



TRI Puno SoftBubble



# Tactile Sensing Timeline



# Haptic vs. Tactile Sensing

## Haptic

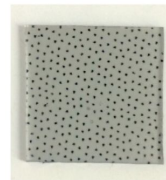
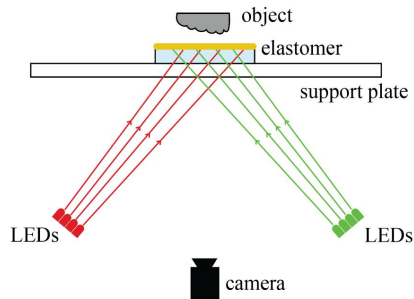
- Overall sensory experiences:
  - Tactile
  - Proprioception
  - Kinesthesia

## Tactile

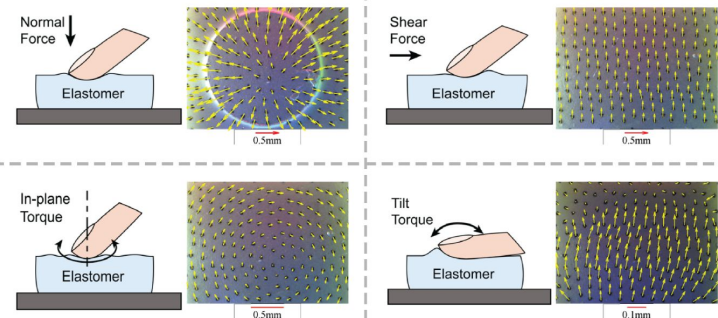
- Detection of physical sensations:
  - Pressure
  - Temperature
  - Texture



# What is Visuotactile Sensing?

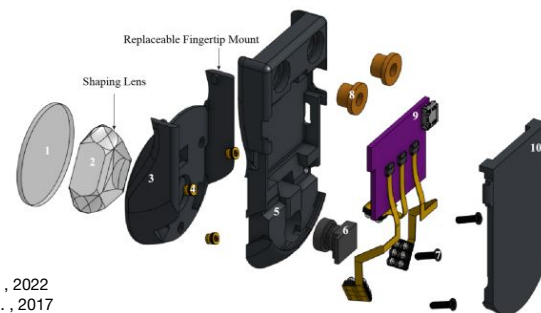
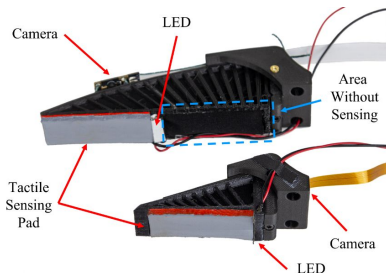
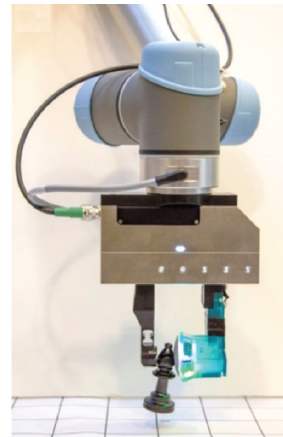
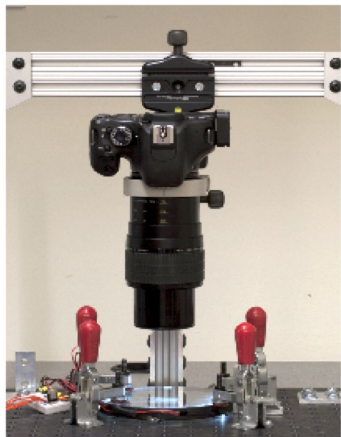


(a)



(b)

# Exploring Gelsight Evolution

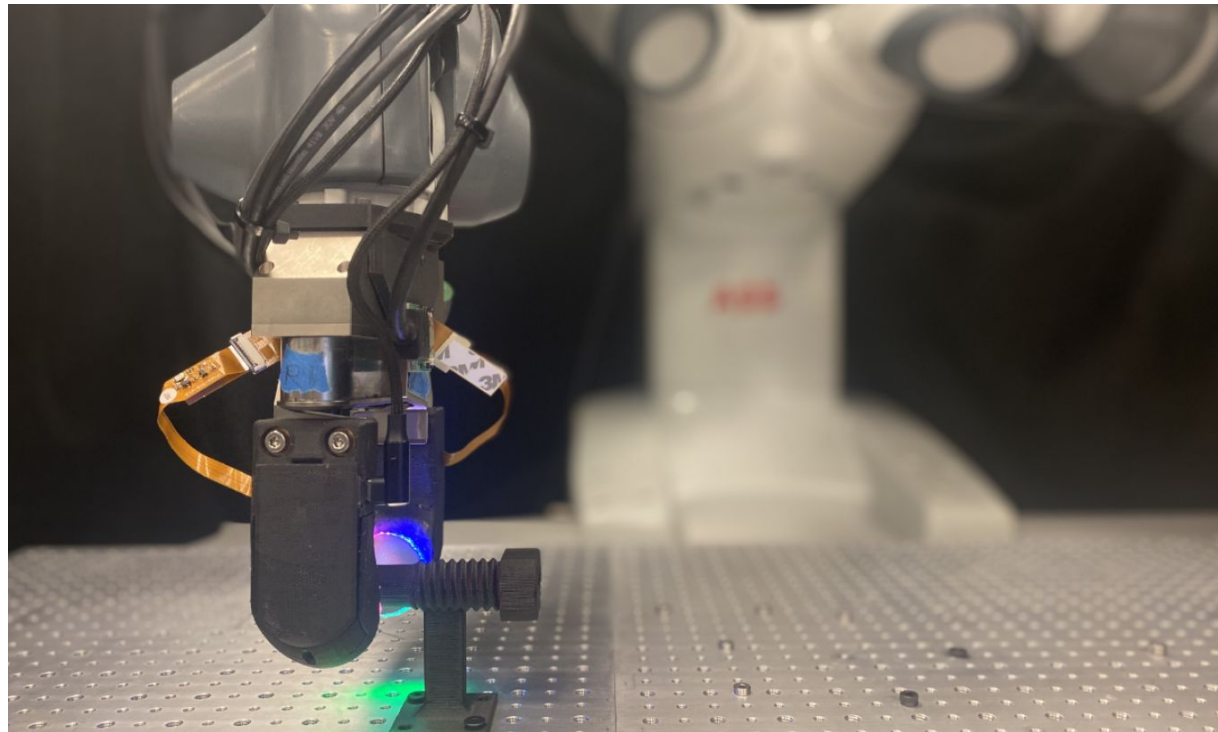


- 1 Elastomer w/ Reflective Skin
- 2 Acrylic Lens
- 3 Fingertip
- 4 Heat Inserts
- 5 Finger-Body
- 6 Camera Module
- 7 Screws
- 8 Mounting Bearing
- 9 Integrated Illumination Controller
- 10 Finger-Back

# Tac2Pose: Tactile Object Pose Estimation from the First Touch.

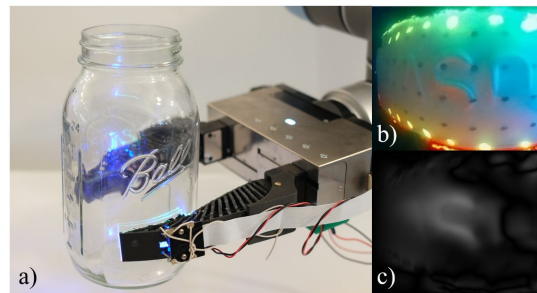
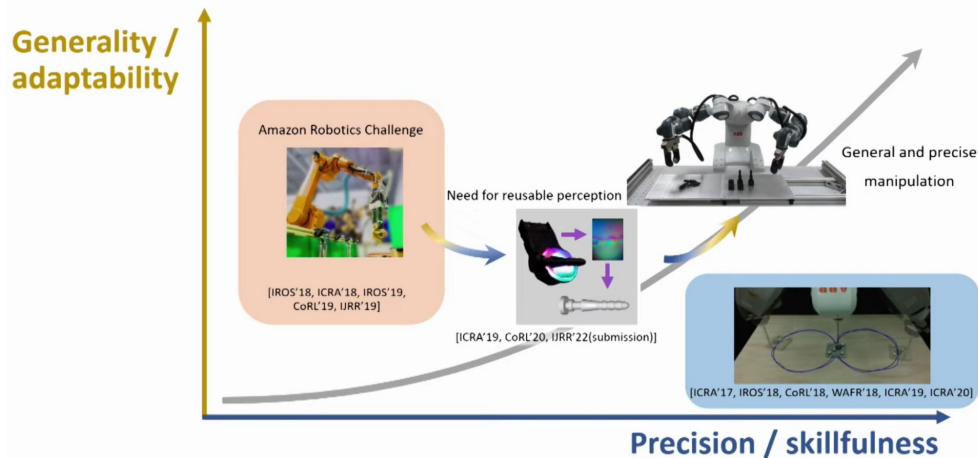
Maria Bauza,  
Antonia Bronars, and  
Alberto Rodriguez

*CORL 2022*

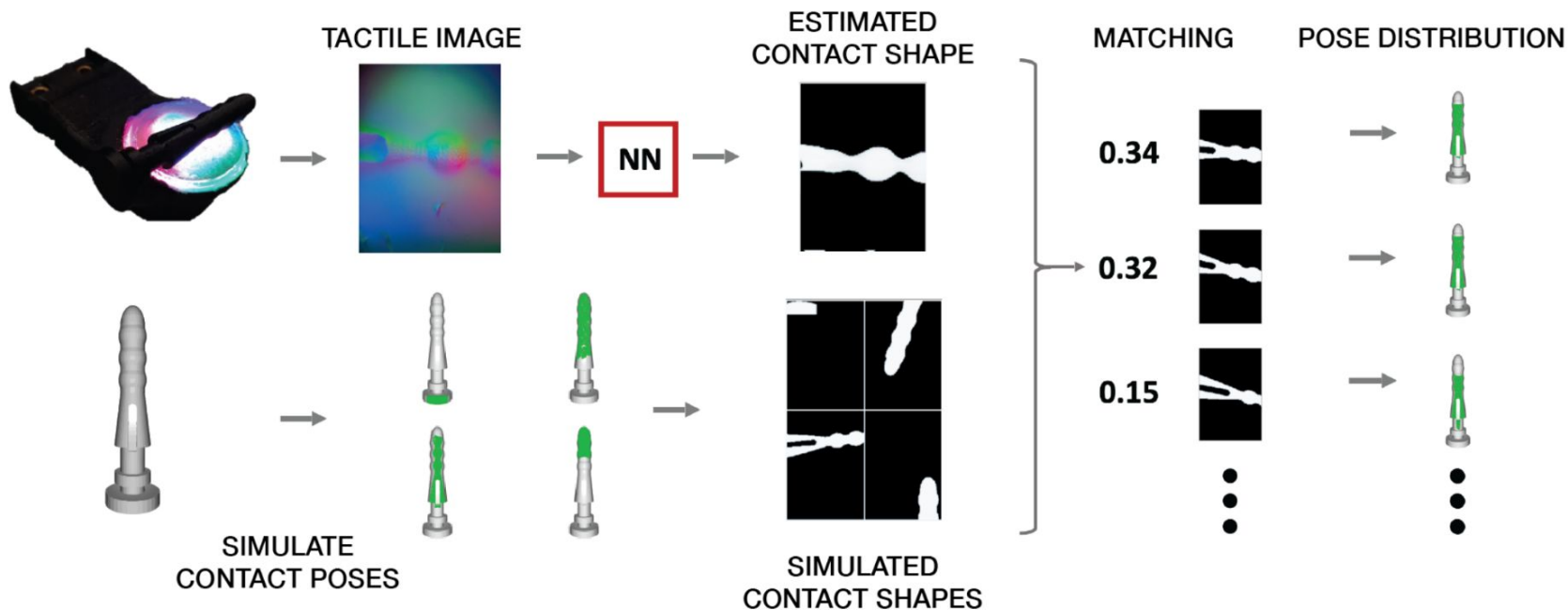


# Motivation

- 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

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# Methods

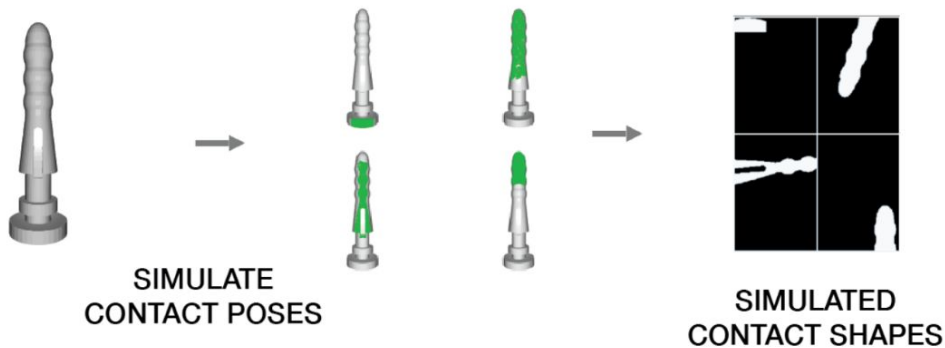
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SIMULATE  
CONTACT POSES

# Methods

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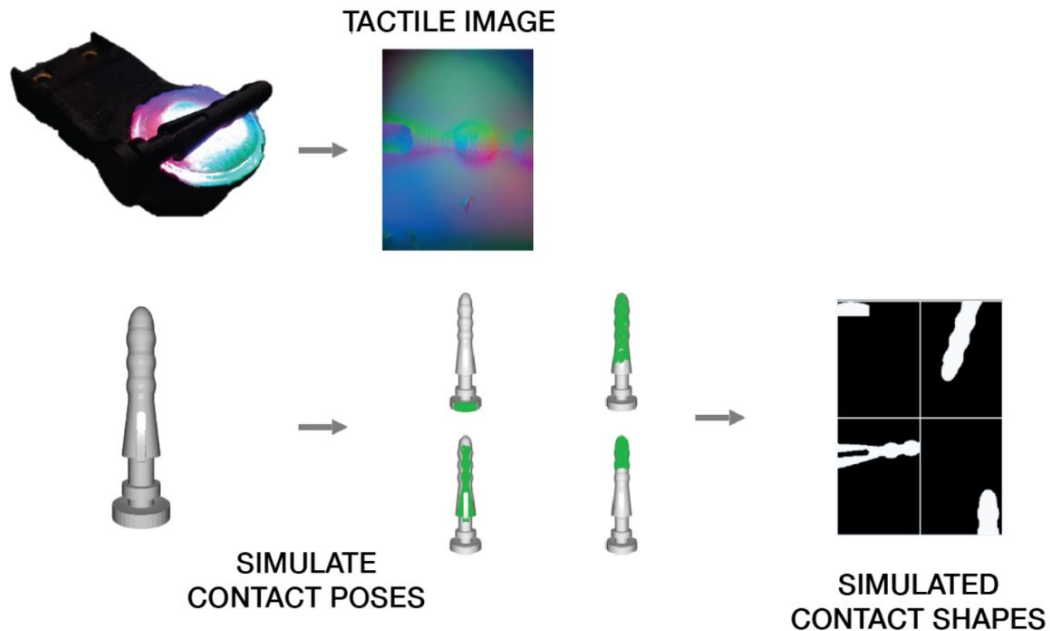
# Methods



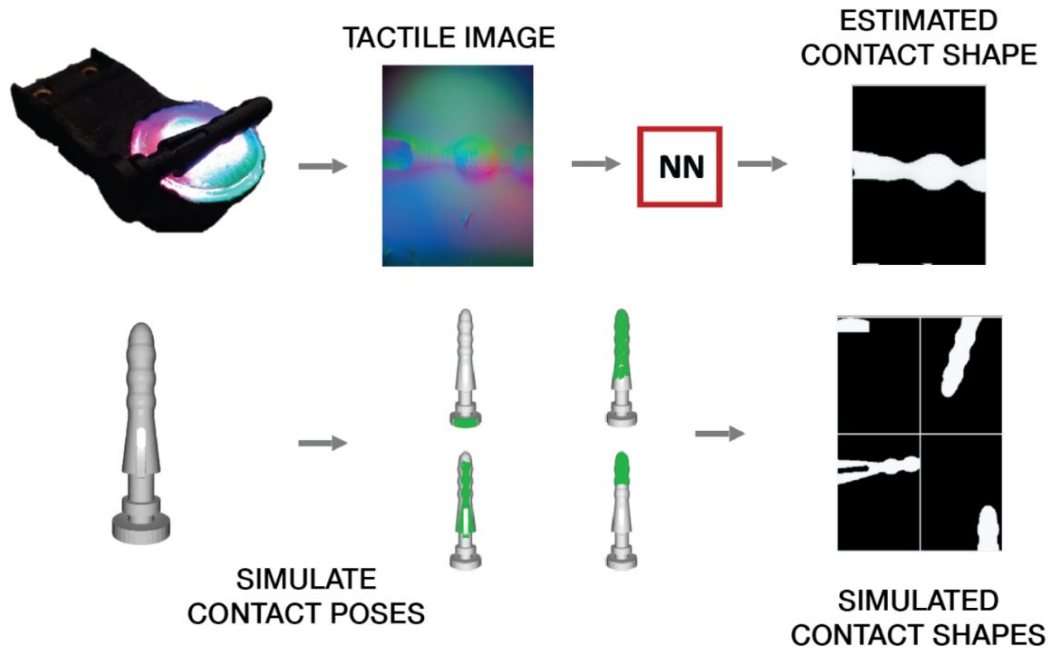
SIMULATE  
CONTACT POSES

SIMULATED  
CONTACT SHAPES

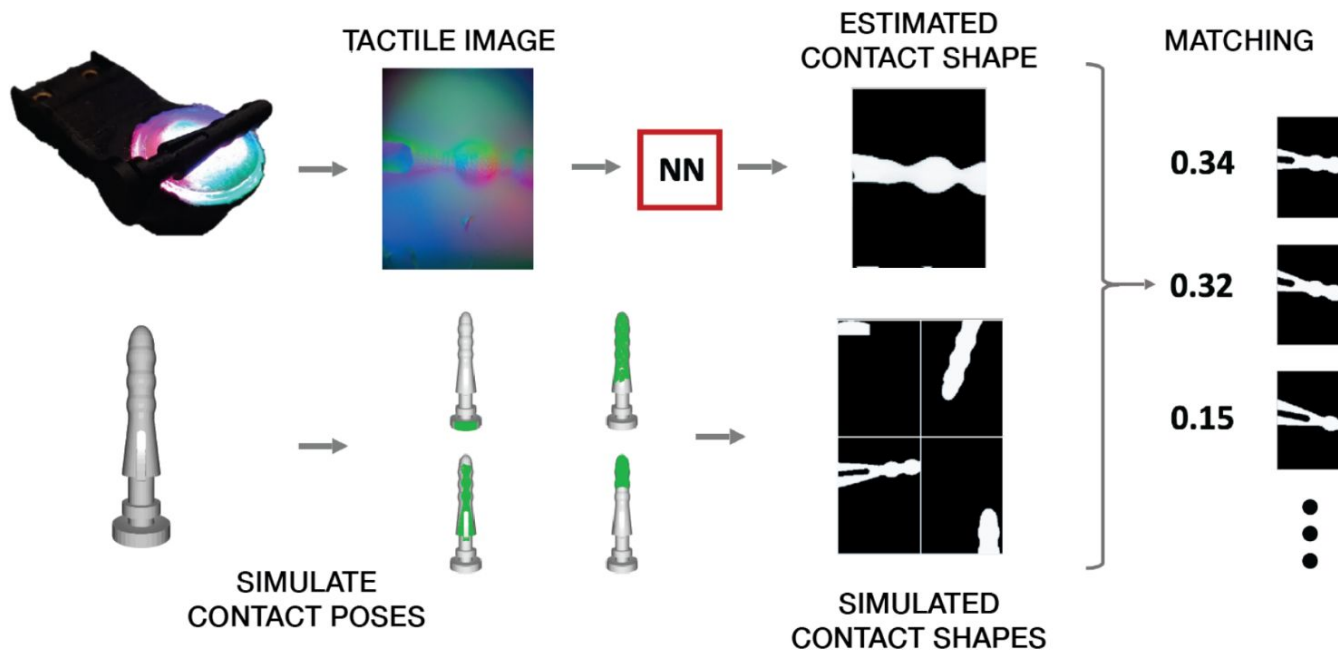
# Methods



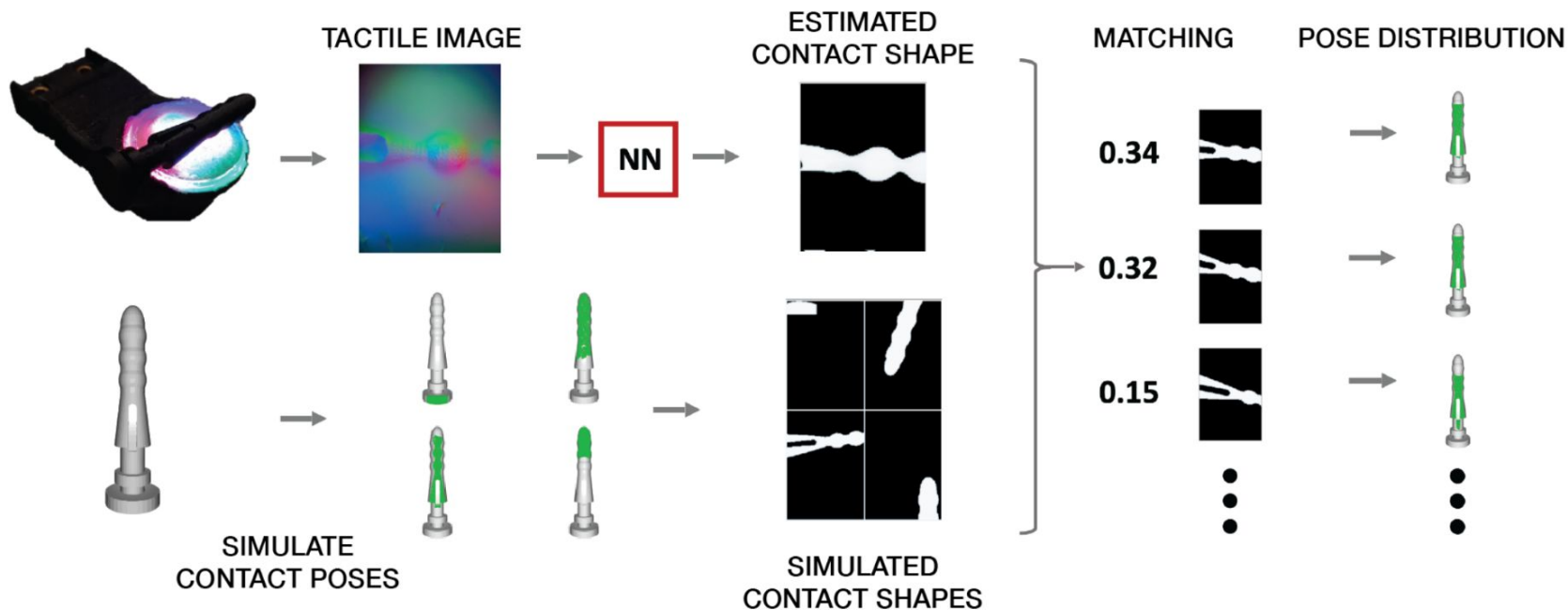
# Methods



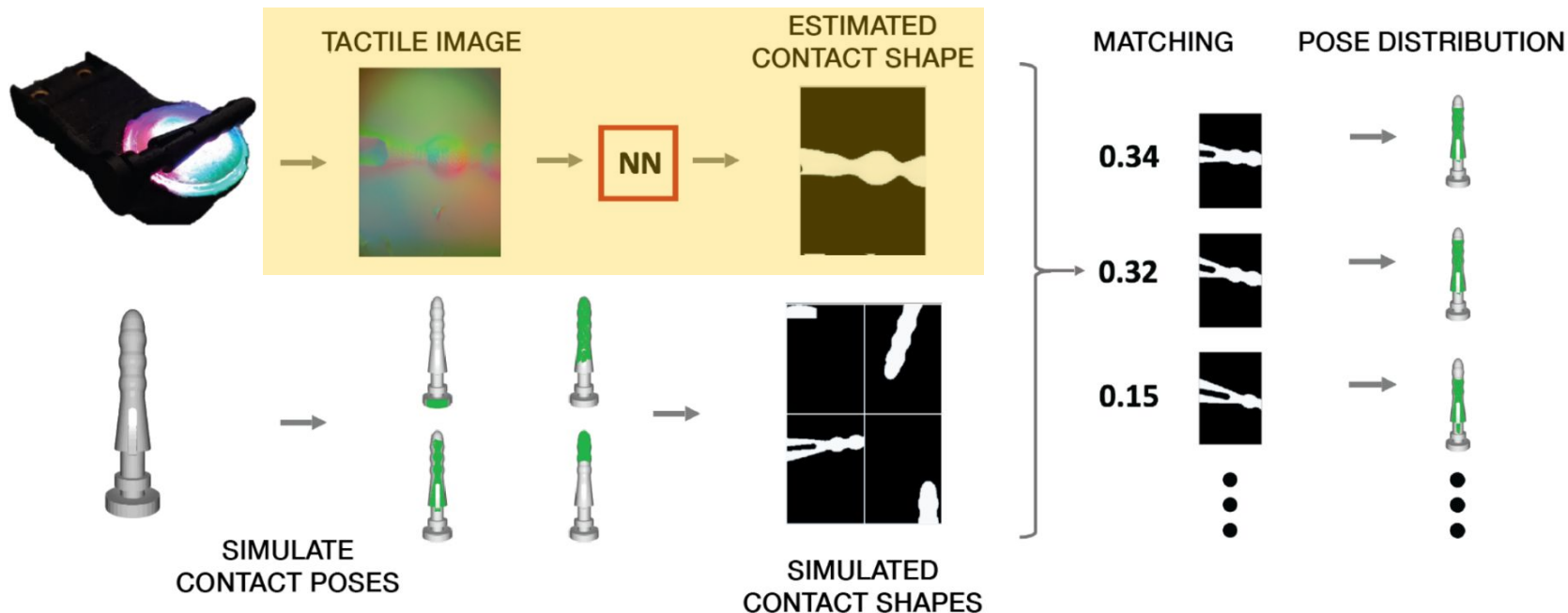
# Methods



# Methods



# Contact Shape Network





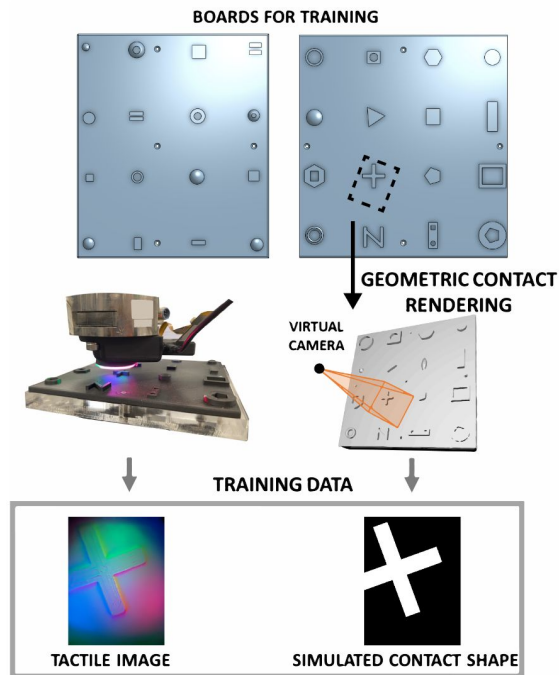
# Contact Shape Network

Known GeSight Pose

- Real image
- Simulated Binary Contact Shape

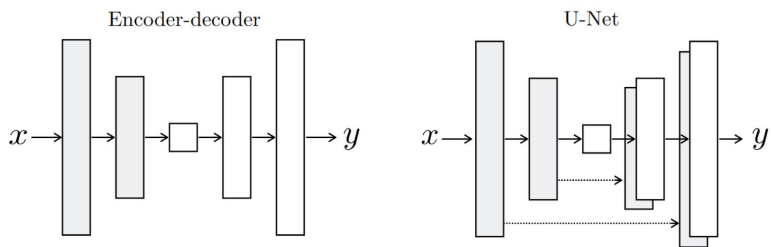
General Enough to work across sensors

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



# Image-to-Image Translation

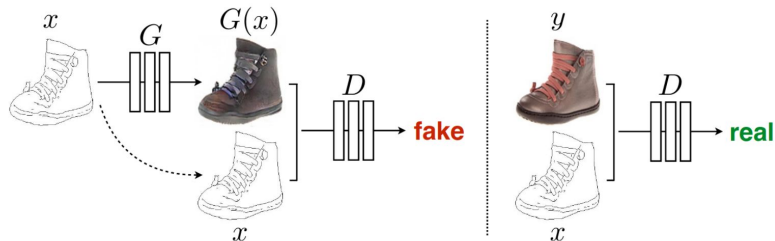
- Input: Real image
  - Output: Estimated Contact Shape
- Trained with ground truth data.



Example: Satellite to Map



Example: Fake shoe to convincing fake shoe



# Image-to-Image Translation

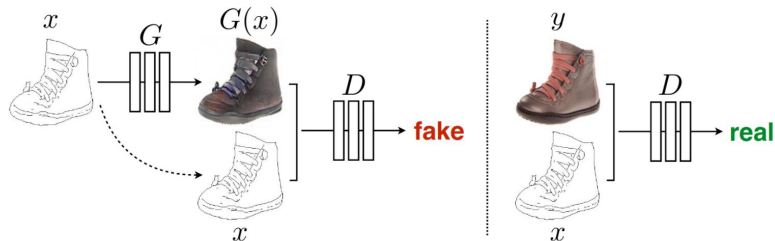
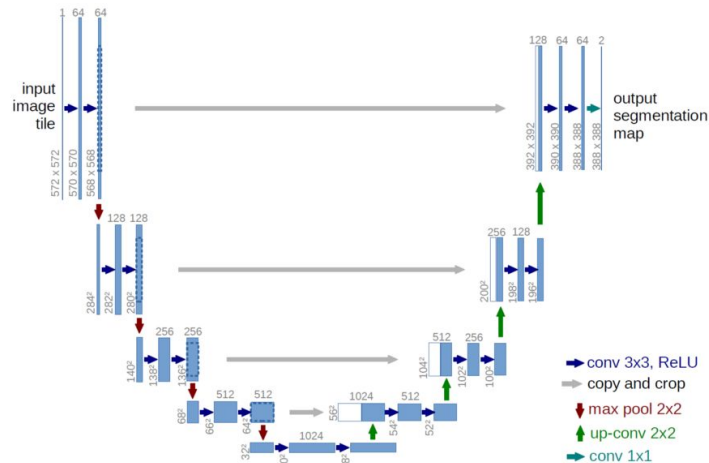
Generator: Creates contact mask  
 Discriminator: Identifies fake images



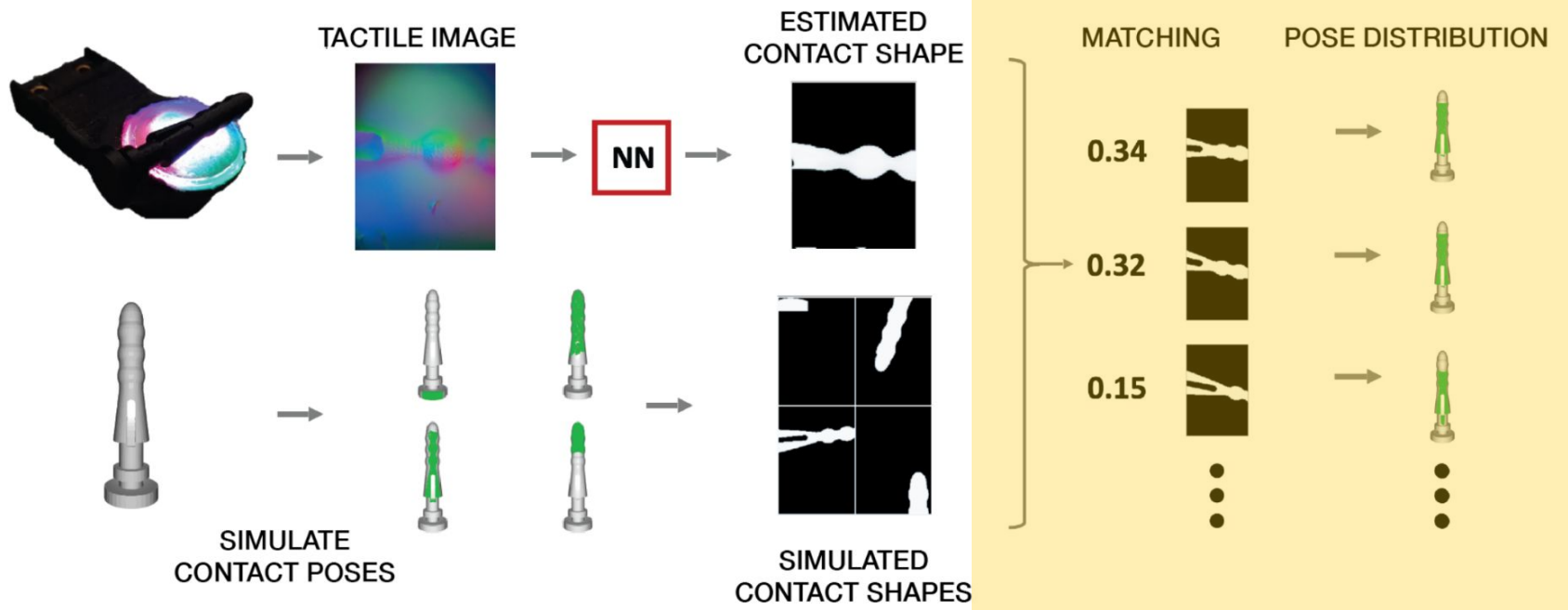
TACTILE IMAGE



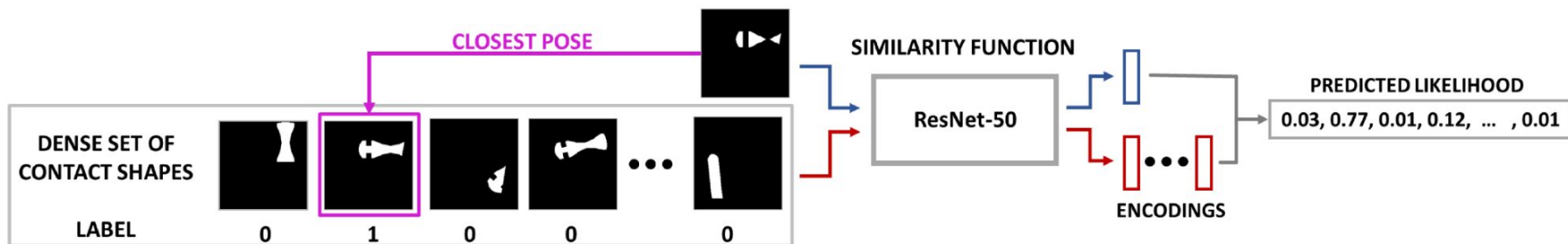
SIMULATED CONTACT SHAPE



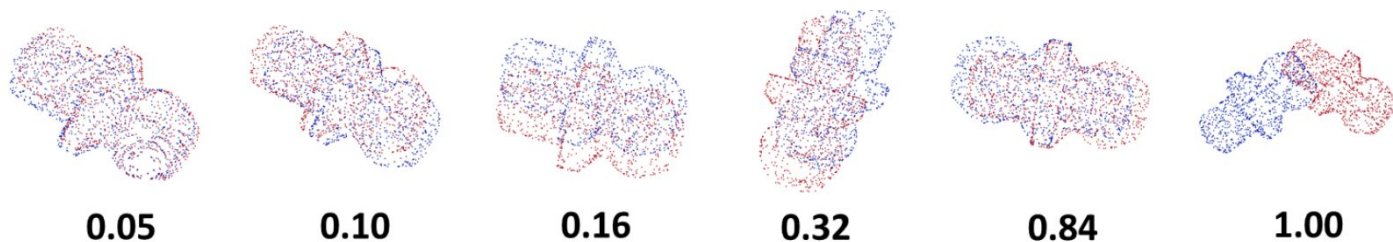
# Pose Matching



# Pose Matching



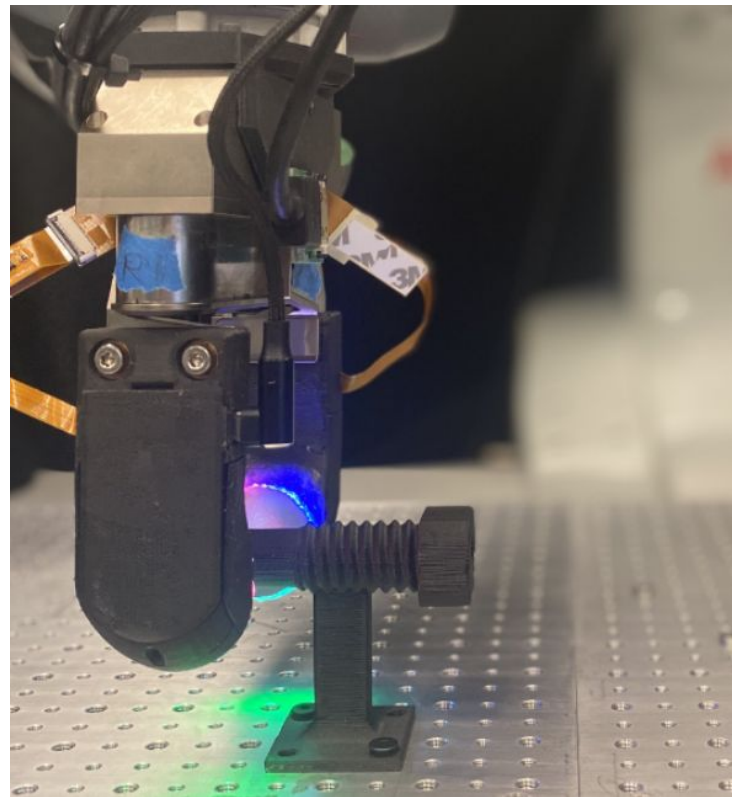
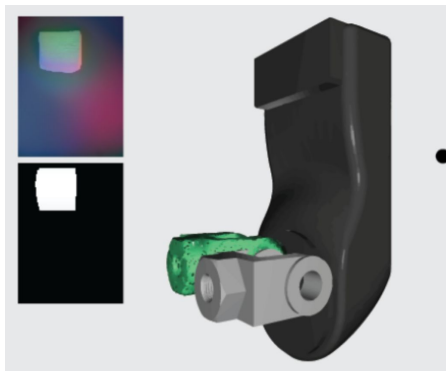
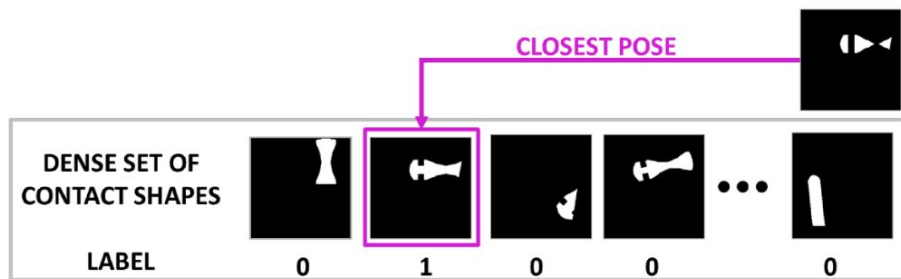
Normalized  
Pose Errors:



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



# Pose Matching



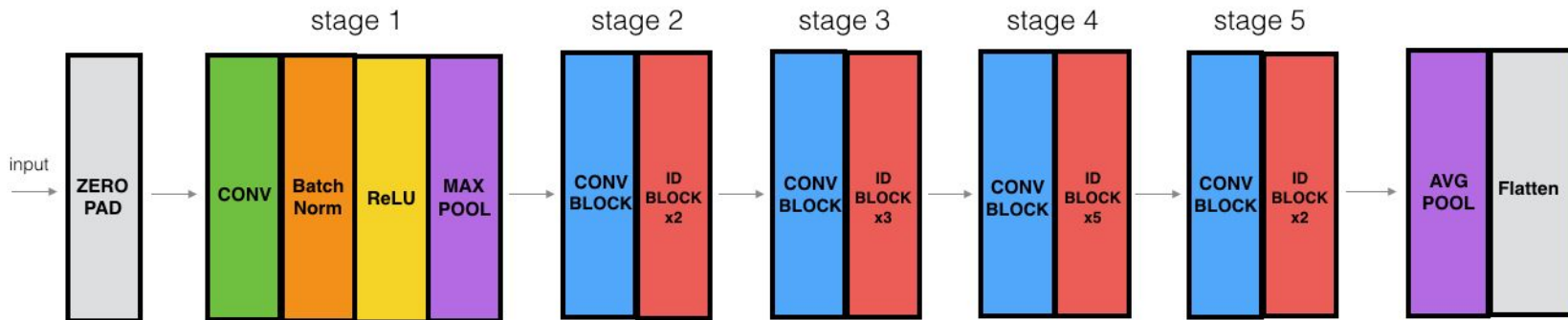
# Pose Matching



Encoder Network:  
Pre-Trained ResNet 50

*Removed Linear Layers*

Trained with: [MoCo](#)



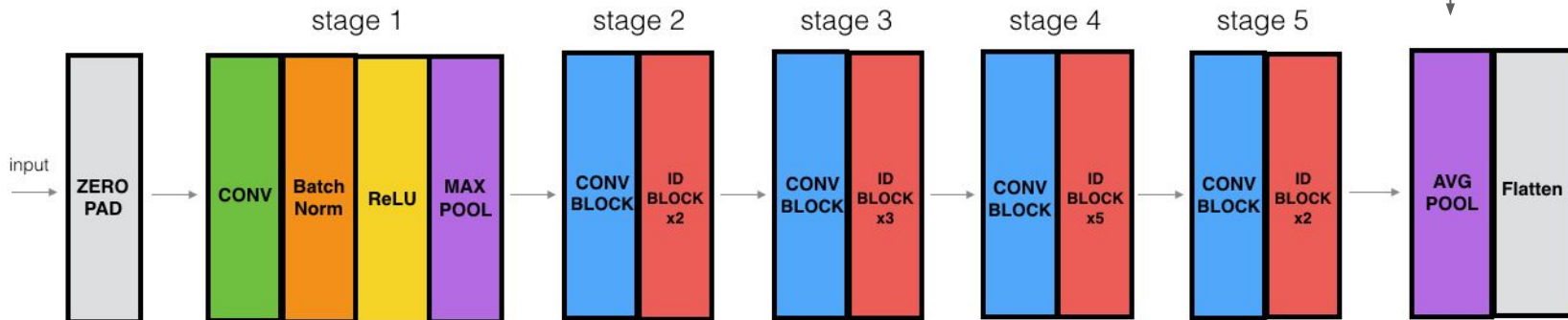
# Pose Matching



It could never be that easy.

The designers this put in an AveragePool!

The AveragePool is removing critical spatial information.





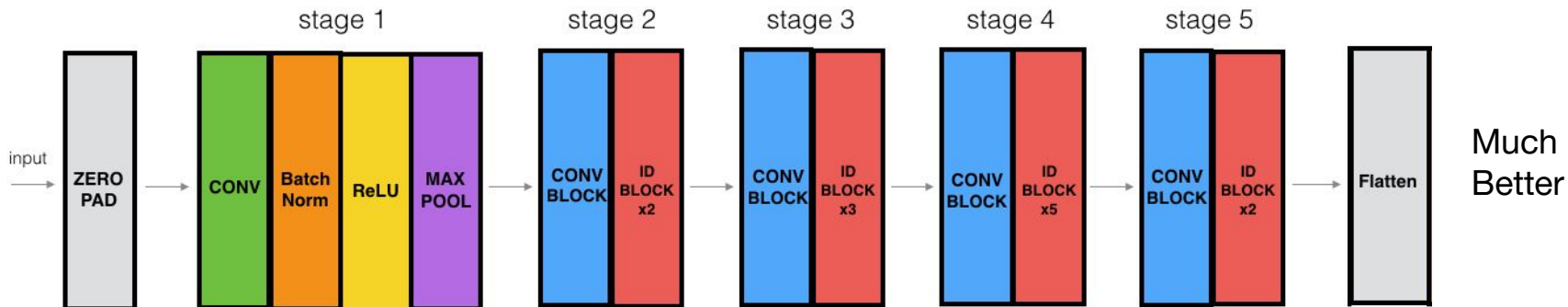
# Pose Matching



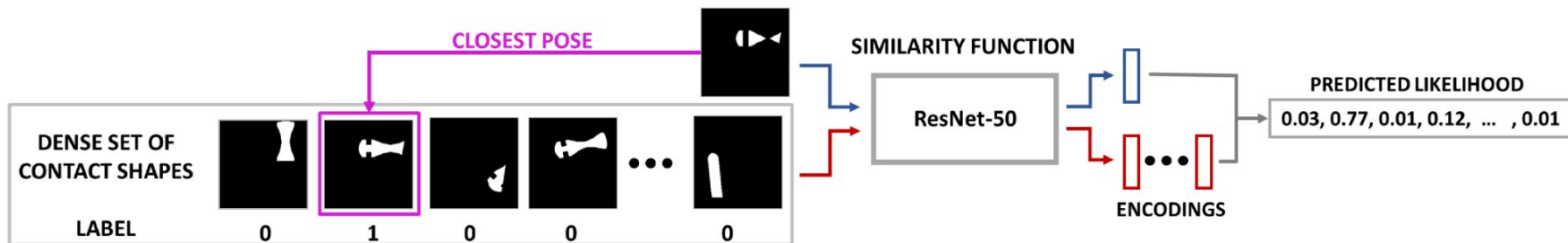
It could never be that easy.

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:  $1 \times S$   
 Encoded simulation mask:  $N \times S$   
 Dot product distances:  $1 \times N$

Probability = SoftMax(Dot product distances)

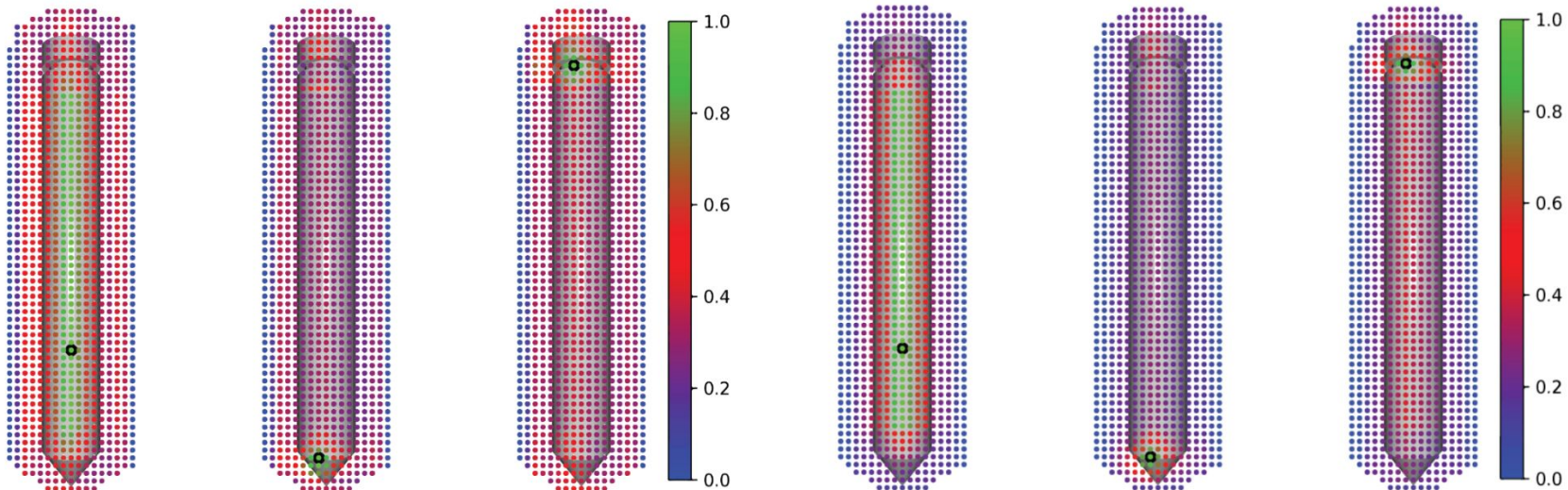


# Look! A pencil, how Fun!

---



# Fun is not allowed



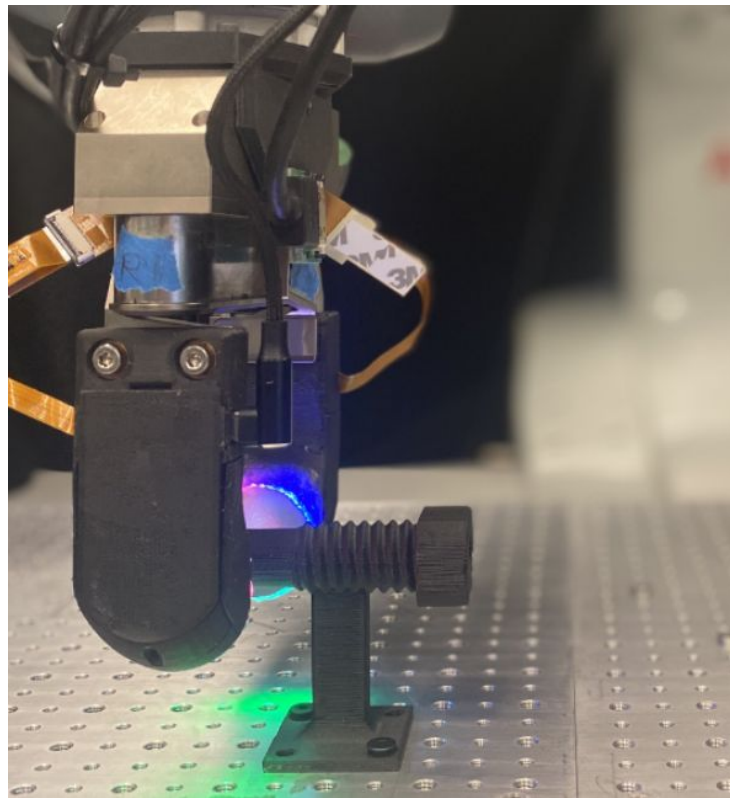
# Pose Distributions



These sensors can be small!

Only a few  $\text{cm}^2$  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

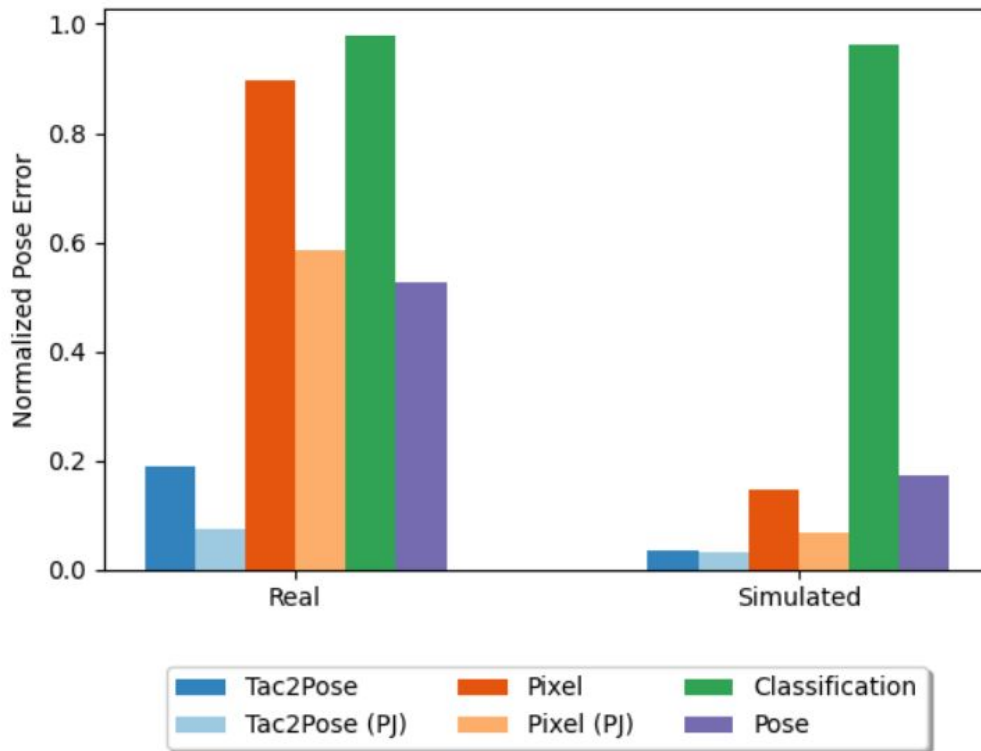
**Tac2Pose:** Method Described above.

**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.*



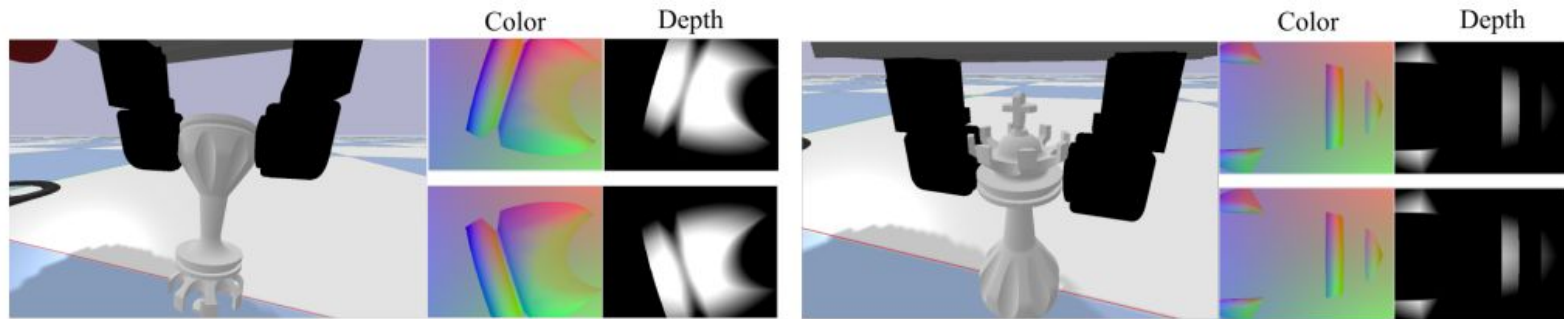
# Comparisons to Other Methods

		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)



**DR**

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

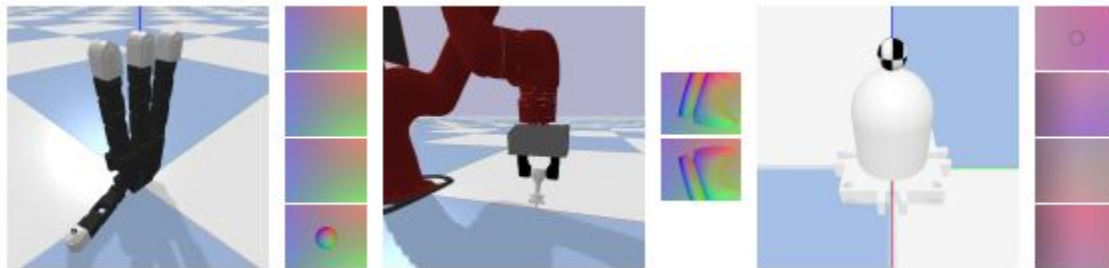


Wang, Shaoxiong, Mike Lambeta, Po-Wei Chou, and Roberto Calandra. *IEEE Robotics and Automation Letters* 7, 2022



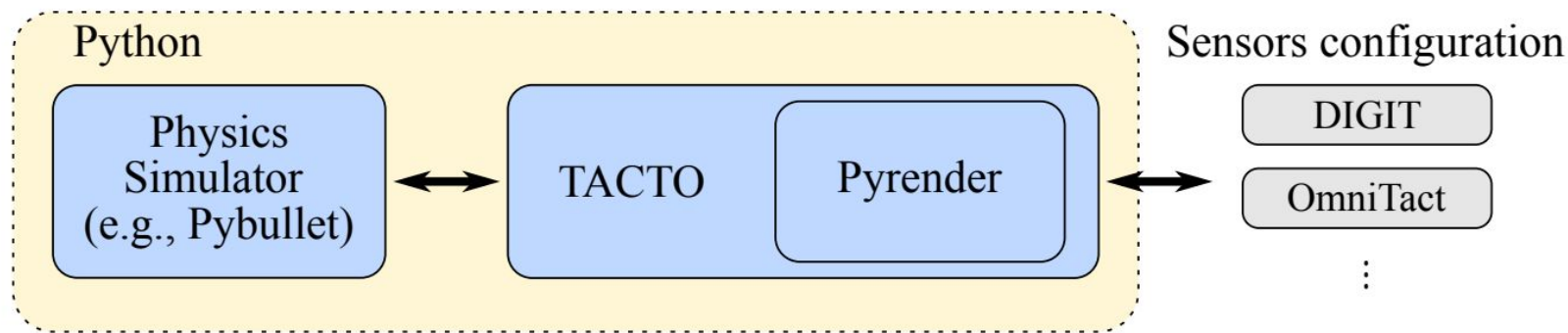


# Motivation



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

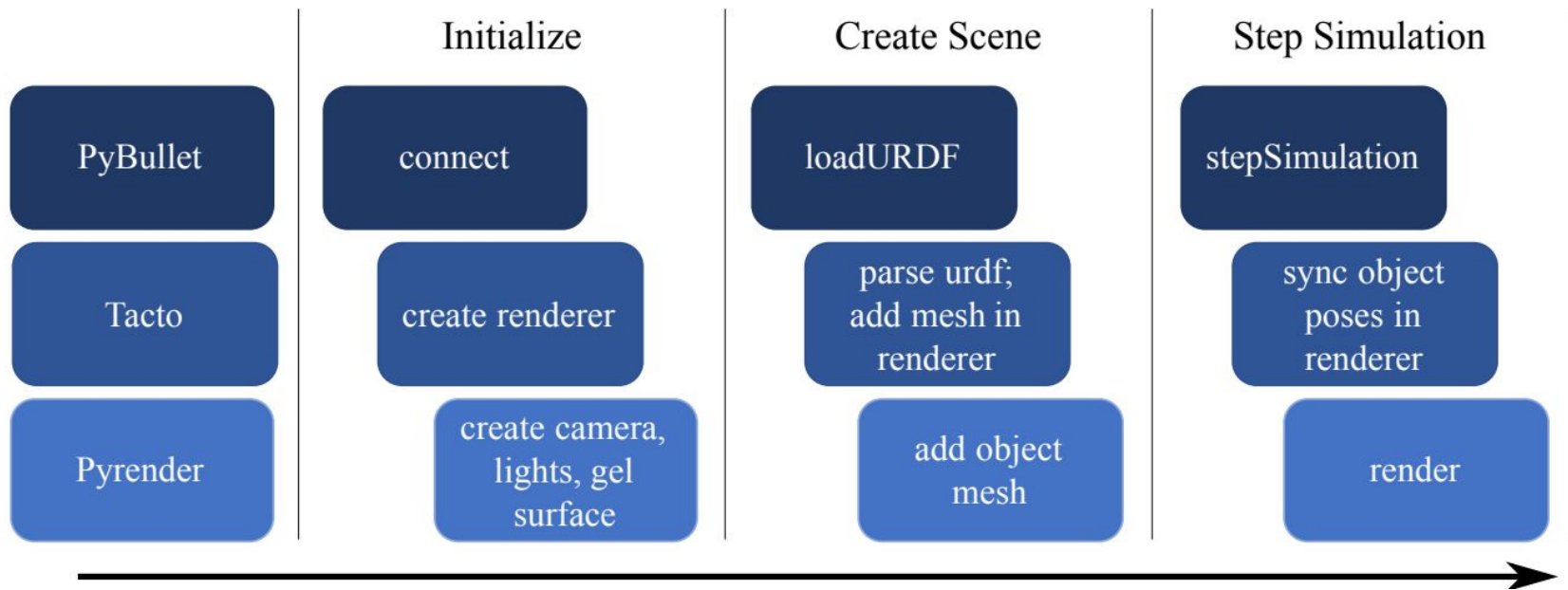
# Methods



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



# Software Architecture



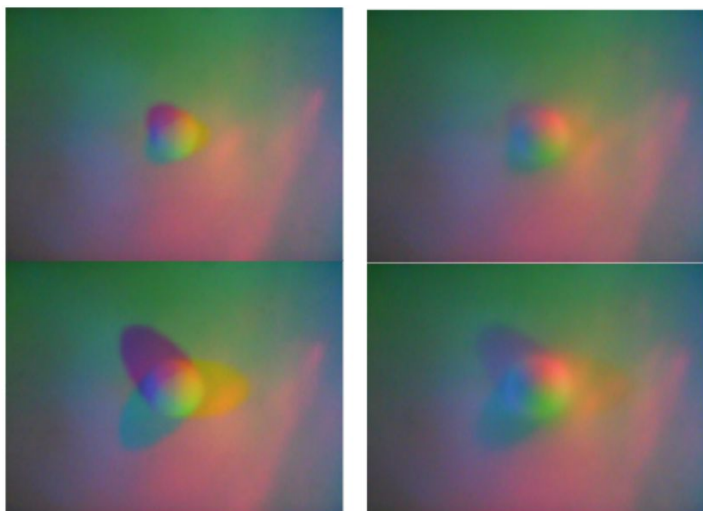
Wang, Shaoxiong, et al. *TACTO: A Fast, Flexible, and Open-Source Simulator for High-Resolution Vision-Based Tactile Sensors*. 2020.



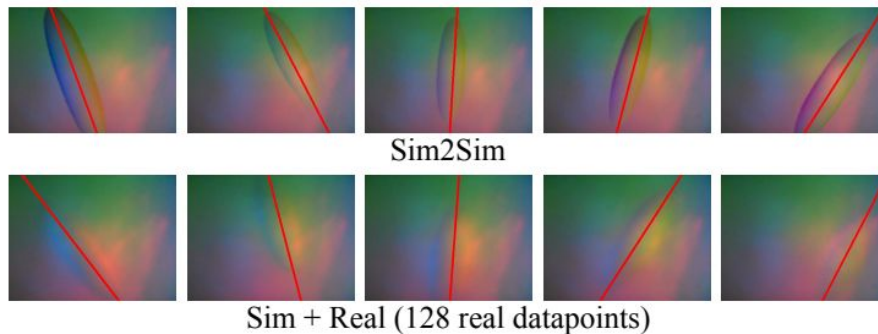
# Sim vs Real

Sim

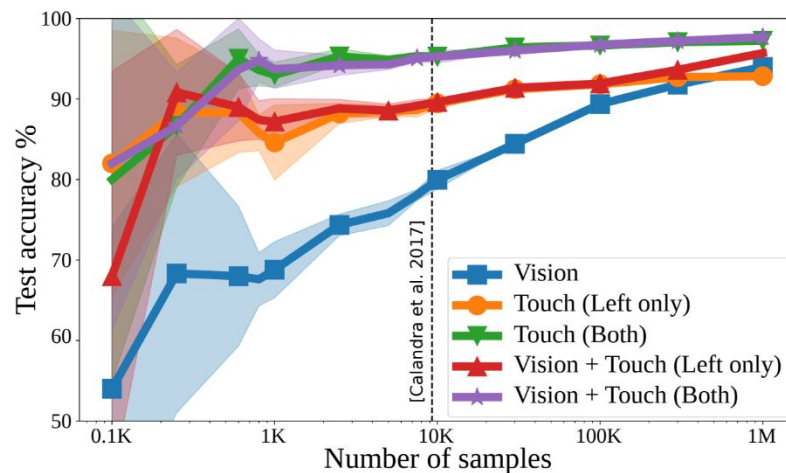
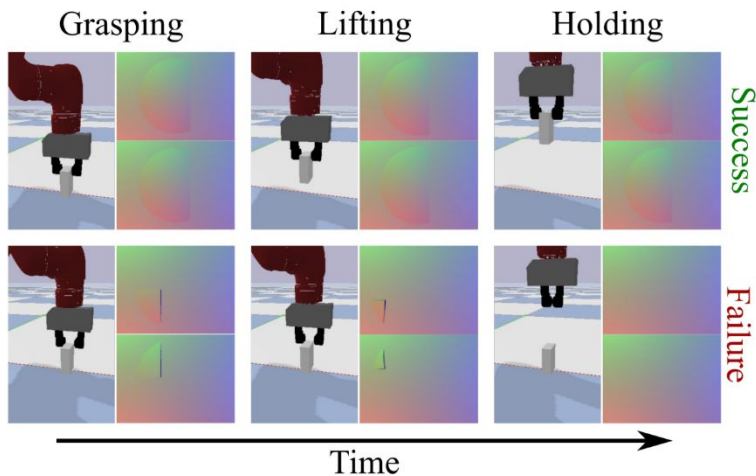
Real



Pose estimation results



# Results

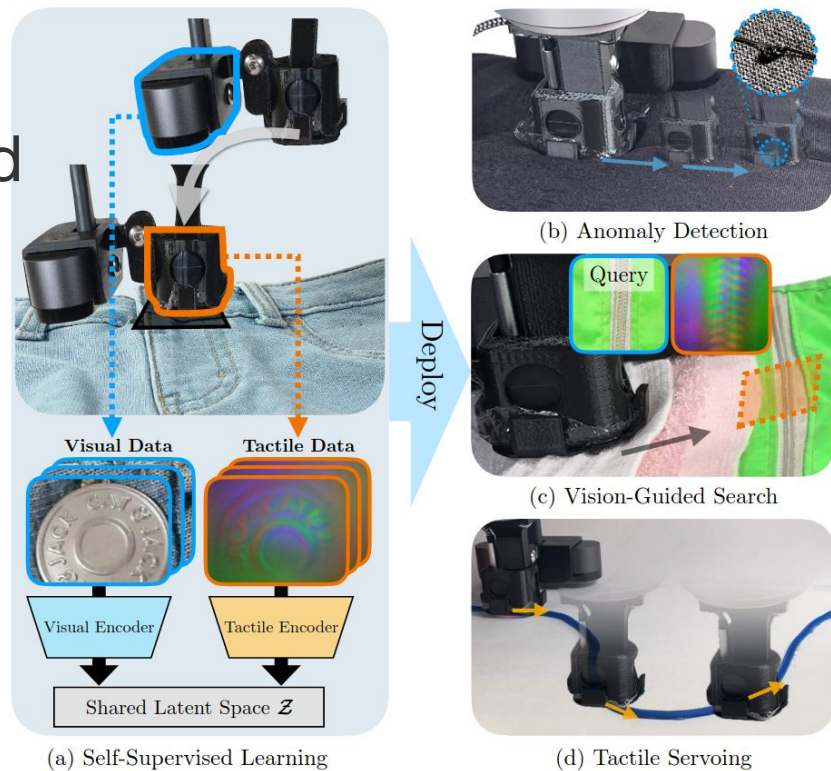


Wang, Shaoxiong, et al. *TACTO: A Fast, Flexible, and Open-Source Simulator for High-Resolution Vision-Based Tactile Sensors*. 2020.

**Questions?**

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

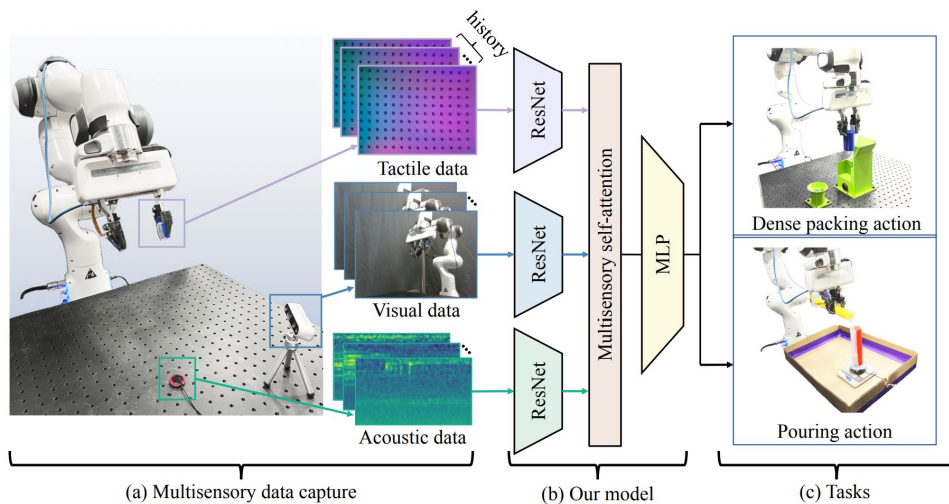
- Align visual and tactile data
  - Train encoders to embed into a shared latent feature space.
  - Uses cross-modal contrastive loss
  - Object agnostic representation.



Kerr et al. (ICRA 2023)

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

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

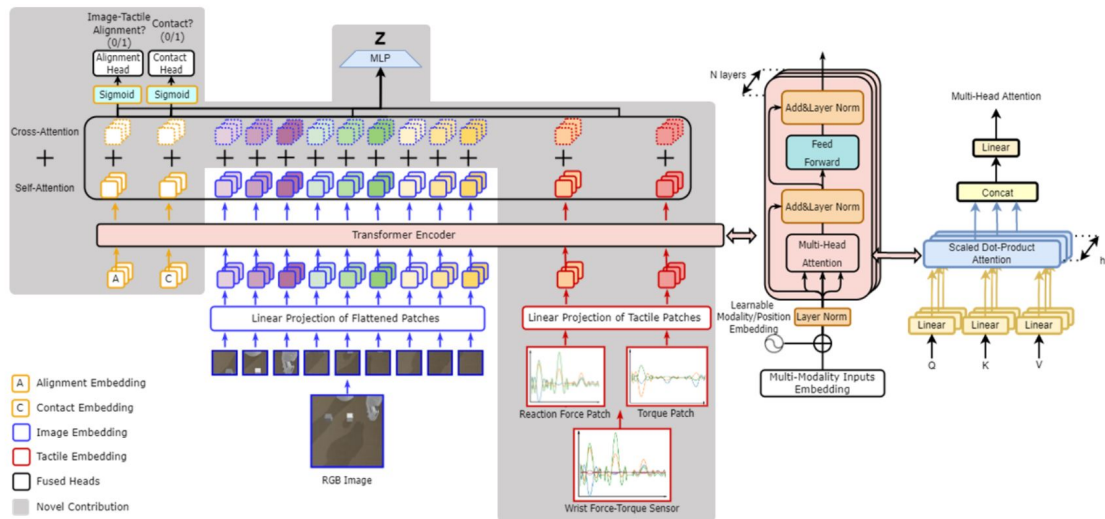


Li, Hao, et al. *See, Hear, and Feel: Smart Sensory Fusion for Robotic Manipulation..*  
DOI.org (Datacite), <https://doi.org/10.48550/ARXIV.2212.03858>.



# 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

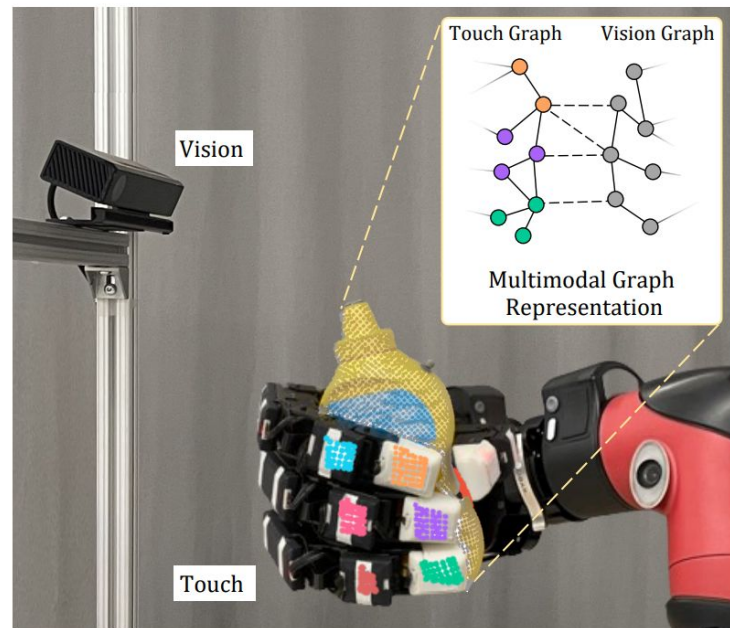


<https://arxiv.org/abs/2210.00121>

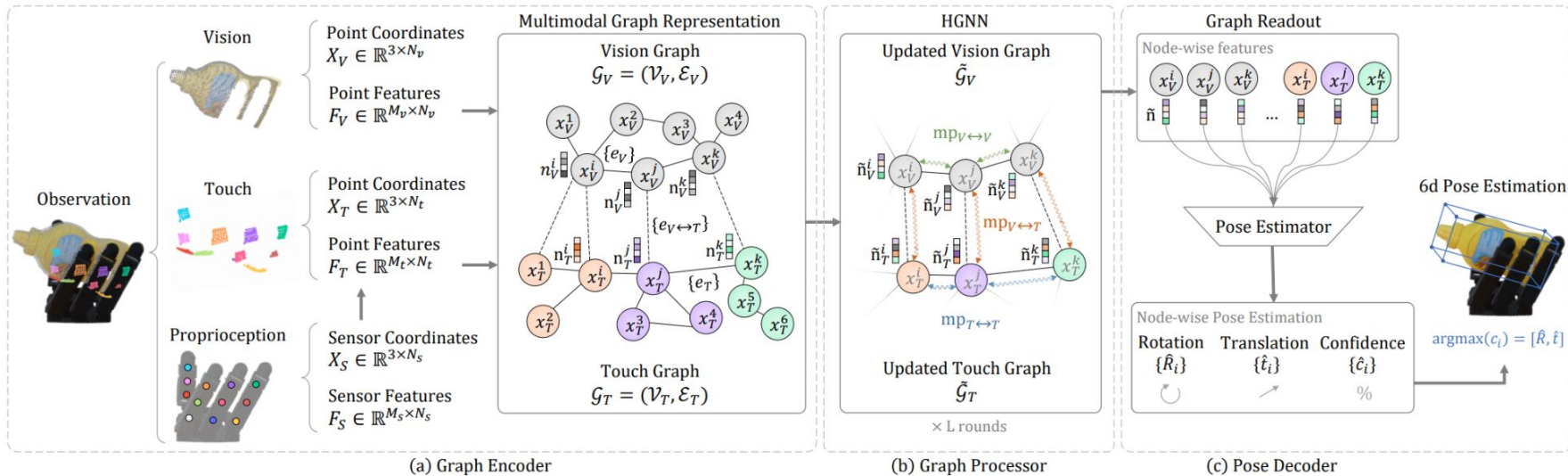
$$\ell_{VTT} = BCE_{logits}(MLP(Al_{head}), Al_{gt}) + BCE_{logits}(MLP(C_{head}), C_{gt})$$

# 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

$$L_i^n = \frac{1}{P} \sum_{p=1 \dots P} \|(R_{gt} x_p + t_{gt}) - (\hat{R}_i x_p + \hat{t}_i)\|$$

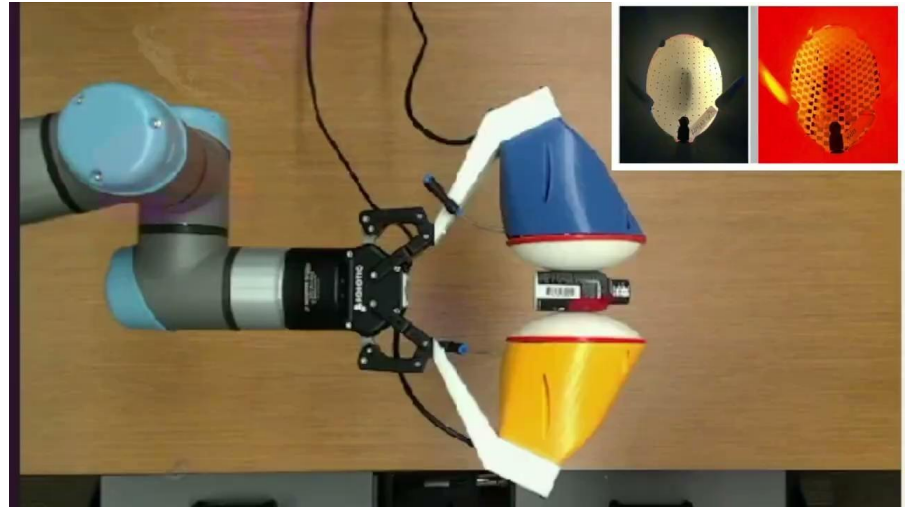
Total loss

$$\longrightarrow L = \frac{1}{K} \sum_{i=1 \dots K} (L_i^n \hat{c}_i - \lambda \log(\hat{c}_i))$$



# Recap

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



**Questions?**