NeuralActuator: Neural Actuation Modeling for Robot Dynamics and External Force Perception

Zhiyang (Frank) Dou [1], John U. Onyemelukwe [1], Hangxing Zhang [1], Heng Zhang [1], Minghao Guo [1], Yunsheng Tian [1], Michal Piotr Lipiec [1], Joshua Jacob [1], Chao Liu [1], Peter Yichen Chen [1], Yuri Ivanov [2], Wojciech Matusik [1]

[1]MIT CSAIL, [2]Amazon Robotics

Project Page   Code & Data

Introduction & Motivation

- **Low-cost robotic platforms are essential for scalable robot learning,** but their inexpensive servo actuators often lack dedicated torque and force sensors.
- **Force control and hybrid force–position control are increasingly important for contact-rich manipulation,** creating a strong need for reliable force perception on low-cost hardware.

Why Are Low-Cost Robot Platforms Challenging?

Limited Force and Torque Sensing

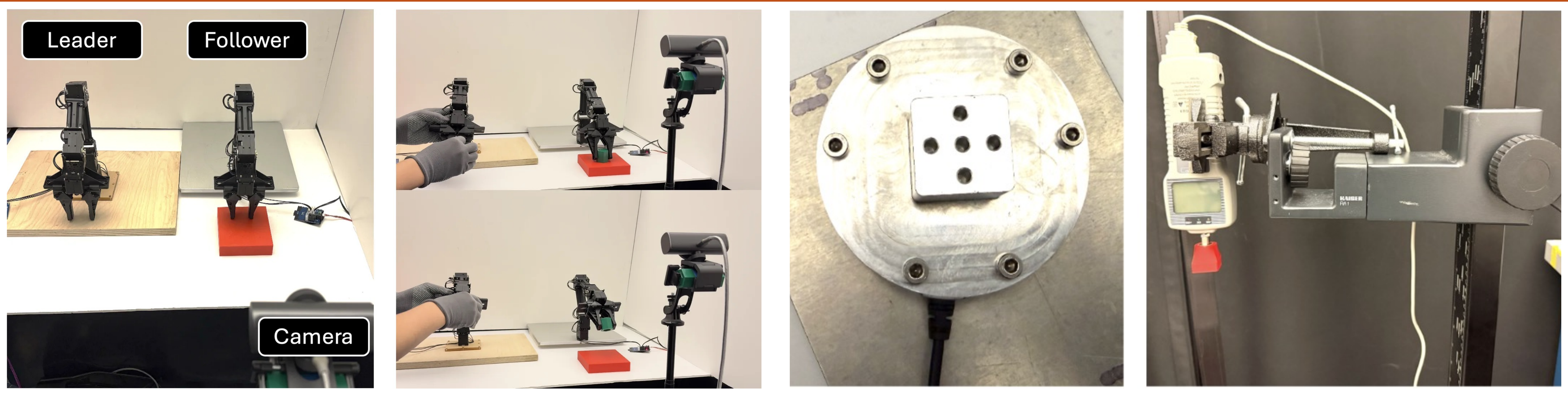
Low-cost servo-driven robots typically lack dedicated joint torque and force sensors, limiting direct feedback from physical interactions.

Nonlinear and Time-Varying Actuation

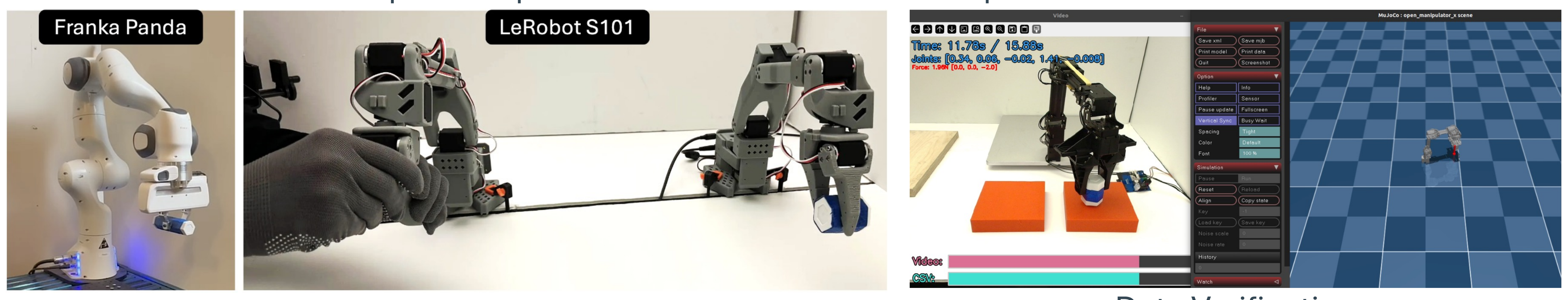
The conventional linear current-to-torque assumption breaks down because of friction, hysteresis, gearbox backlash, current saturation, and thermal drift.

The goal of this research is to turn the low-cost actuator itself into both a dynamics model and a sensing channel, enabling torque modeling, external-force estimation, and motor-condition monitoring without dedicated torque sensors.

Neural Actuation Dataset (NAD)



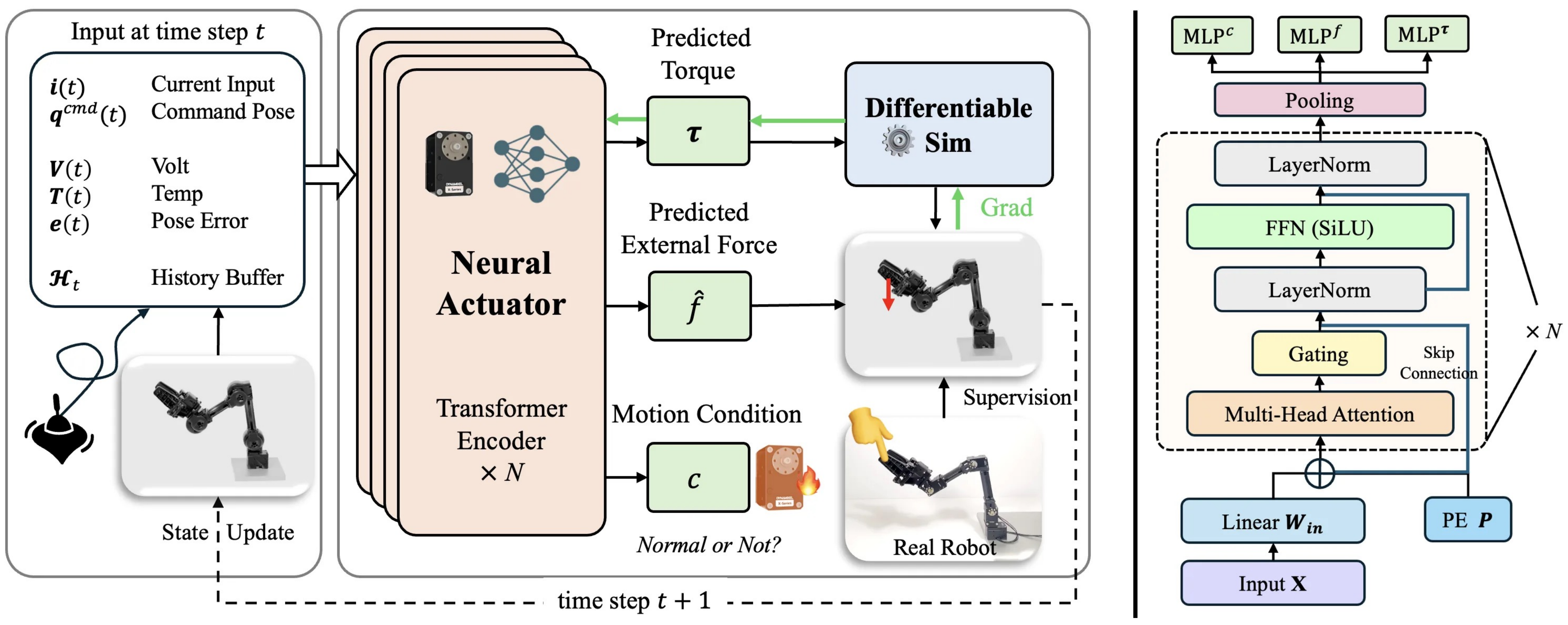
Data Collection: OpenManipulator-X   Torque Sensor and Force Sensor



Data Collection: Franka Panda and LeRobot-S101   Data Verification

NAD is collected with a twin-arm teleoperation setup that records commanded pose, measured pose, current, voltage, temperature, and force supervision from F/T sensors, force gauges, and known payloads.

Pipeline - NeuralActuator



NeuralActuator pipeline. A Transformer-based model jointly predicts torque, external forces, and motor conditions within a differentiable simulation loop.

- **Torque-Supervision-Free Actuator Learning**
  Learns actuator torque from pose trajectories via differentiable simulation, eliminating the need for dedicated torque sensors, which are unavailable on many low-cost platforms.

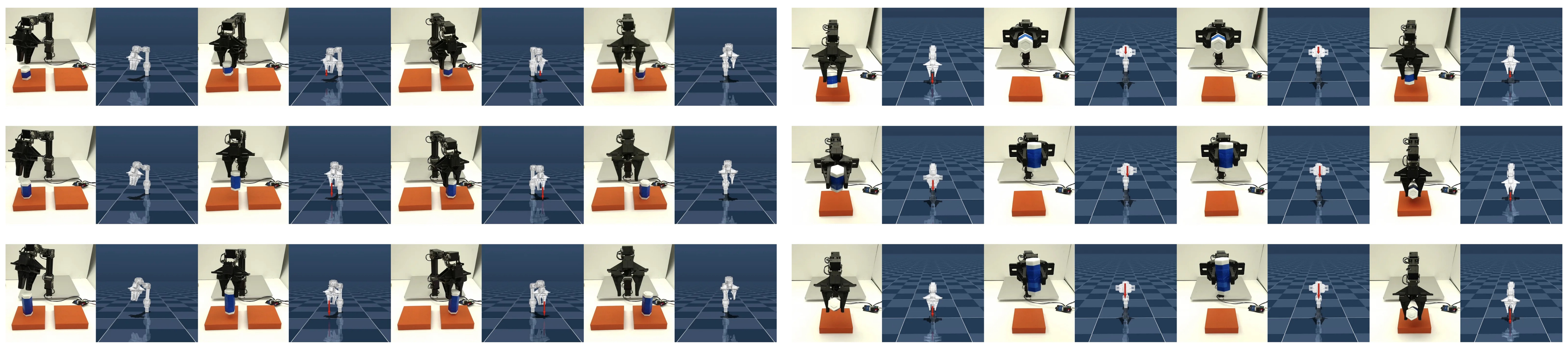
$$\min_\theta \left\| \mathrm{DiffSim}(f_\theta(\cdot)) - q^{real} \right\|$$

- **Neural Modeling of Nonlinear Actuator Dynamics**
  Captures history-dependent actuator behaviors beyond linear current–torque models, including friction, backlash, hysteresis, and thermal effects.
- **Unified Actuation Modeling and Force Perception**
  Jointly predicts torque, external forces, and motor conditions, enabling sensorless force-aware control on low-cost robots.

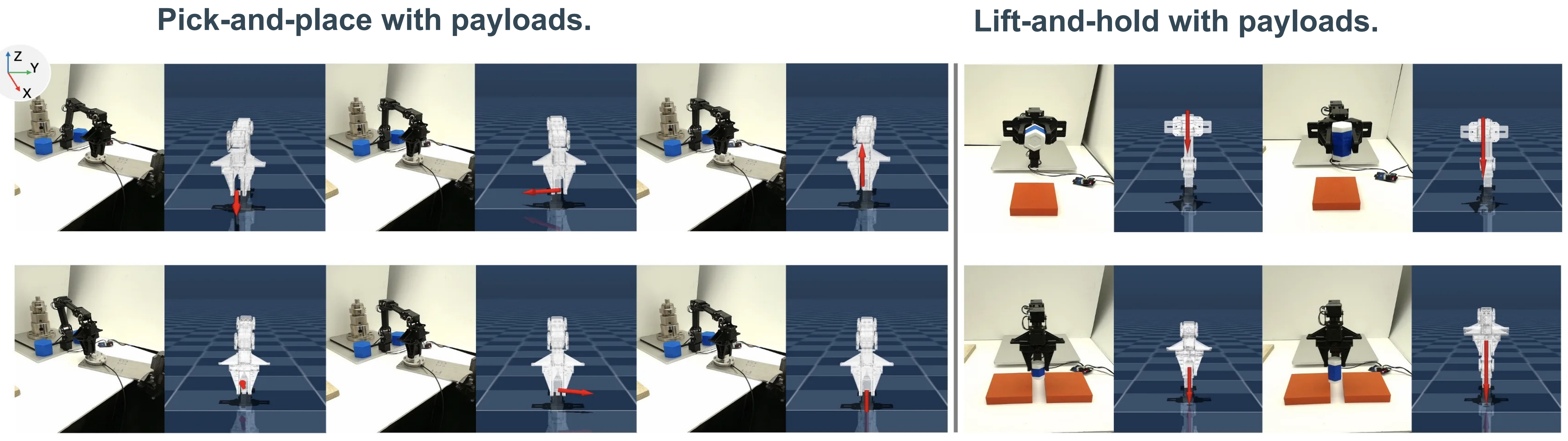
$$\boxed{M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q)} = \boxed{\tau} + \boxed{\tau_{ext}}$$

System Calibration+ Robot States

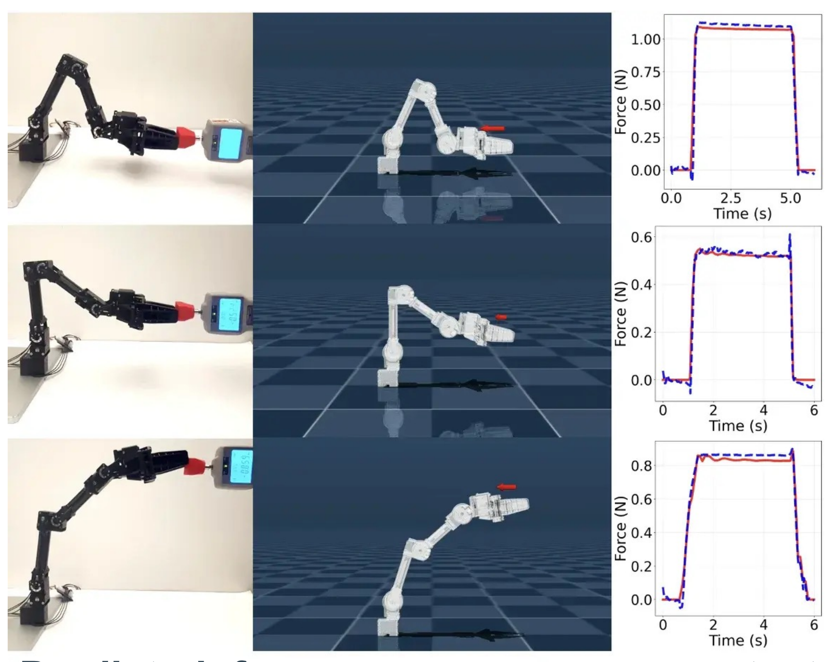
Experimental Results – External Force Estimation



Pick-and-place with payloads.   Lift-and-hold with payloads.



External Force Estimation (GTs from F/T Sensor)



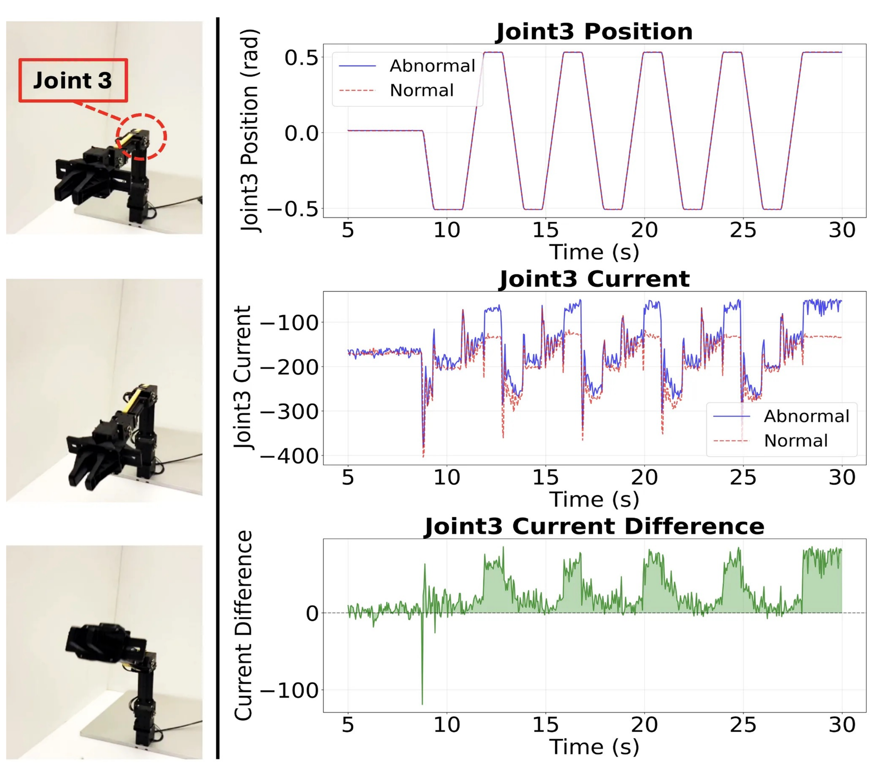
Predicted force curves across contact onset, steady force, and release.

Novel contact geometries. Predicted vs. ground-truth forces for unseen objects: 2.80 N vs. 2.56 N (261 g) and 2.40 N vs. 2.21 N (226 g).

Method	Go Up 200g (N)	Go Up 300g (N)	Go Up 400g (N)	Pick 200g (N)	Pick 300g (N)	Pick 400g
ID-Linear	1.37	1.81	2.30	0.72	0.95	1.22
ID-Friction	1.06	1.59	2.15	0.62	0.82	1.10
GMO	0.58	0.66	1.23	0.33	0.47	0.63
NeuralActuator	**0.12**	**0.20**	**0.07**	**0.24**	**0.00**	**0.19**

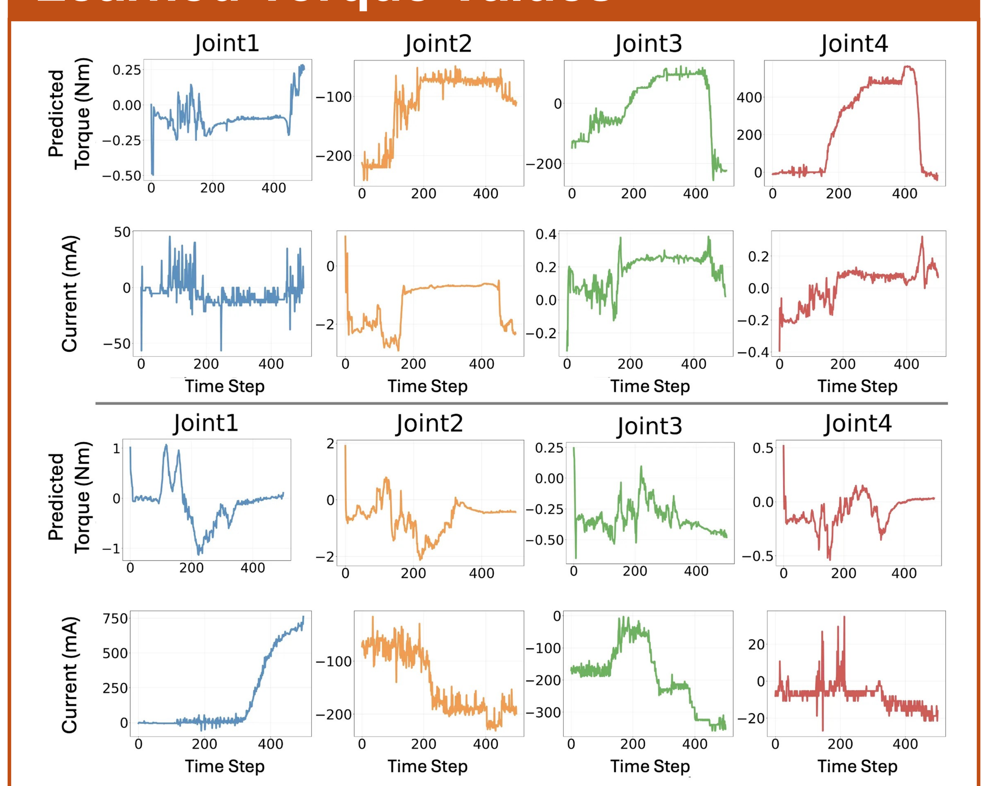
Comparison with previous methods

Motor Condition Monitoring



Abnormal resistance produces higher current under similar position trajectories.

Learned Torque Values



The effective current-to-torque mapping varies across joints and operating phases.

Runtime Performance

METRIC	VALUE	UNIT
Parameters	1.42M	-
FLOPs (forward)	5.46M	-
Parameter memory	5.43	MB
Mean time	0.25	ms
P95 time	0.31	ms
Throughput (batch=1)	4,019	Hz
Throughput (batch=32)	10,992	Hz

The model is lightweight for real-time simulation and control.

Future Work

- **Synthetic-to-Real Actuator Pretraining**
  Leverage large-scale synthetic actuator data for pretraining, followed by real-world fine-tuning to reduce costly hardware data collection.
- **Cross-Morphology Actuation Learning**
  Extend NeuralActuator toward different robot morphologies and actuator families for more generalizable actuation modeling.
- **Scalable Whole-Body Force Perception**
  Move beyond single-arm end-effector force estimation toward multi-joint and whole-body force-aware robot control.
- …