

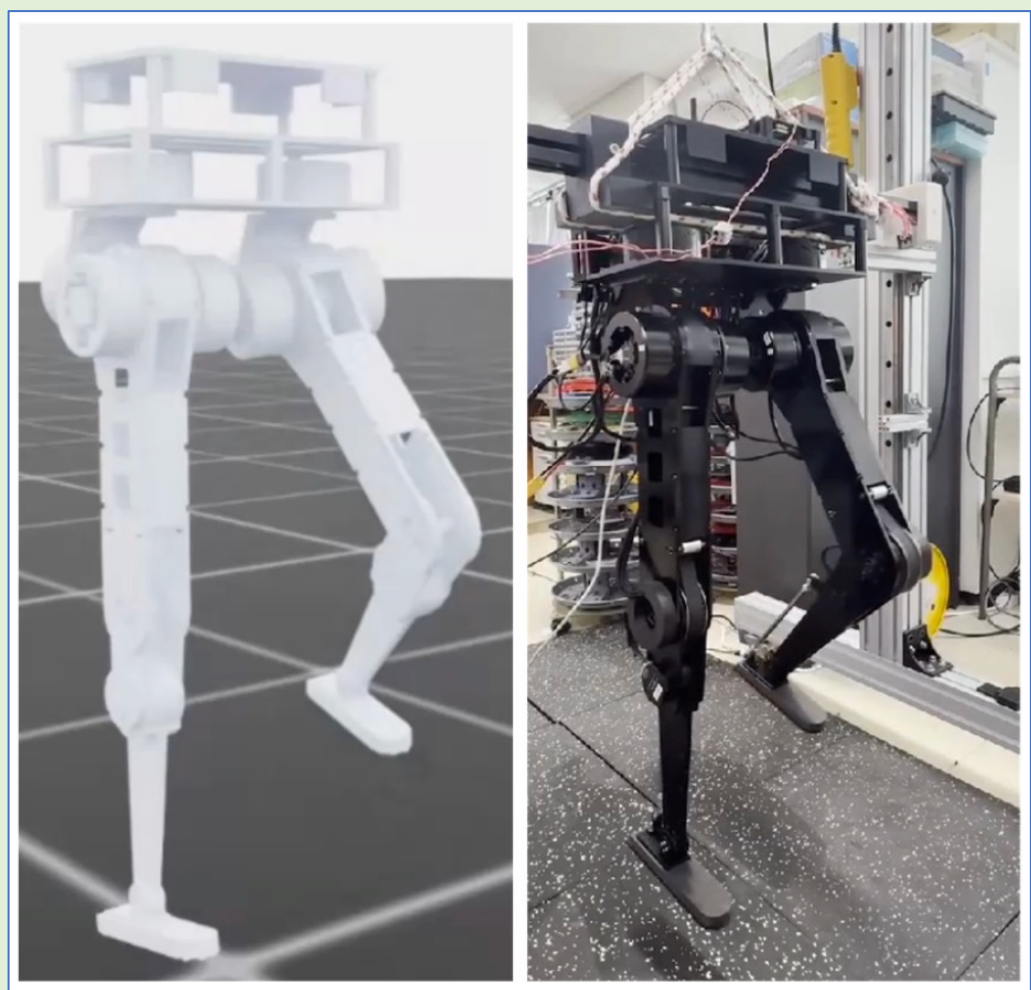
# Residual Dynamics for Reducing the Simulation-to-Real Gap in Zero-Shot Humanoid Skill Deployment

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## Introduction

Bridging the sim-to-real gap remains a key challenge in deploying reinforcement learning (RL) policies on legged and humanoid robots.



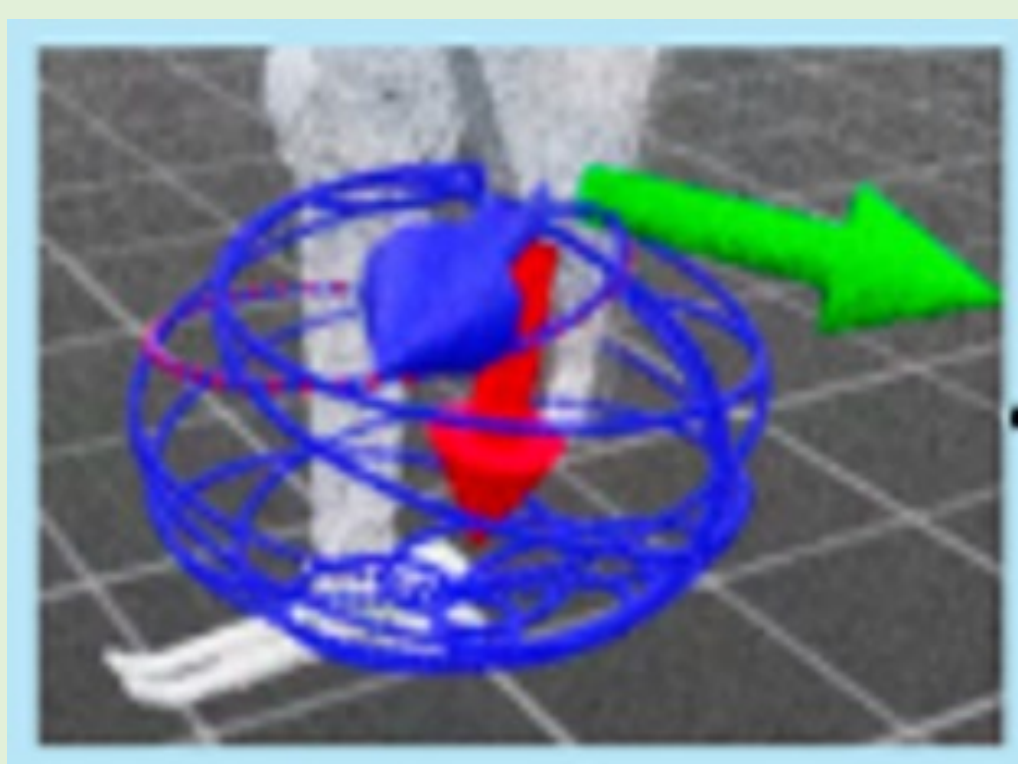
Many existing methods depend on motion capture, torque sensors, or detailed actuator models, which limit practicality and scalability.

Could we bridge the sim gap with minimal sensing device and RL framework?

## Method

### 1) Data collection

To capture dynamics above 100 Hz, excitation must span a broad frequency range to avoid oscillations. Use elliptical foot trajectories on ellipsoidal surface



### 2) Training Residual Dynamic Model

**Policy Observations.** Joint states  $\{q_t, \dot{q}_t, \ddot{q}_t\}$  and joint commands  $q_t^{cmd}$  could compensate joint friction and mass matrix mismatches, ...

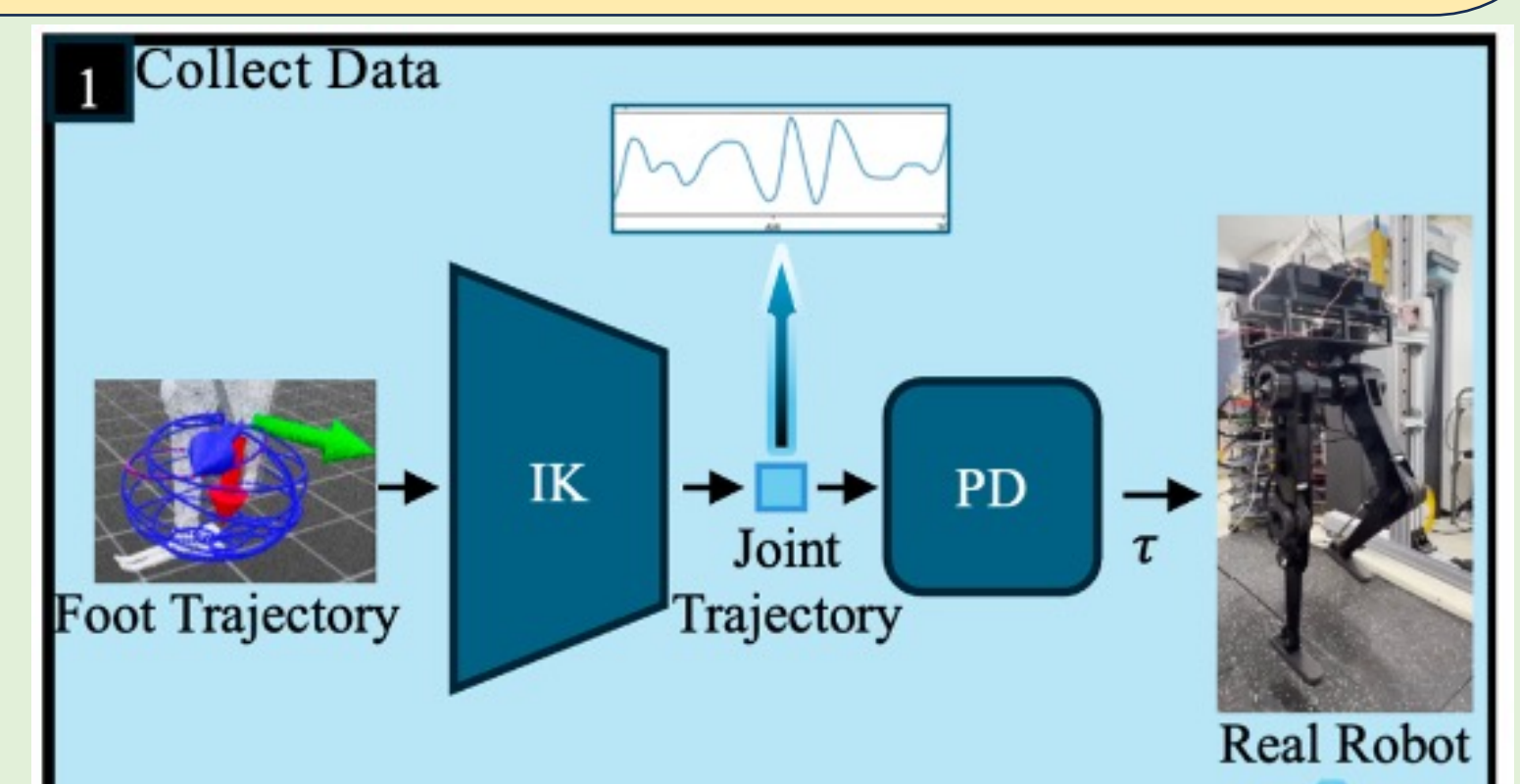
**Policy Representation.** policy architecture employs MLPs with ELU activations.

**Rewards.** combine mimic and regularization terms

## Key Ideas

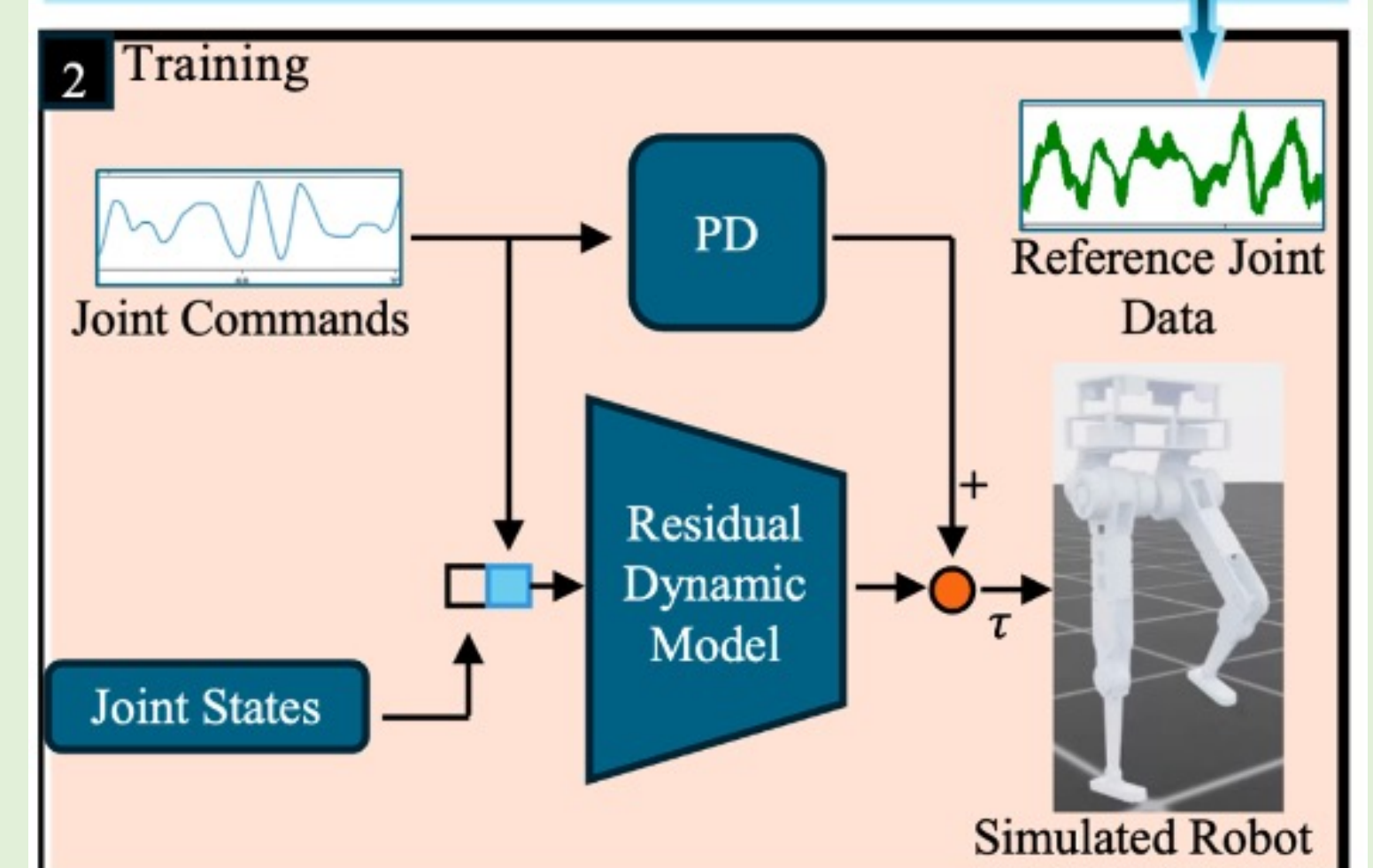
System Identification with RL formula.  
Train policy simulation tracks real state.

1) Compute IK from foot trajectories, send to robot, then collect joint states.



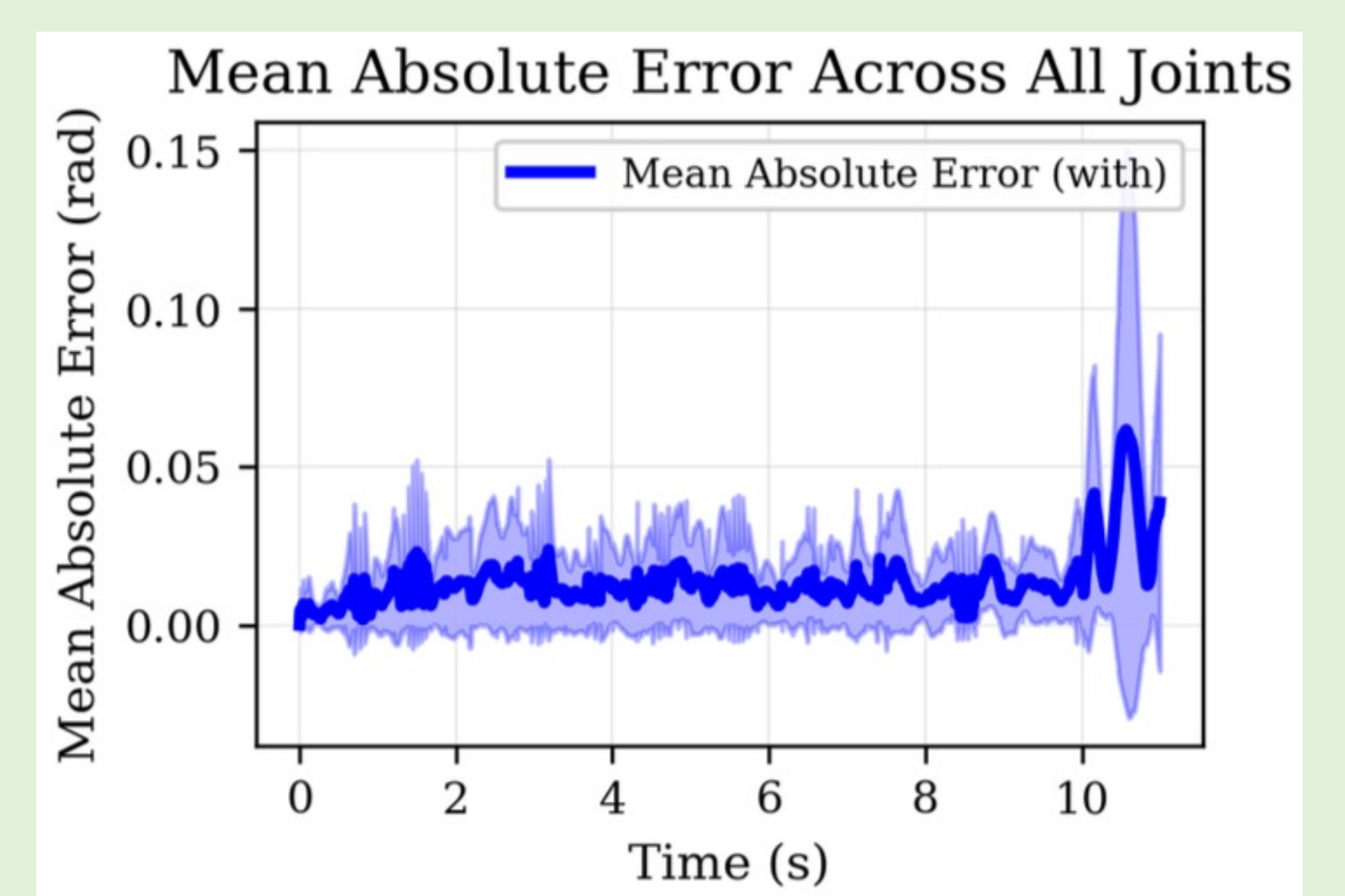
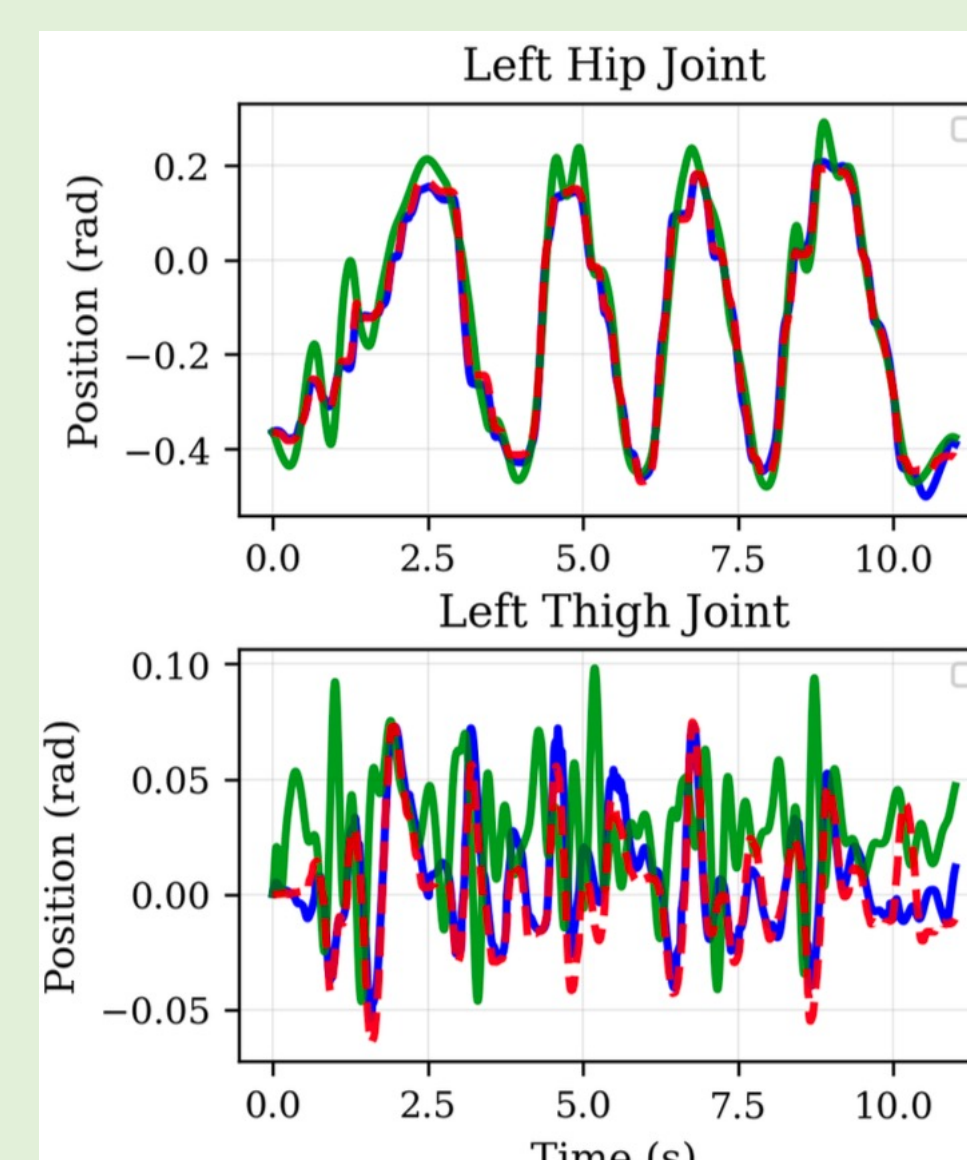
2) Train model  $\tau_{res}$  with RL formulation, such that  $M\ddot{q} + f = \tau_{pd} + \tau_{res}$

Made simulated robot matching the real one



## Result

MLP with RL is an effective compensator aligns simulator with real-world states.



MLP vs GRU+MLP Architecture Comparison

