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Computer Science

Teleoperation of Quadruped Robots via Learning-Based Gait Classification of Human Locomotion Data

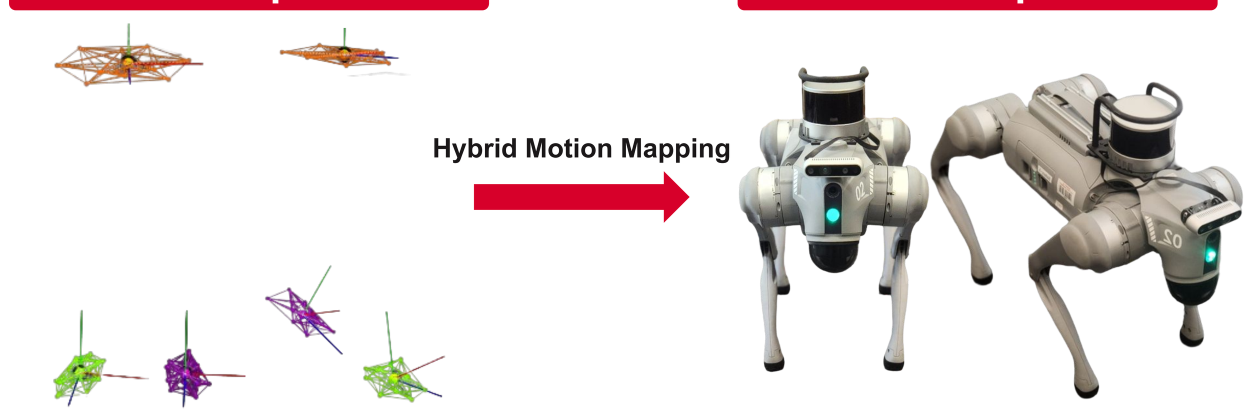
HIER LAB

Nicholas Sutton† and Jaemin Lee*
Department of Computer Science†, Department of Mechanical and Aerospace Engineering*

Introduction

Motion-driven teleoperation is a promising control method for robots in complex environments where fully autonomous methods may fail. However, most cross-morphology teleoperation systems adopt end-to-end learning, limiting flexibility, interpretability, and stability guarantees. Furthermore, these systems cannot transfer to new platforms without retraining. To address these limitations, we propose a **hybrid approach** combining **data-driven gait classification** with **whole-body control for motion tracking**. Our approach enables accurate human motion transfer across morphologically distinct platforms without the constraints of end-to-end learning as well as remaining **platform agnostic**. We validate our reults across various real-time teleoperation scenarios consisting of single gait locomotion and mixed-gait athletic locomotion on a **Unitree Go2 Quadruped** Robot.

Human Operator | **Quadruped**



Background

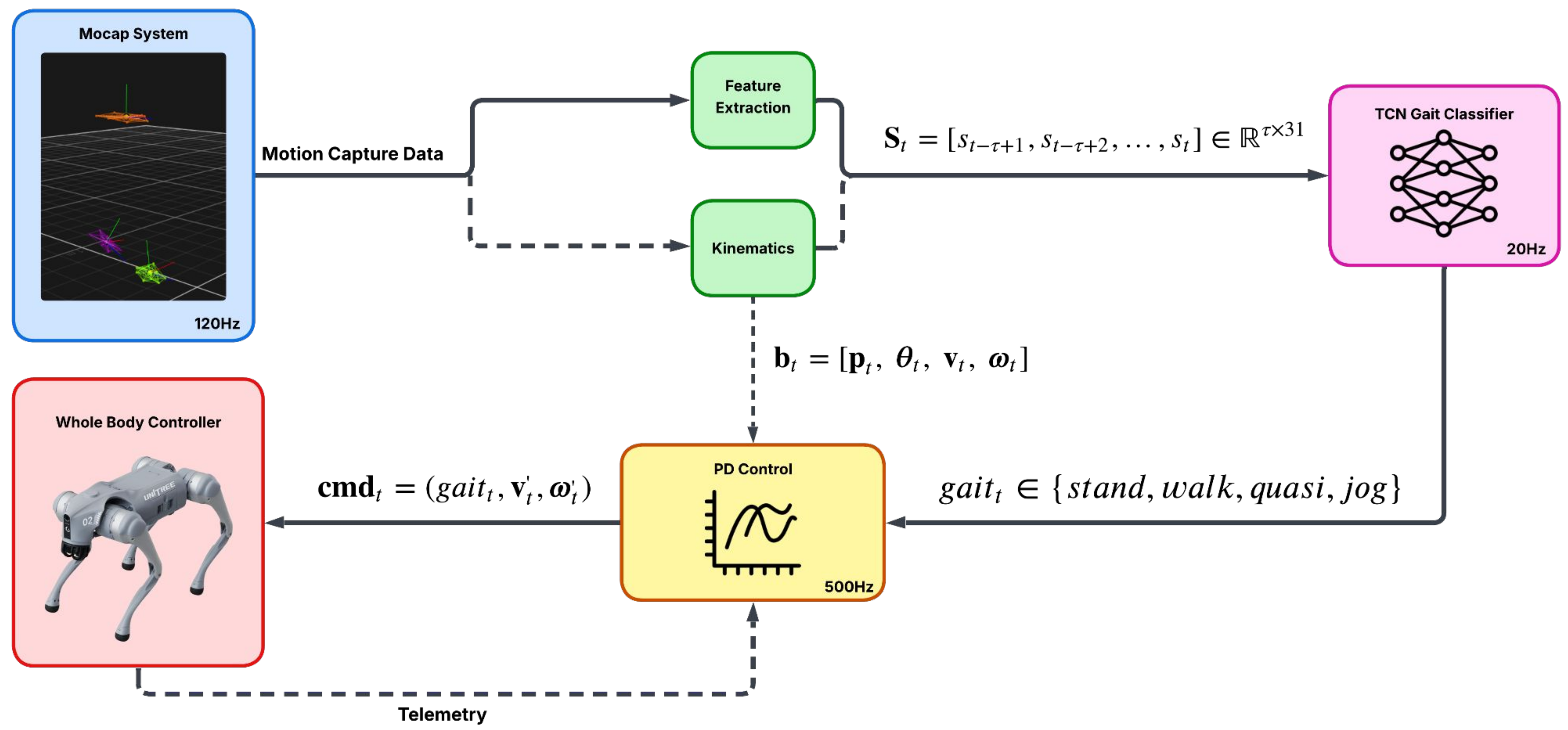
1) Motion Driven Teleoperation

- Human motion provides an **intuitive control interface**, that captures **full-body intent**, enabling complex robot operation, as well as scalable collection of demonstration.
- Existing motion-driven teleoperation systems bridge the morphology gap between human operators and robotic platforms through **end-to-end learning**, producing controllers that **cannot generalize without retraining**.

2) Our Approach (Hybrid) Vs End-to-End Learning

Feature	Hybrid Approach	End-to-End Learning
Generalizability	Transferable without retraining	Requires retraining between platforms
Stability and Safety	Formal Guarantees	Dependent on Data
Morphology	Applicable to various Morphologies	Targets Humanoid Robots

Methods

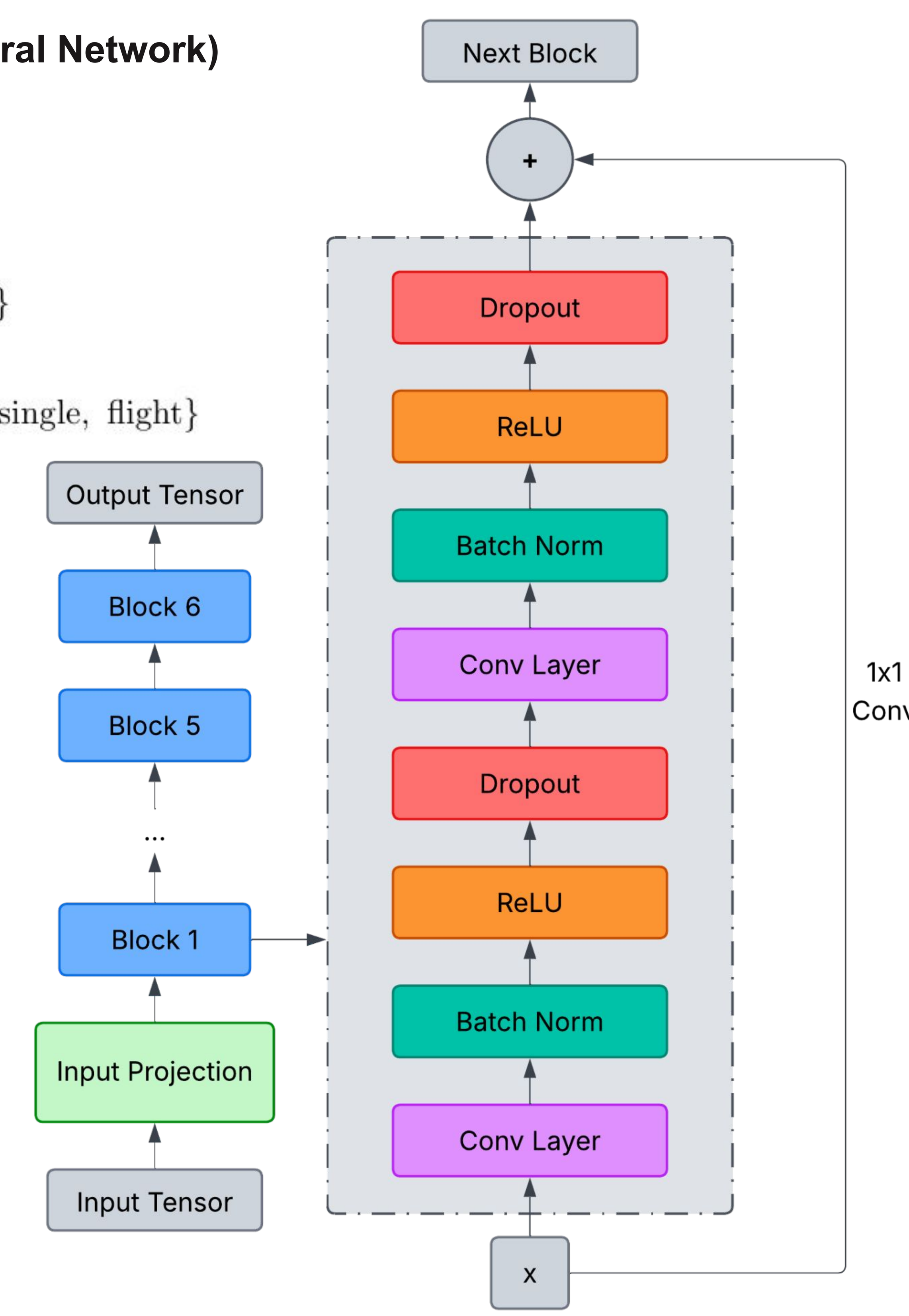


1. Motion Capture System and Data Preparation

- Motion data was captured using **six Optitrack Prime 13x** Motion capture cameras.
- **36 IR markers** were distributed among the tracking subjects **waist and feet**.
- Human motions are represented by the **kinematics** of the waist and feet rigid bodies, as well as a set of **derived gait features.**

2. Gait Classification (Temporal Convolution Neural Network)

- **Model Input:** $\mathbf{S}_t = [s_{t-\tau+1}, s_{t-\tau+2}, \dots, s_t] \in \mathbb{R}^{\tau \times 31}$
  - State Vector: $\mathbf{s}_t = [\mathbf{b}_t,\ \mathbf{f}_t^L,\ \mathbf{f}_t^R,\ \mathbf{g}_t,\ \mathbf{c}_t] \in \mathbb{R}^{31}$
  - Base Kinematics: $\mathbf{b}_t = [\mathbf{p}_t,\ \boldsymbol{\theta}_t,\ \mathbf{v}_t,\ \boldsymbol{\omega}_t] \in \mathbb{R}^{12}$
  - Foot Kinematics: $\mathbf{f}_t^f = [\mathbf{v}_t^f,\ \mathbf{p}_t^f] \in \mathbb{R}^6,\ f \in \{L, R\}$
  - Gait Metrics: $\mathbf{g}_t = [l_t,\ w_t,\ h_t,\ h_t^{\max}] \in \mathbb{R}^4$
  - Contact State: $\mathbf{c}_t = [\sigma_t,\ p_t^L,\ p_t^R],\ \sigma_t \in \{\text{double, single, flight}\}$
- **Model Output:** $\mathbf{gait}_t \in \{\text{stand, walk, quasi, jog}\}$



3. Motion Imitation (PD Control)

- A **PD controller** runs at **~500 Hz**, computing corrective velocities from position and heading error. **Command velocities are capped per gait class** with a lookahead term targeting the human's predicted position 0.25 s ahead.
- **PD Control Formulation:**

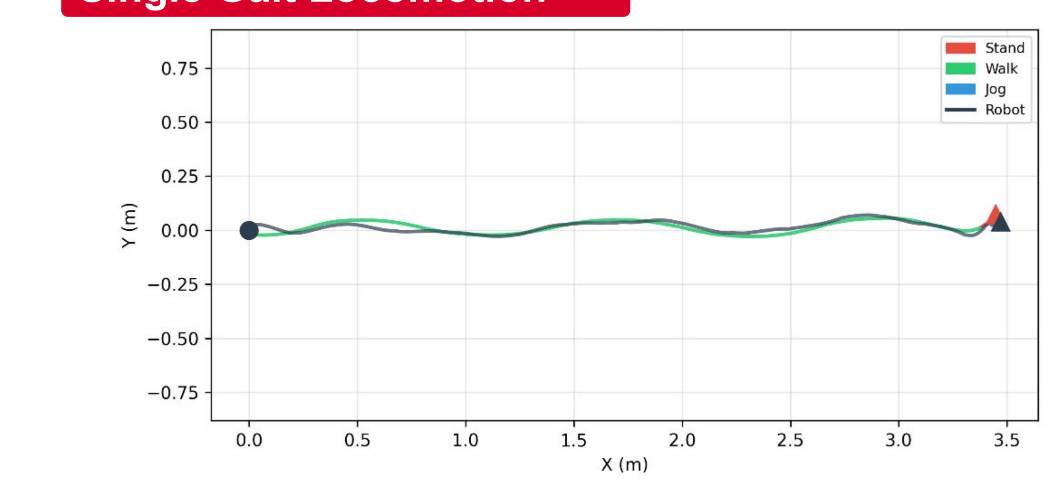
$$\mathbf{e} = \mathbf{p}_h + \tau\dot{\mathbf{p}}_h - \mathbf{p}_r$$

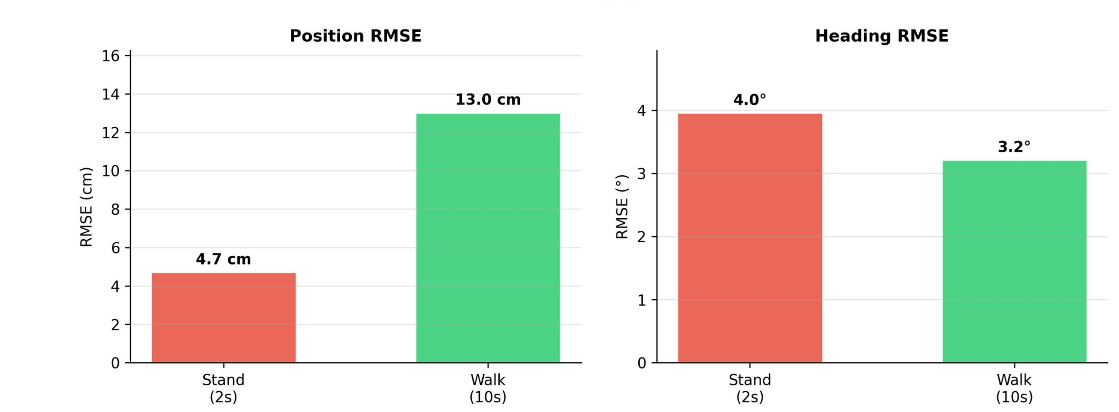
$$\mathbf{u} = K_p\mathbf{e} + K_d\dot{\mathbf{e}}, \quad |\mathbf{u}| \le v_{\max}(\hat{g})$$

$$\omega = K_{p,\psi}, e_\psi + K_{d,\psi}, \dot{\psi}_h$$

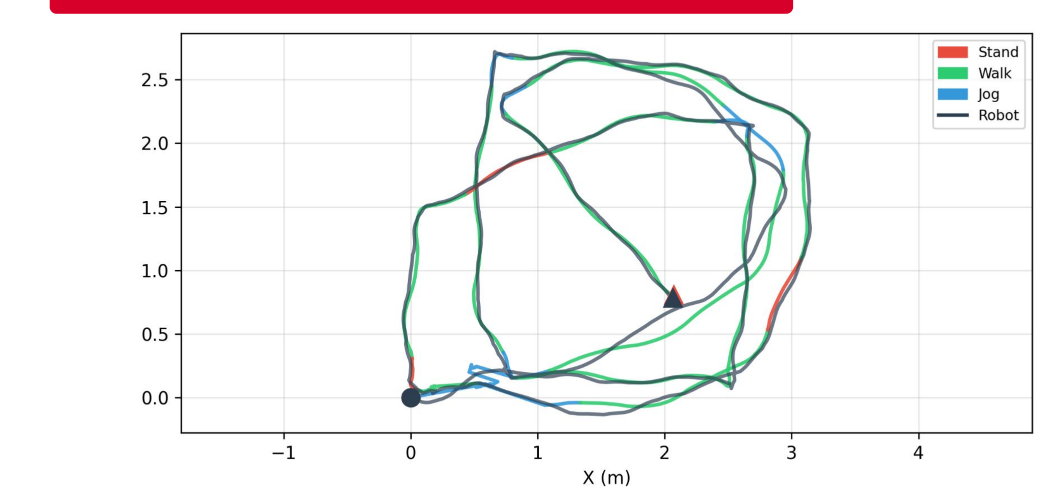
Experimentation

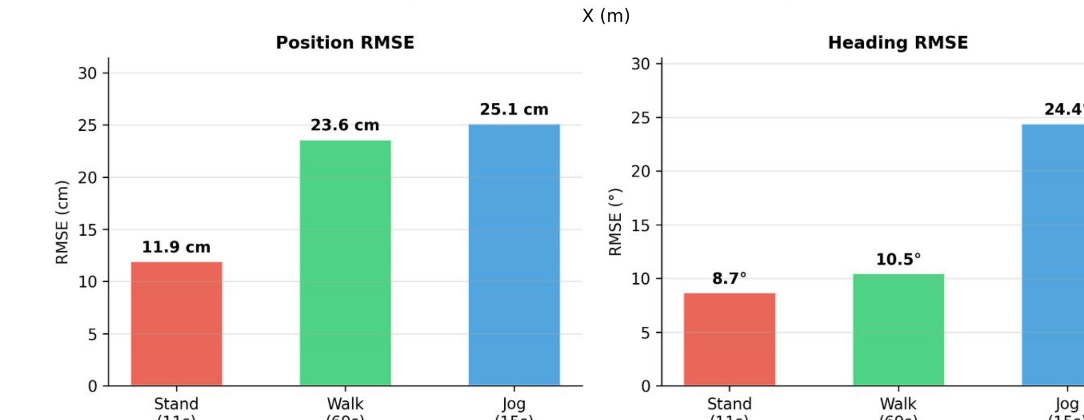
Single Gait Locomotion





Mixed-Gait Athletic Locomotion





Scenario	Position RMSE(cm)	Heading RMSE(°)	Tracking Acc(%)
Single Gait locomotion	11.6 ± 0.5 cm	3.5 ± 0.2°	99.8%
Mixed-Gait Athletic Locomotion	26.46 ± 2.9 cm	23.25 ± 2.2°	45.3%

Future Work

Our results demonstrate consistent tracking in simple locomotion scenarios, though performance degrades during athletic motion and frequent gait transitionsThe poor performance in these scenarios primarily due to the kinematic constraints of the quadruped hardware. Future work will integrate a **Control Barrier Function (CBF) safety filter** for autonomous obstacle avoidance and safe velocity enforcement, as well as a controller switching mechanism that activates an **MPPI-based planner** when tracking error exceeds a defined threshold or exact motion imitation becomes infeasible.