



Learning Gentle Grasping from Human-Free Force Control Demonstration

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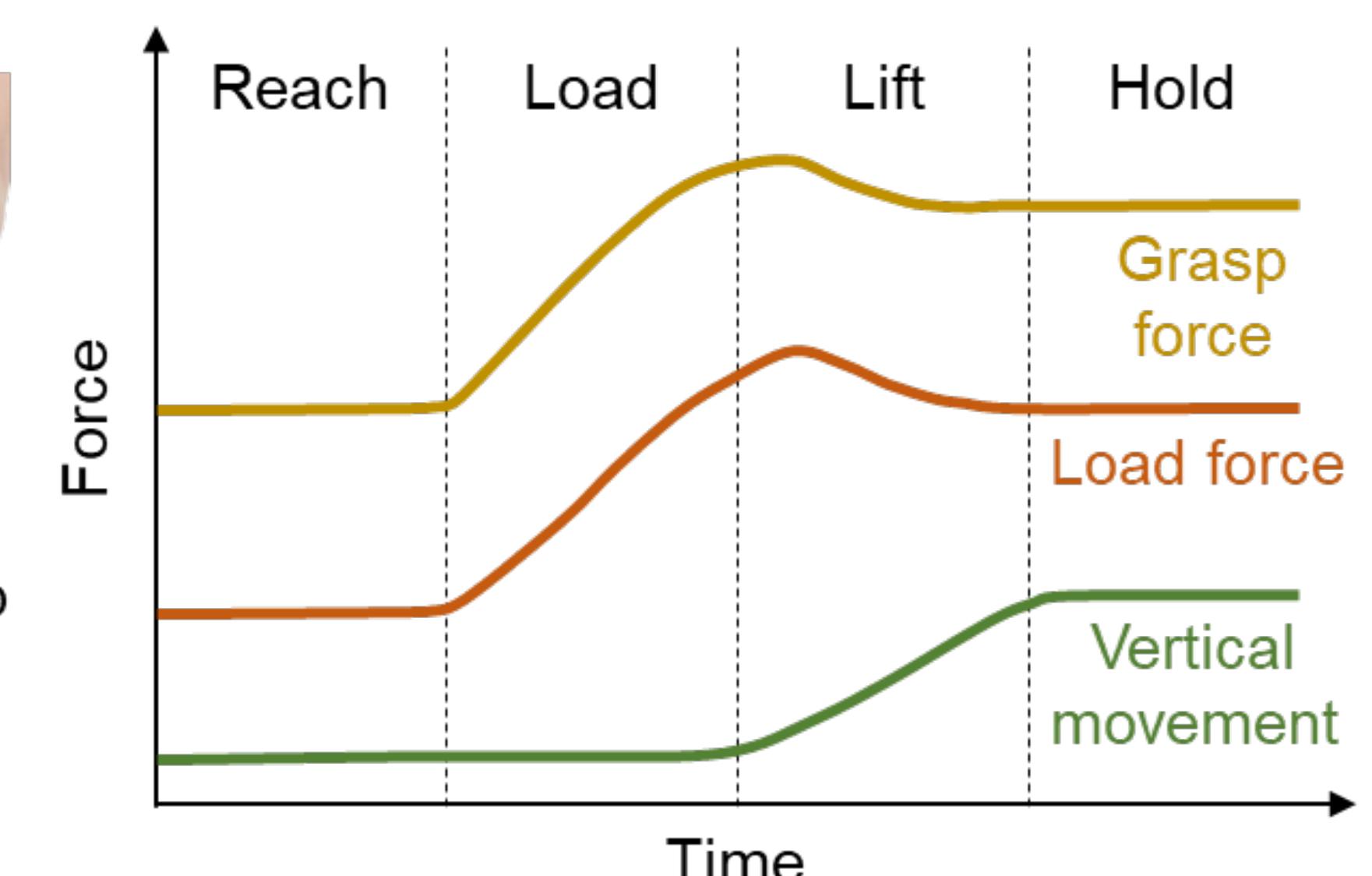
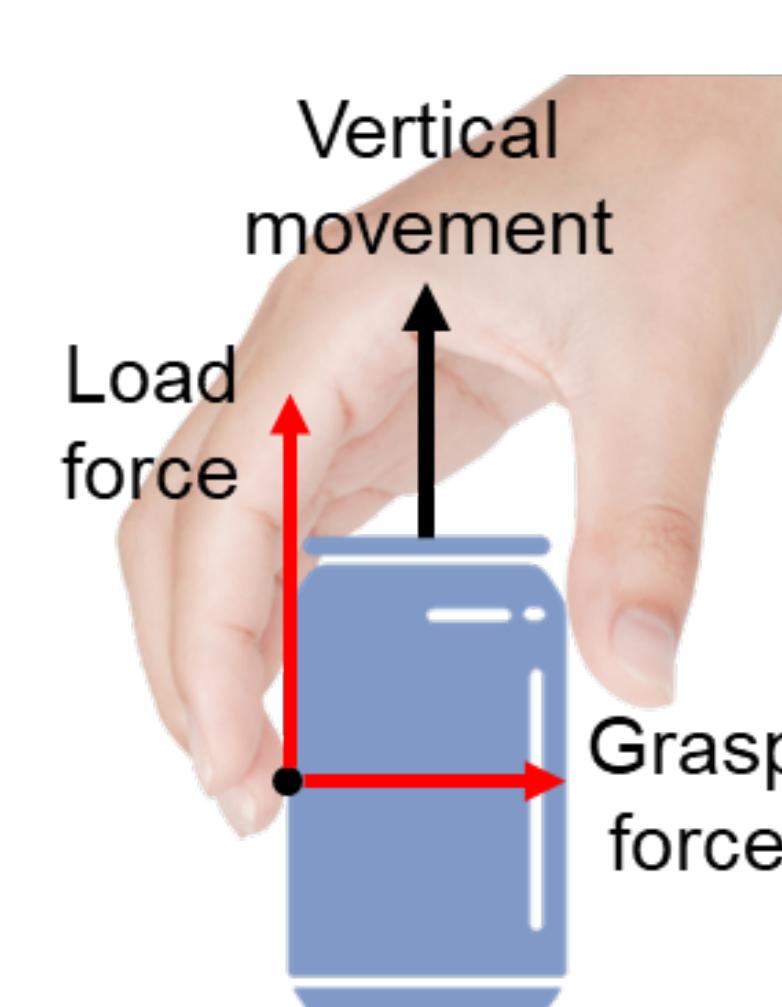
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Motivations

Human gentle grasping: Humans can **stably and safely grasp unfamiliar objects** based on tactile perception.

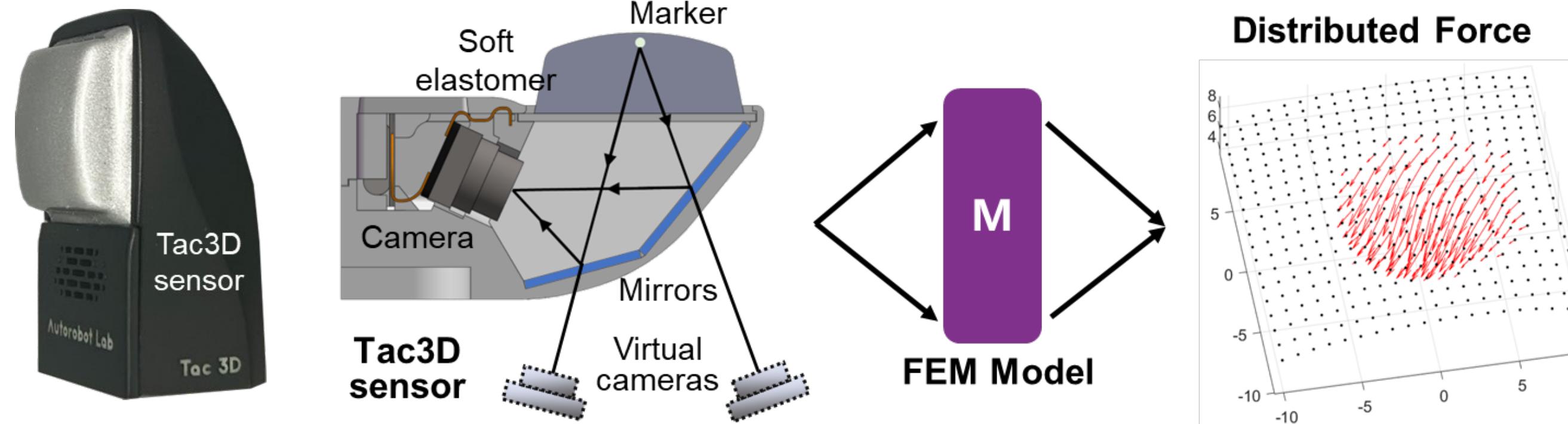
- ✓ **Stability boundary:** The force should **not be too small** to avoid object slip (above the minimum force)
- ✓ **Safety boundary:** The force should **not be too large** to prevent damage (typically no more than 60%).

Challenges for robots: Learning accurate grasp-force predictions and control strategies that **can be generalized from limited data**.



Methodology

Tactile Sensing and Force Reconstruction:



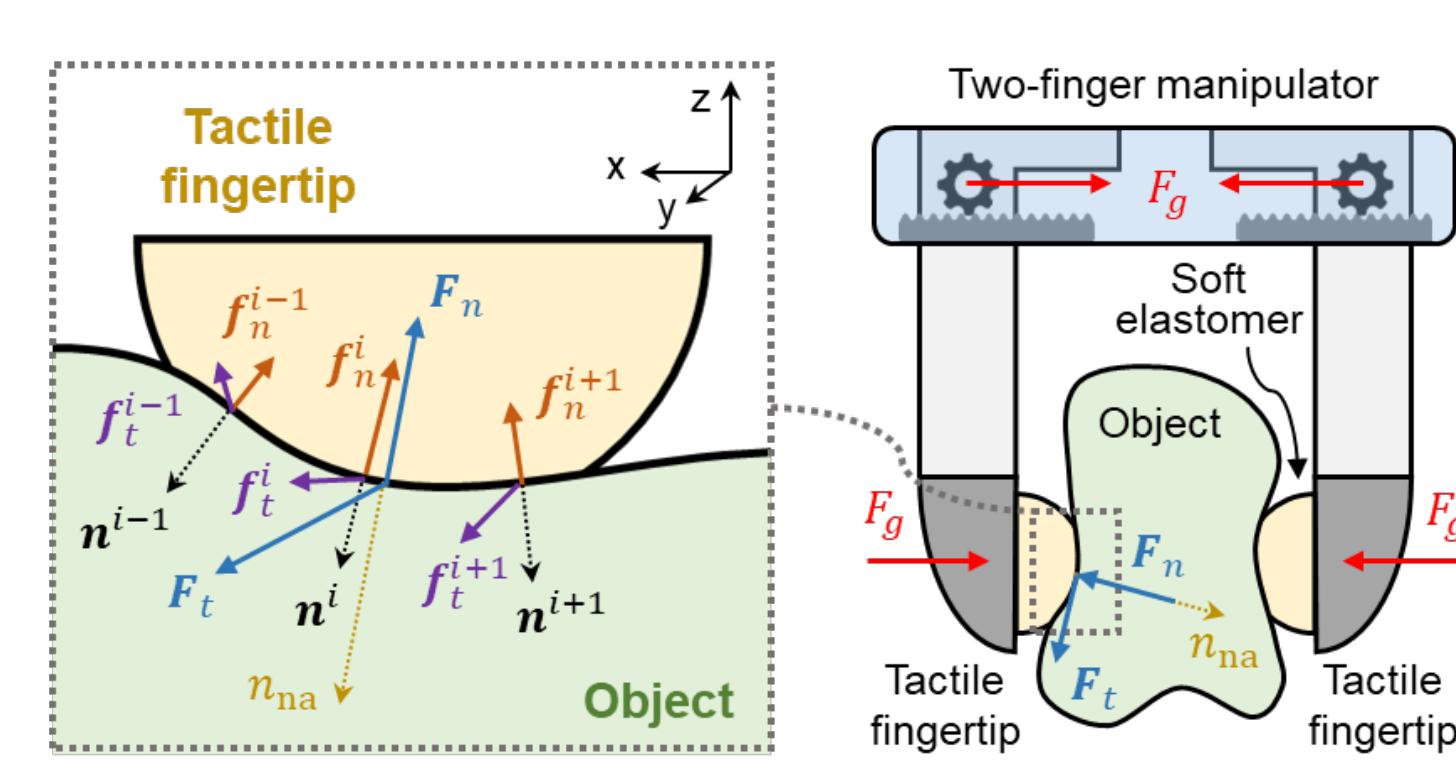
Generation of Force Control Demonstrations:

• **Micro-element resultant forces**

$$F_{MER,n} = \int_S \|f_n^i\| \cdot dA = \int_S \|(f^i \cdot n^i) \cdot n^i\| \cdot dA$$

$$F_{MER,t} = \int_S \|f_t^i\| \cdot dA = \int_S \|(f^i - (f^i \cdot n^i) \cdot n^i\| \cdot dA$$

$$F_g = \int_S (f^i \cdot \hat{z}) \cdot dA = (F_n + F_t) \cdot \hat{z}$$



• **Estimation with historical information**

$$\beta = \begin{cases} \beta_{\max}, & \text{if } t \geq t_m \\ \beta_{\min} + \frac{\beta_{\max} - \beta_{\min}}{1 + \exp(-k \cdot (t - t_{bias}))}, & \text{if } t < t_m \end{cases}$$

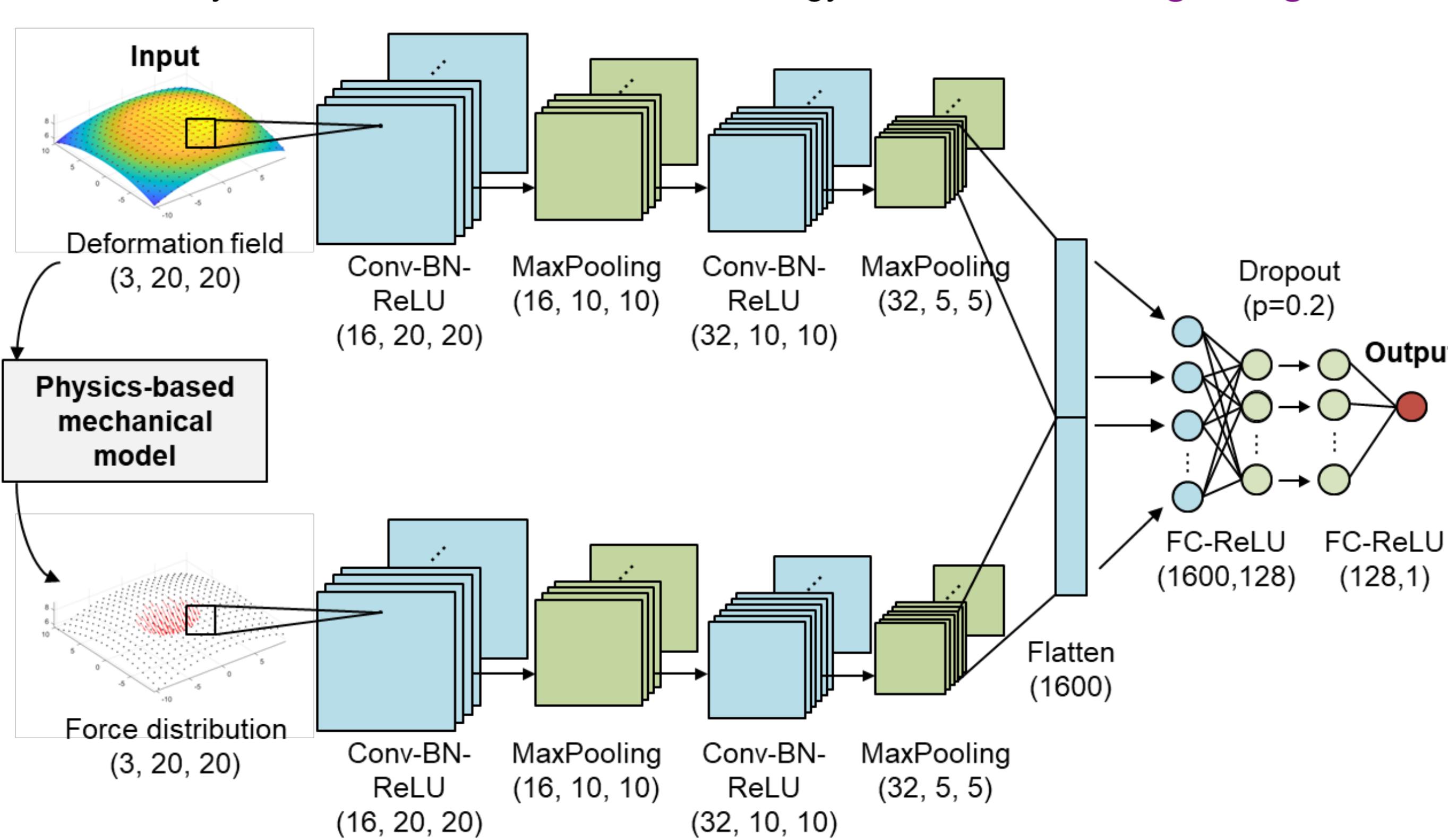
$$F_{Target,n}^{k+1} = \beta \mu^{-1} \cdot \max(F_{MER,n}^k, F_{Target,n}^{k-1})$$

$$F_g^{k+1} = \begin{cases} F_g^k, & \text{if } F_{MER,n}^{k-1} = F_{MER,n}^k \\ F_g^k + (F_g^k - F_g^{k-1}) \cdot \frac{F_{Target,n}^{k+1} - F_{MER,n}^k}{F_{MER,n}^{k+1} - F_{MER,n}^k} & \text{if } F_{MER,n}^{k-1} \neq F_{MER,n}^k \end{cases}$$

- **Time-dependent function of safety margin**
- ✓ Initially, the grasping force is relatively small, and the tangential force increases rapidly, requiring a **larger safety margin**;
 - ✓ As the grasping force gradually approaches the final target value and the tangential force increase rate decreases, a **smaller safety margin** is needed to prevent overshooting.

Target Force Prediction and Online Force Control:

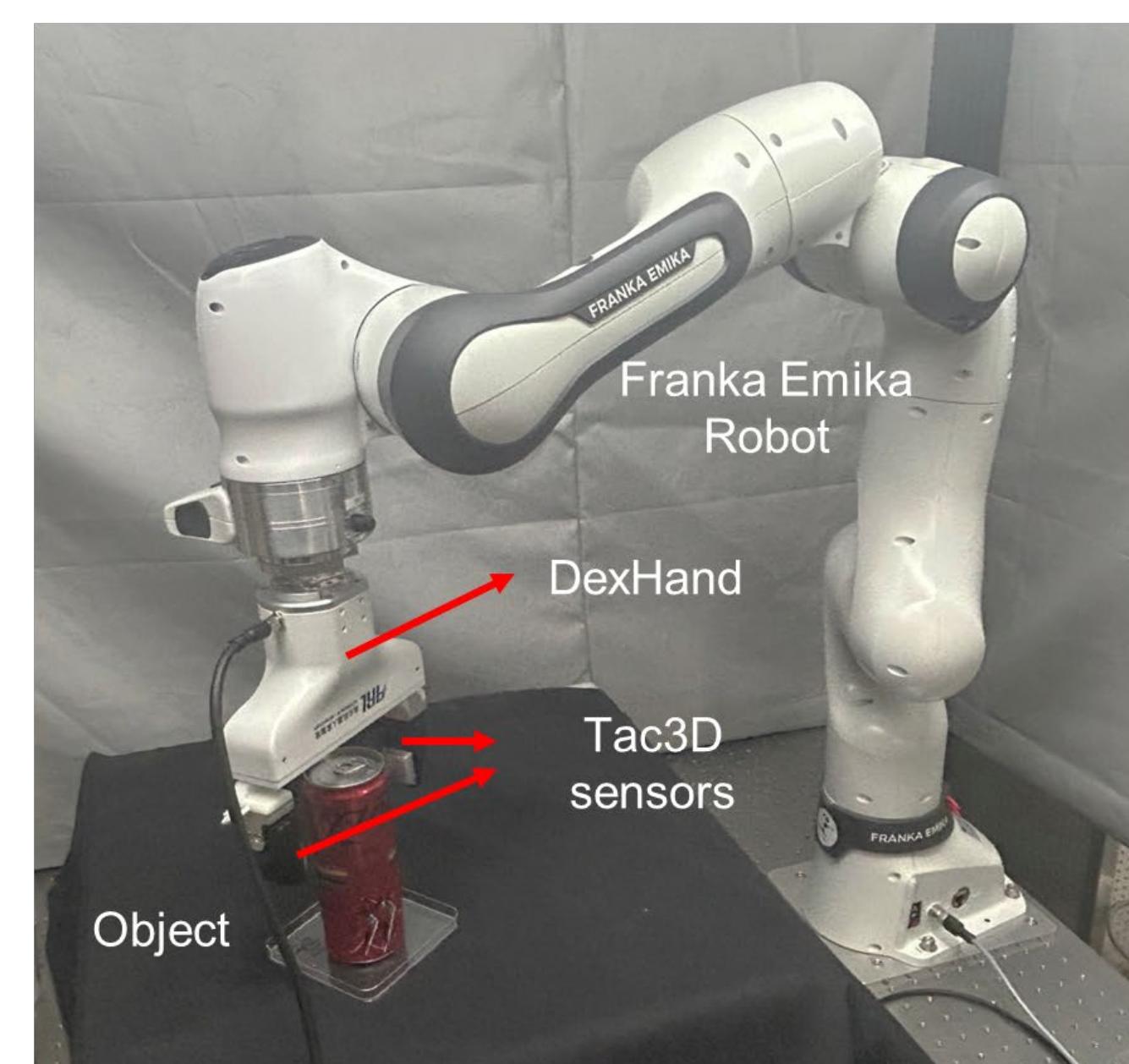
- ✓ Implicitly encode temporal dependencies → enables focused **spatial feature learning**
- ✓ Focus on key contact states and reference strategy → **less data and lightweight network**



Experimental Results

Offline Evaluation:

Experiment platform:



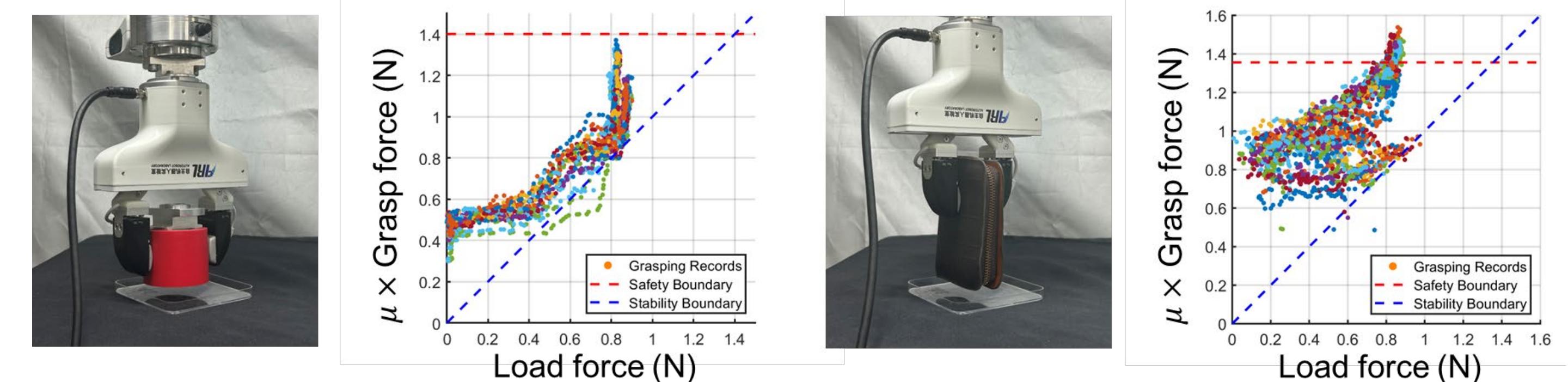
Test object and friction coefficient:



Real value (N)	Prediction (N)	Accuracy Score
231	38 49 63 0 0 0 0 0 0 0 0 0 0 0 0 0	0.6933
116	3 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	

✓ Force reconstruction module can improve the accuracy of target force prediction

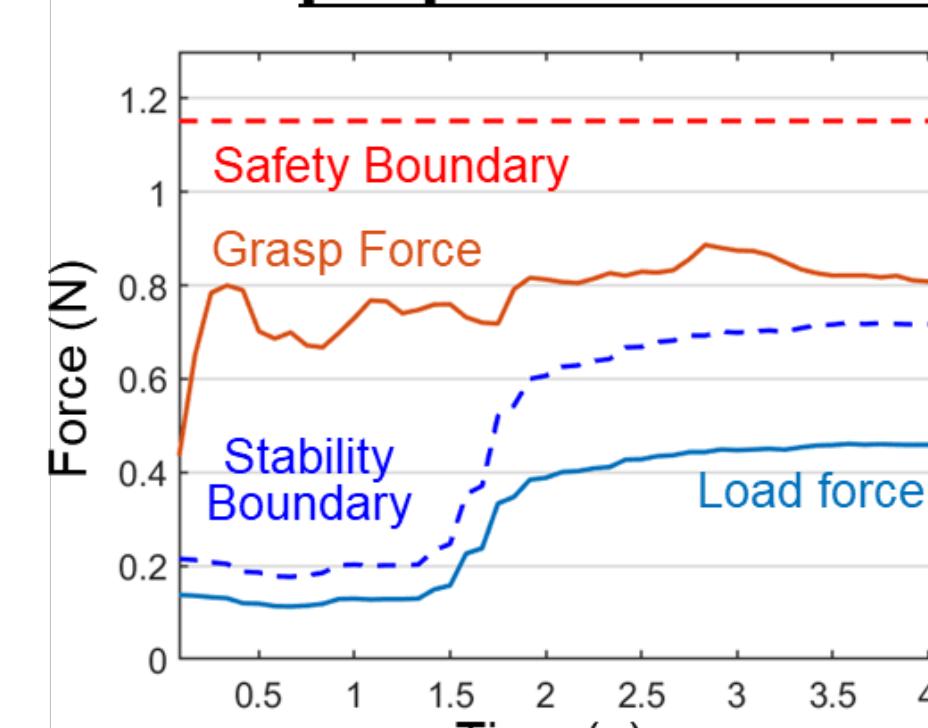
Online Evaluation:



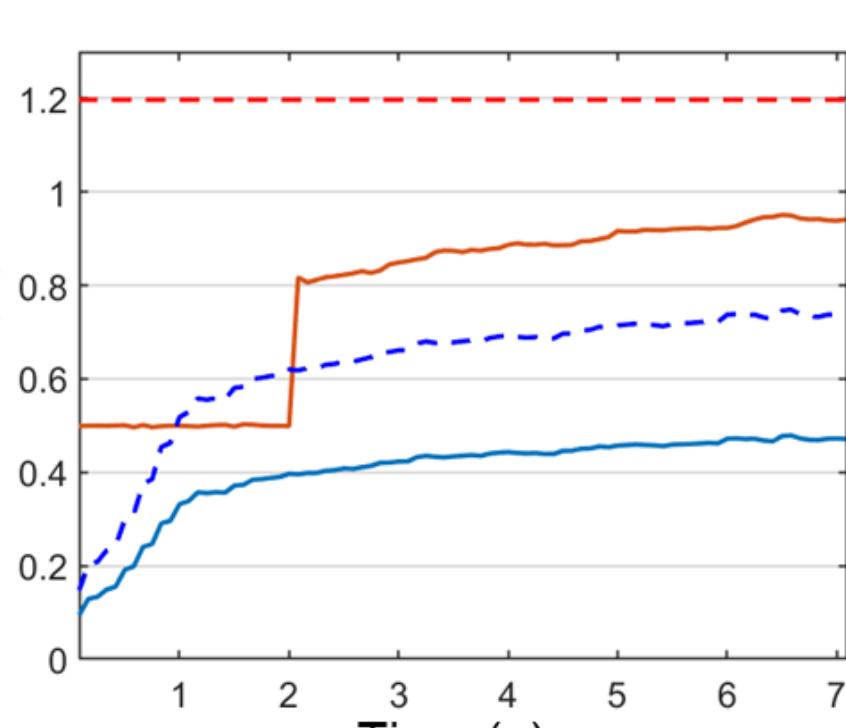
✓ Control the grasping force between the **safety boundary** and **stability boundary**

Comparative Experiment:

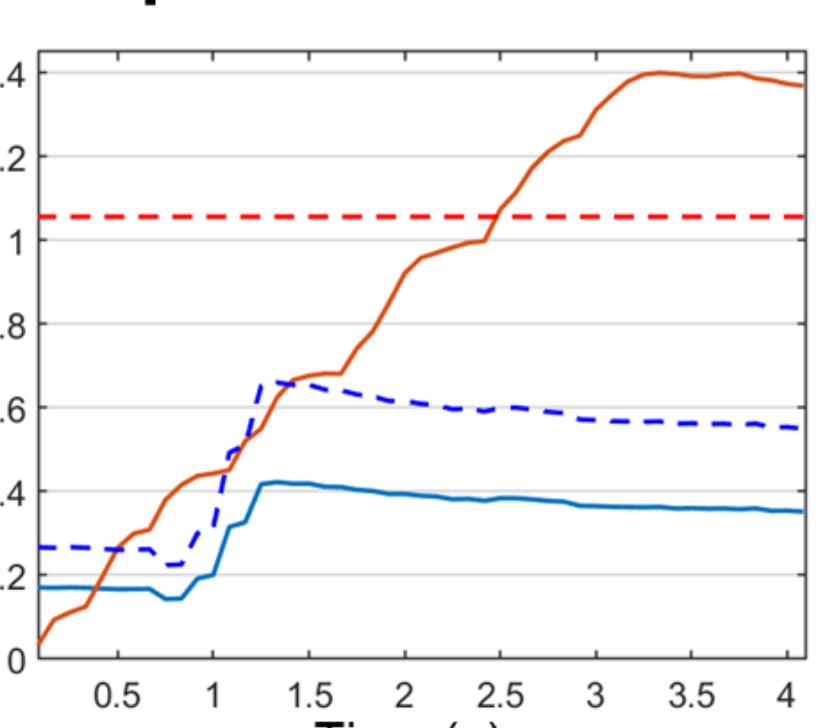
Grasping based on the proposed method



Grasping based on friction measurement



Grasping based on slip detection model



✓ Eliminate the need of **object's characteristics** and shorten **the loading phase duration**

Conclusion

Results: This work utilizes objects with known contact characteristics to **automatically generate reference force curves without human demonstrations**. The described method can be applied in vision-based tactile sensors and teaches robots to gently and stably grasp objects.

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