

# Robust Grasping by Integrating Machine Learning with Physical Models

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<http://biorobotics.harvard.edu/research.html>

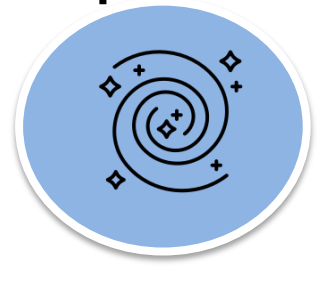
## Abstract

**Contact sensing** is essential for reliable robotic grasping in unstructured environments, but existing methods have not been effective, and requirements for effective sensors are unknown. This project aims to establish the foundation for effective grasp stability prediction and control by developing new ways to integrate machine learning with physical sensor models. **Physical sensor models** will be characterized in grasping experiments and validated against **independent ground truth** measurements. Physical models based on mechanical principles (grasp analysis) will be augmented using **parametric and nonparametric machine learning methods**, allowing interpretability and generalizability. Analysis of these models will guide the creation of a new sensor suite that, together with the carefully-crafted models, will form the basis for reliable robotic grasping systems.

## Intellectual Merit



Interpretability

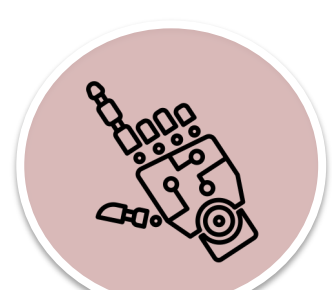


Generalizability

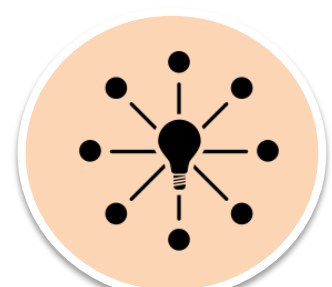


Clarify Hardware Requirements

## Broader Impacts



Reliable Robot Grasping

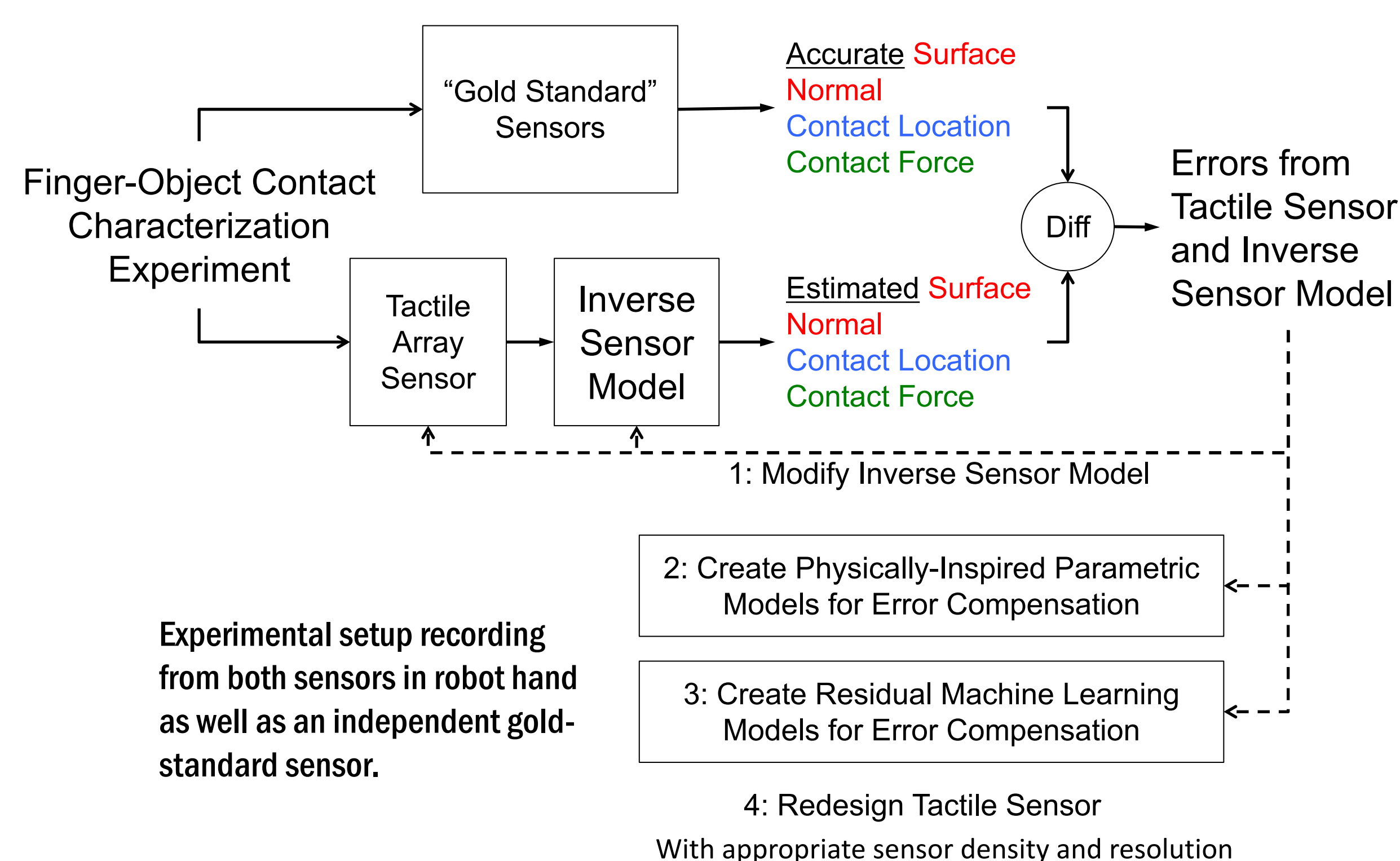


Data & Design Made Available

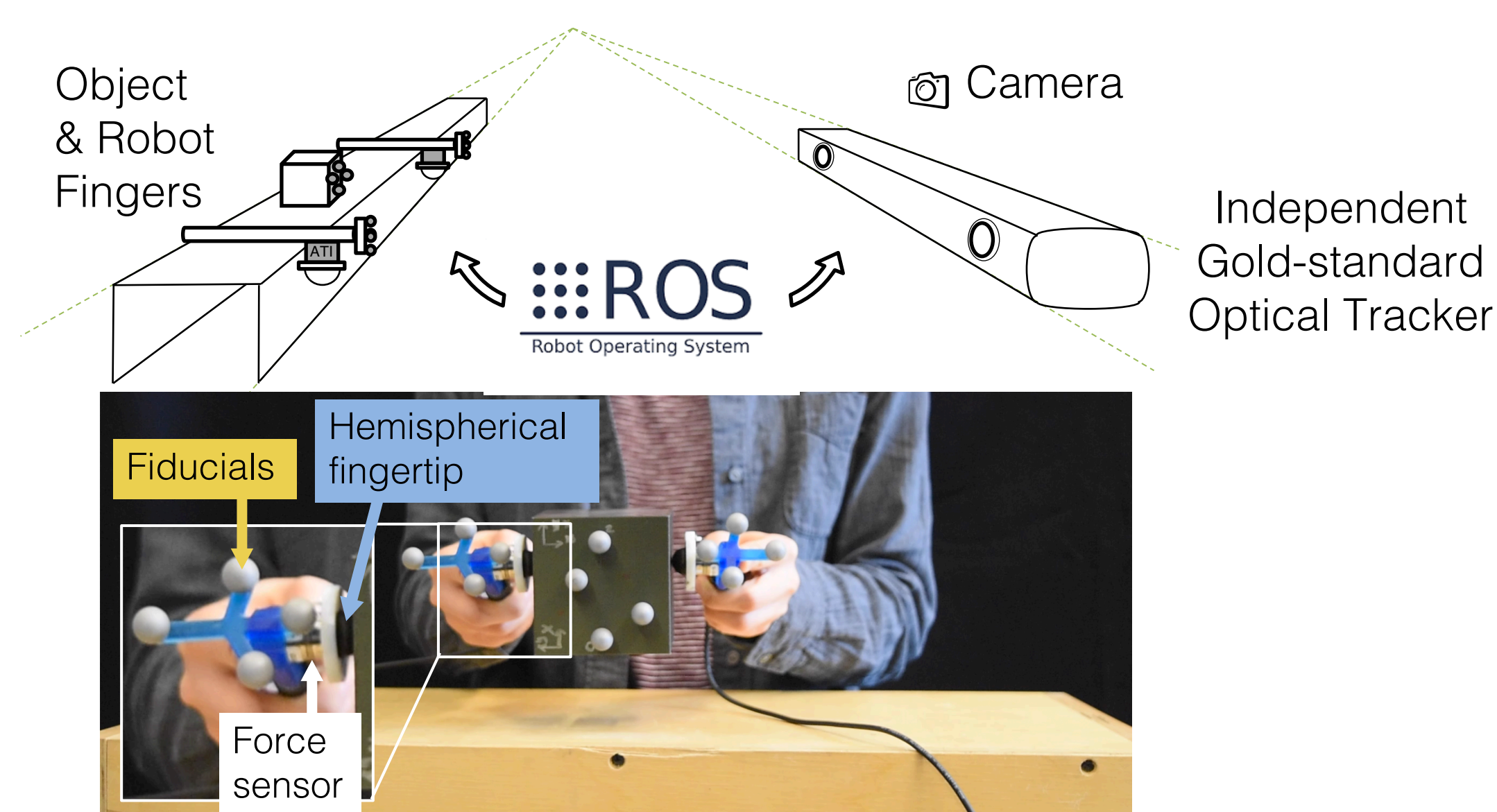


Undergraduate Involvement

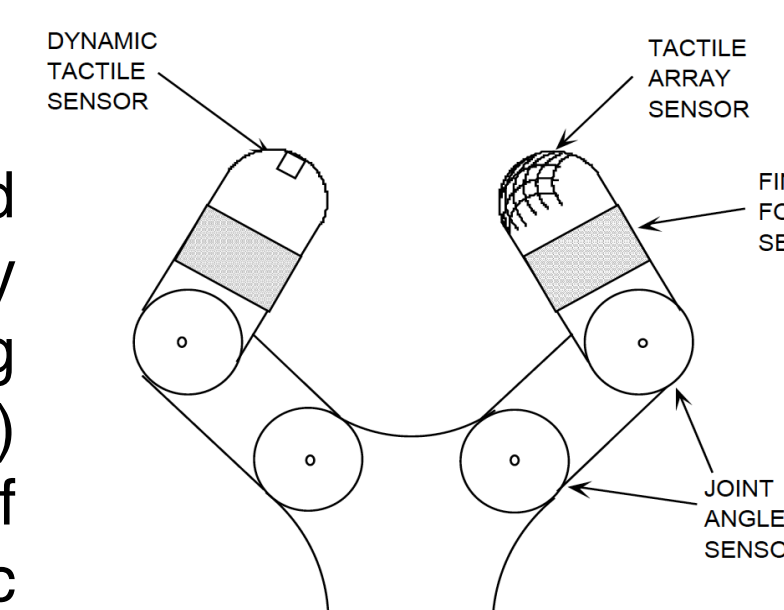
## Technical Approach



## Experimental Setup



The experimental setup includes two hand-held robot fingers with high accuracy force/torque sensors and fiducials for position tracking, an object with fiducials for position tracking, high accuracy position tracking device, and a webcam. All sensor data collection is connected and synchronized through ROS.



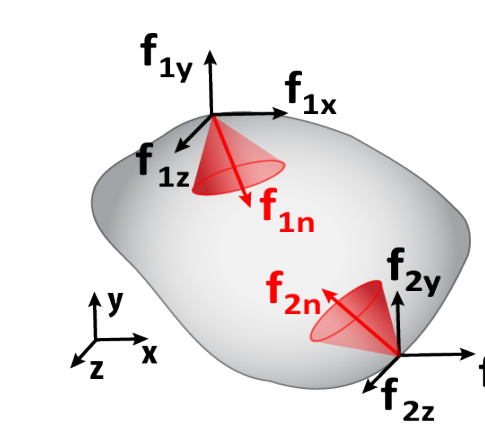
### Sensor Signals

- Tactile Array
- Force-Torque
- Joint Angles

### Inverse Sensor Model

### Physically-Inspired Parametric Model

### Residual Machine Learning

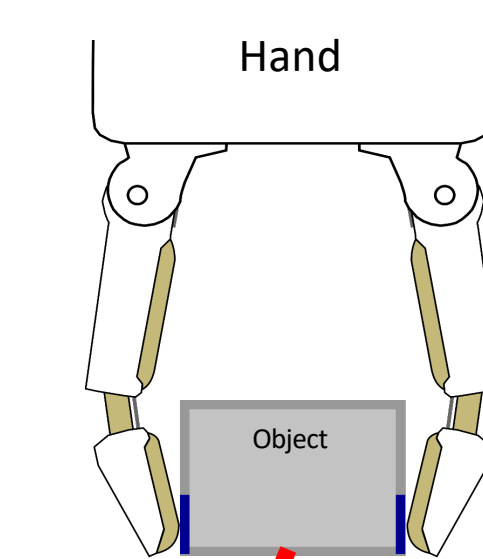


- ### Grasp Parameters
- Contact Locations
  - Surface Normal
  - Contact Forces

### Grasp Stability Model

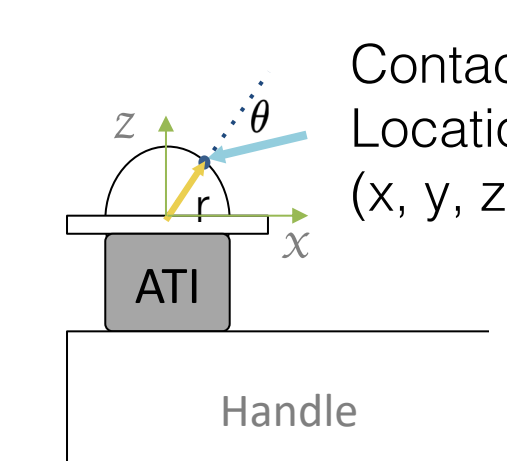
### Physically-Inspired Parametric Model

### Residual Machine Learning



- ### Grasp Stability Prediction
- Grasp Quality
  - Maximum Task Wrench

## Grasp Parameters Estimation Method



Contact Location  $(x, y, z)$

$$\begin{cases} x^2 + y^2 + z^2 = r^2 \\ \vec{\tau} = \vec{p} \times \vec{f} \end{cases}$$

$$\vec{p} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}, \vec{f} = \begin{bmatrix} F_x \\ F_y \\ F_z \end{bmatrix}, \vec{\tau} = \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix}$$

For Contact Location: Solve for  $\vec{p} = \begin{bmatrix} x \\ y \\ z \end{bmatrix}$

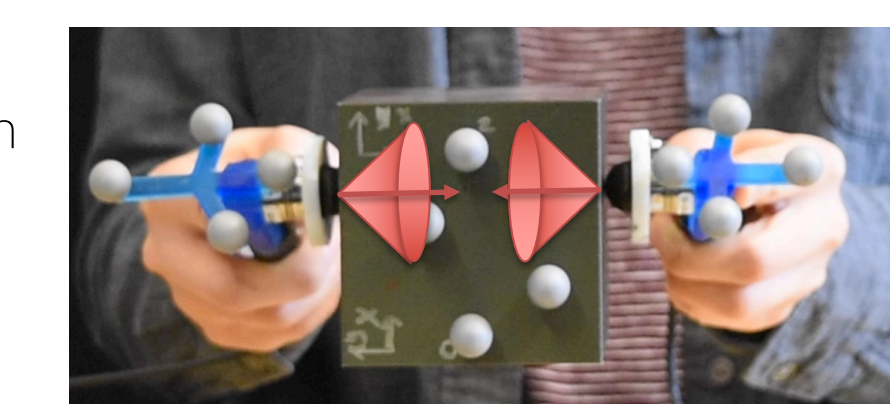
For Surface Normal: Solve for  $\vec{n} = \frac{\vec{p}}{|\vec{p}|_2}$

Contact location is estimated based on intrinsic sensing (Salisbury 1984<sup>[1]</sup>). Due to the hemispherical fingertip, surface normal is the direction from the center of the hemisphere to the contact location. Contact wrench is directly measured from force/torque sensor (ATI) with high precision.

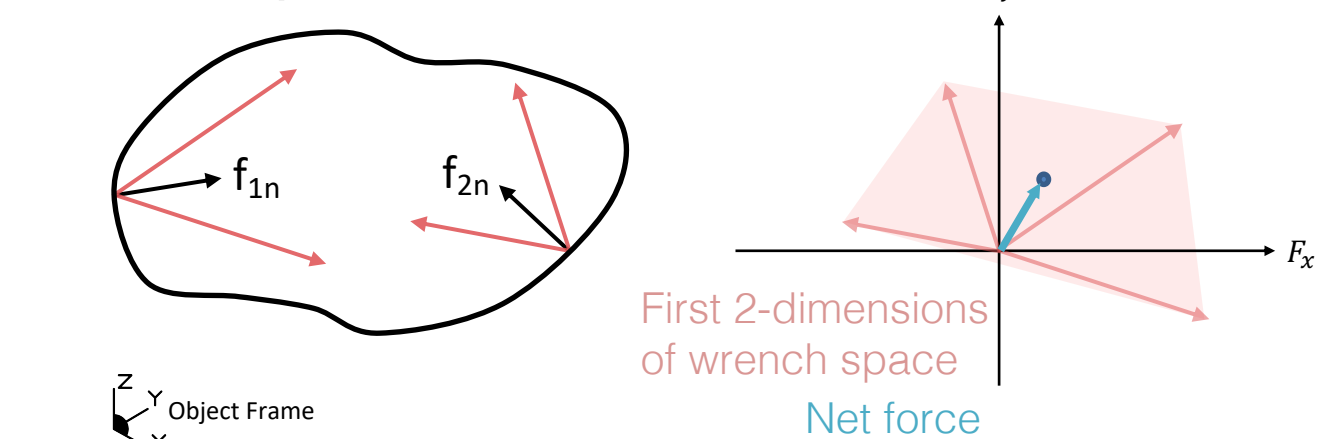
## Grasp Analysis

$$G = \text{Convex Hull}(\bigoplus_{i=1}^n \omega_{i,1}, \dots, \omega_{i,m}), \omega_i = [\vec{f}^T, \vec{\tau}^T]^T: \text{wrench}$$

Grasp quality  $G$  can be evaluated via Grasp Analysis (Ferrari and Canny 1992<sup>[2]</sup>) using grasp parameters as estimated above.

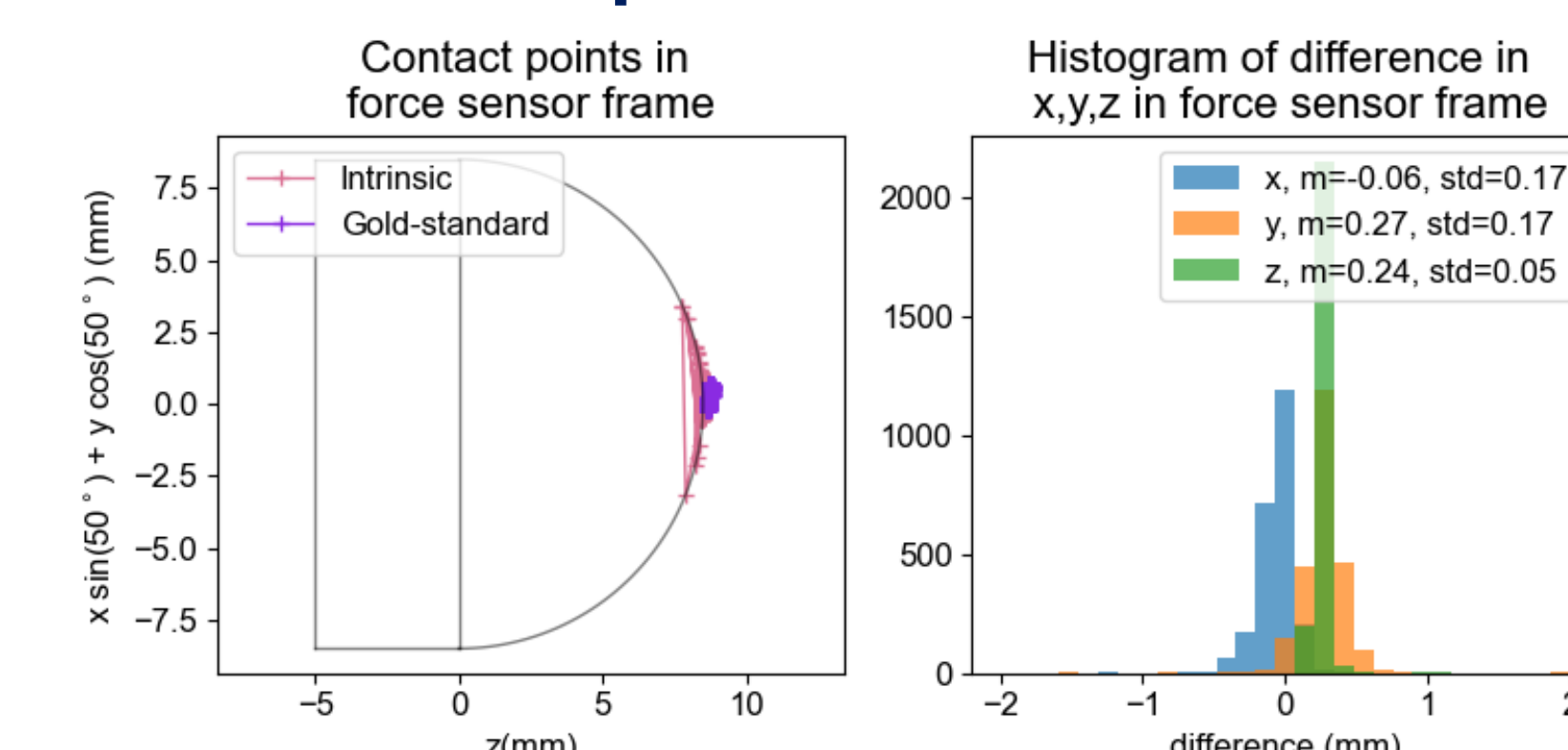


### 2D Example:



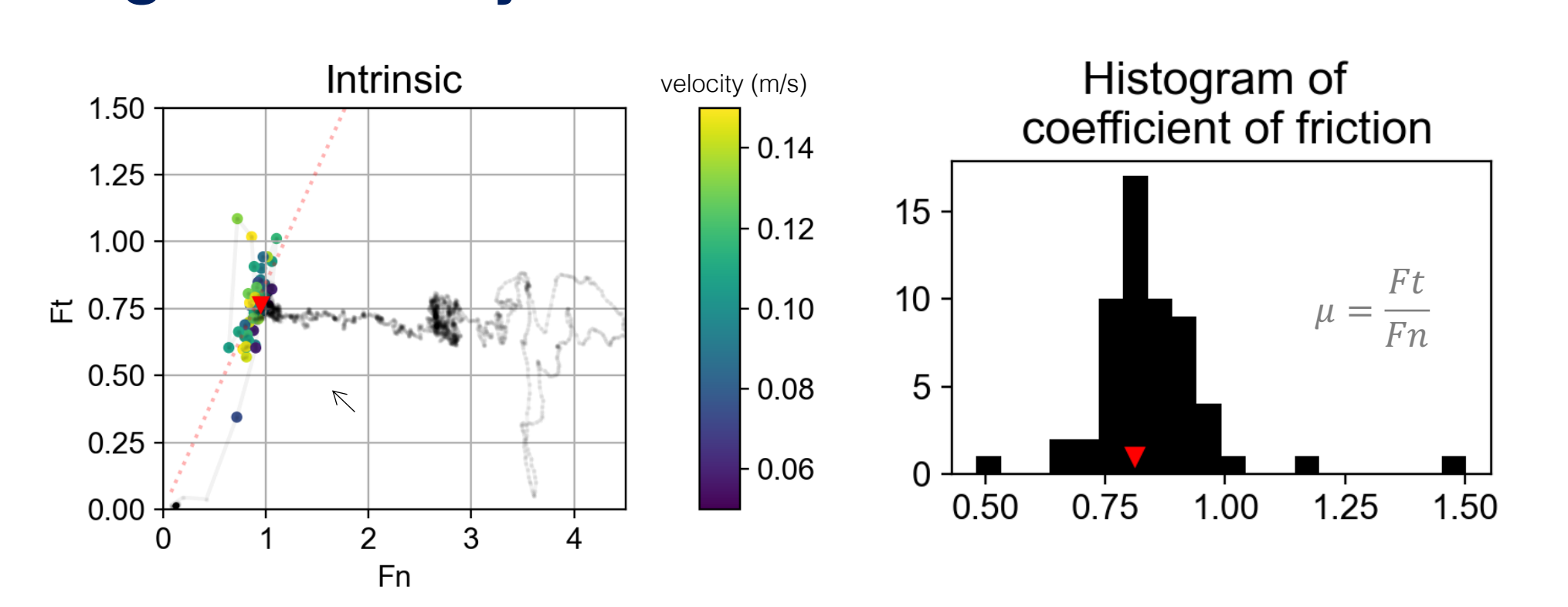
## Results

### Accurate Grasp Parameters Estimation



Estimating grasp parameters contact location and contact surface normal via intrinsic sensing (Salisbury 1984<sup>[1]</sup>), as shown above. Validation results show high estimation accuracy.

### High variability in coefficient of friction



By evaluating tangential vs. normal force during a slip, analysis show that the coefficient of friction is highly variable, indicating sources of error when assuming Coulomb's Law of Friction.

### Next Steps

- Using grasp analysis for to predict onset of slip relies on accurate coefficient of friction, which is shown highly variable.
- To account for variability in coefficient of friction, machine learning can efficiently learn the coefficient friction as a multivariable function.
- This method can retain interpretability when the grasping condition becomes increasingly complex by building a ROC curve that maximizes AUC by setting a threshold to the distance from the net force in wrench space to the nearest hyperplane in the convex hull in grasp analysis.

Reference: [1] Salisbury, J., 1984, March. Interpretation of 'contact geometries from force measurements. In Proceedings, 1984 IEEE International Conference on Robotics and Automation (Vol. 1, pp. 240-247). IEEE.  
 [2] Ferrari, C. and Canny, J.F., 1992, May. Planning optimal grasps. In ICRA (Vol. 3, pp. 2290-2295).