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Benchmarking Model Predictive Control and Reinforcement Learning for Legged Robot Locomotion

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Background and Objective

Background:

- Quadrupeds have diverse applications: industrial transport, package delivery, search and rescue, etc.
- Trending control methods are Model Predictive Control (MPC) and Reinforcement Learning (RL).

Objectives:

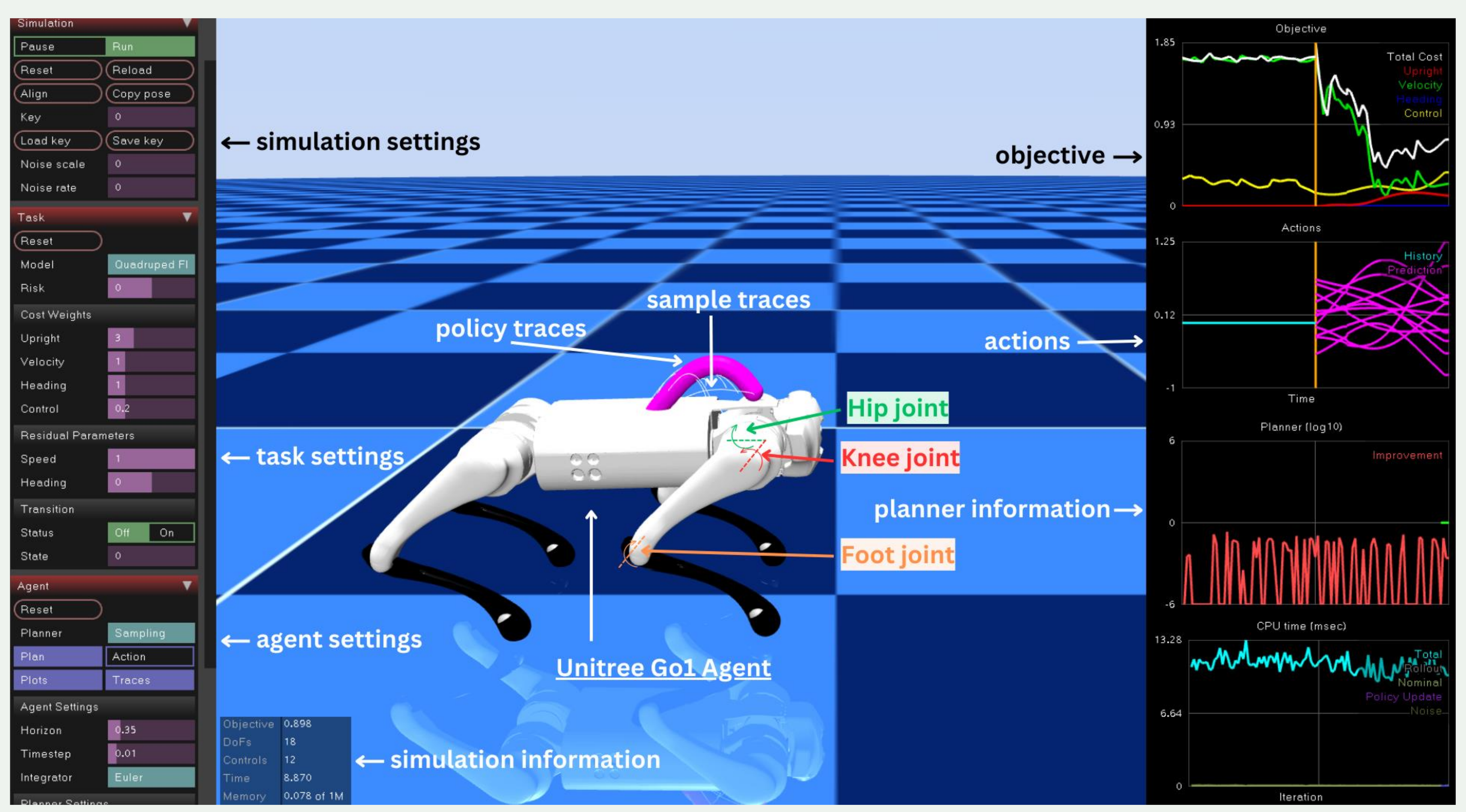
- Comparative study of MPC and RL controllers on Unitree Go1 quadrupedal robot.
- Experiments used for evaluation are performance under perturbation and model uncertainty.
- Provide insights to help researchers make informed decisions when designing locomotion controllers.

Environment Setup

Robot: Unitree Go1 quadruped.

Environment:

- Simulation is based on MuJoCo physics engine [1].
- Integrate a realistic XML model of Go1 robot in MJPC [2] and Open AI Gym MuJoCo framework [3,4].
- Real-time monitoring of Go1's actions, states, and interactions with the environment in MJPC [2].



Acknowledgement

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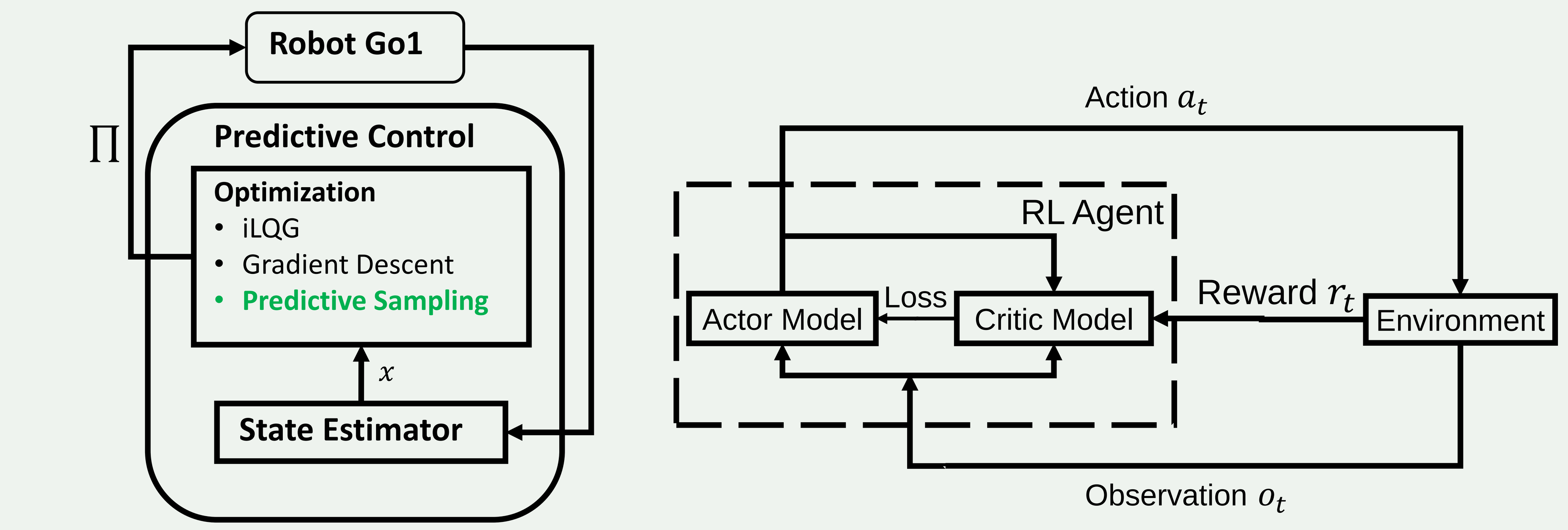
Controller

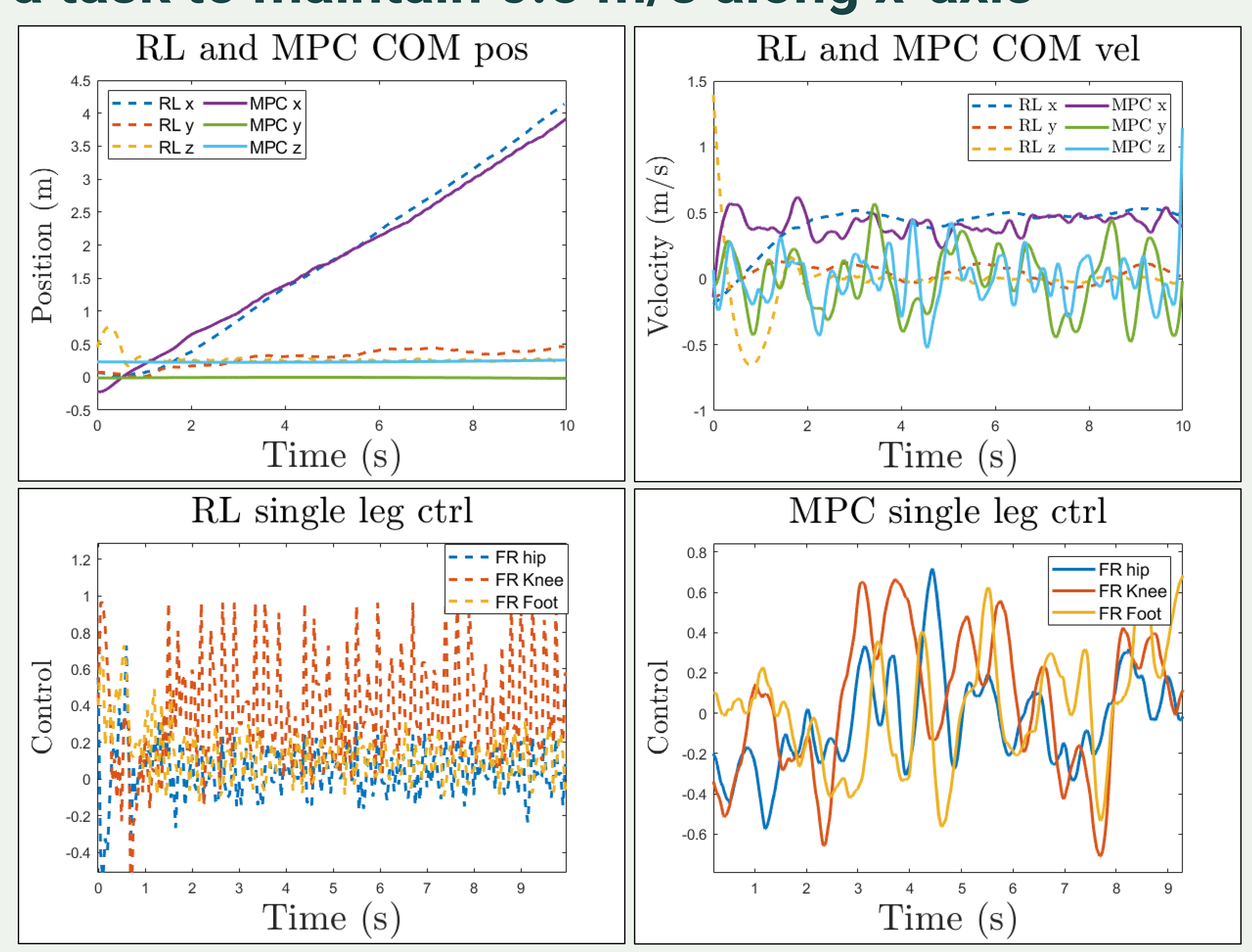


Model Predictive Control **Reinforcement Learning**

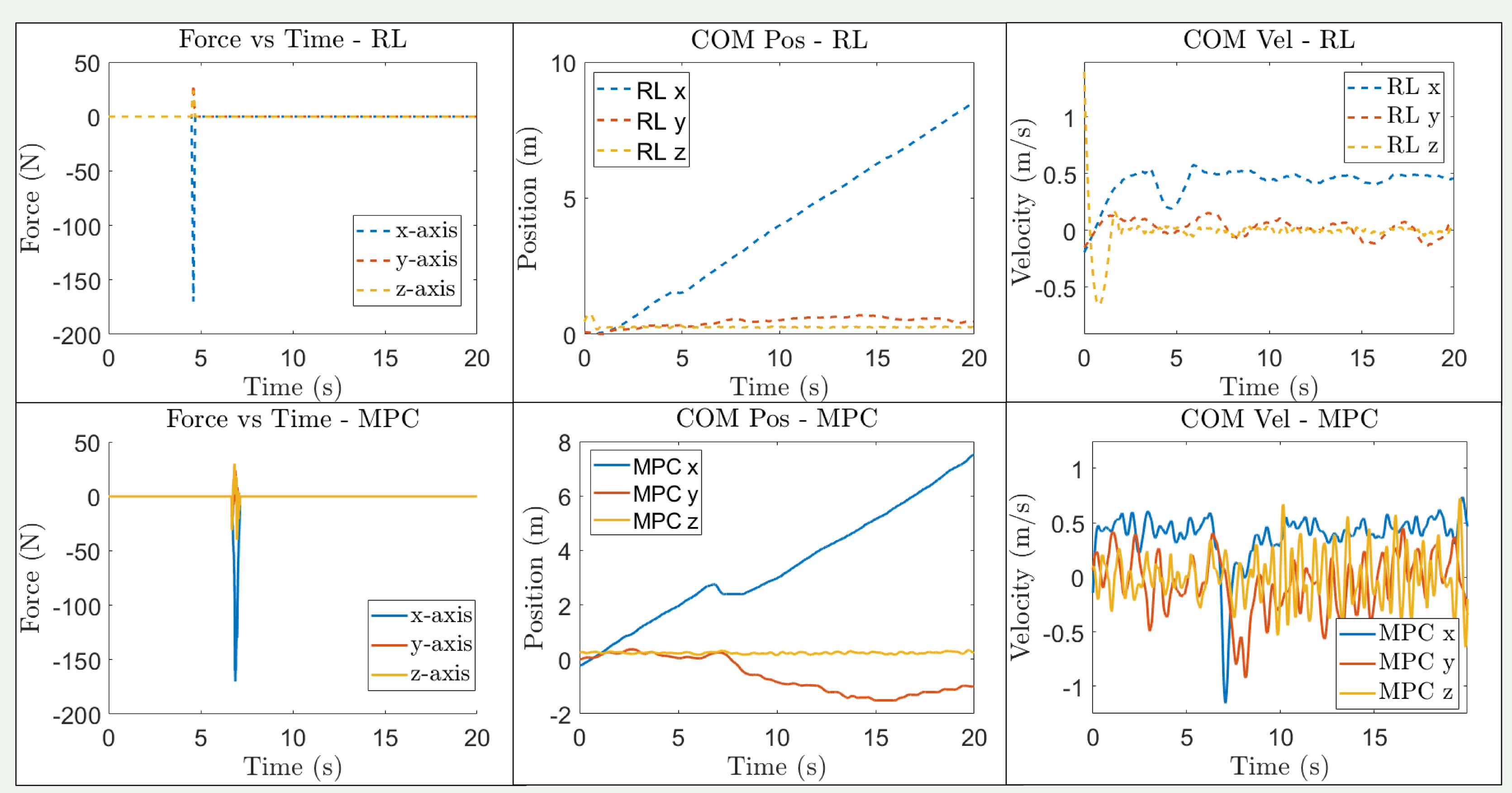
Results

Experiment 1: Task standardization

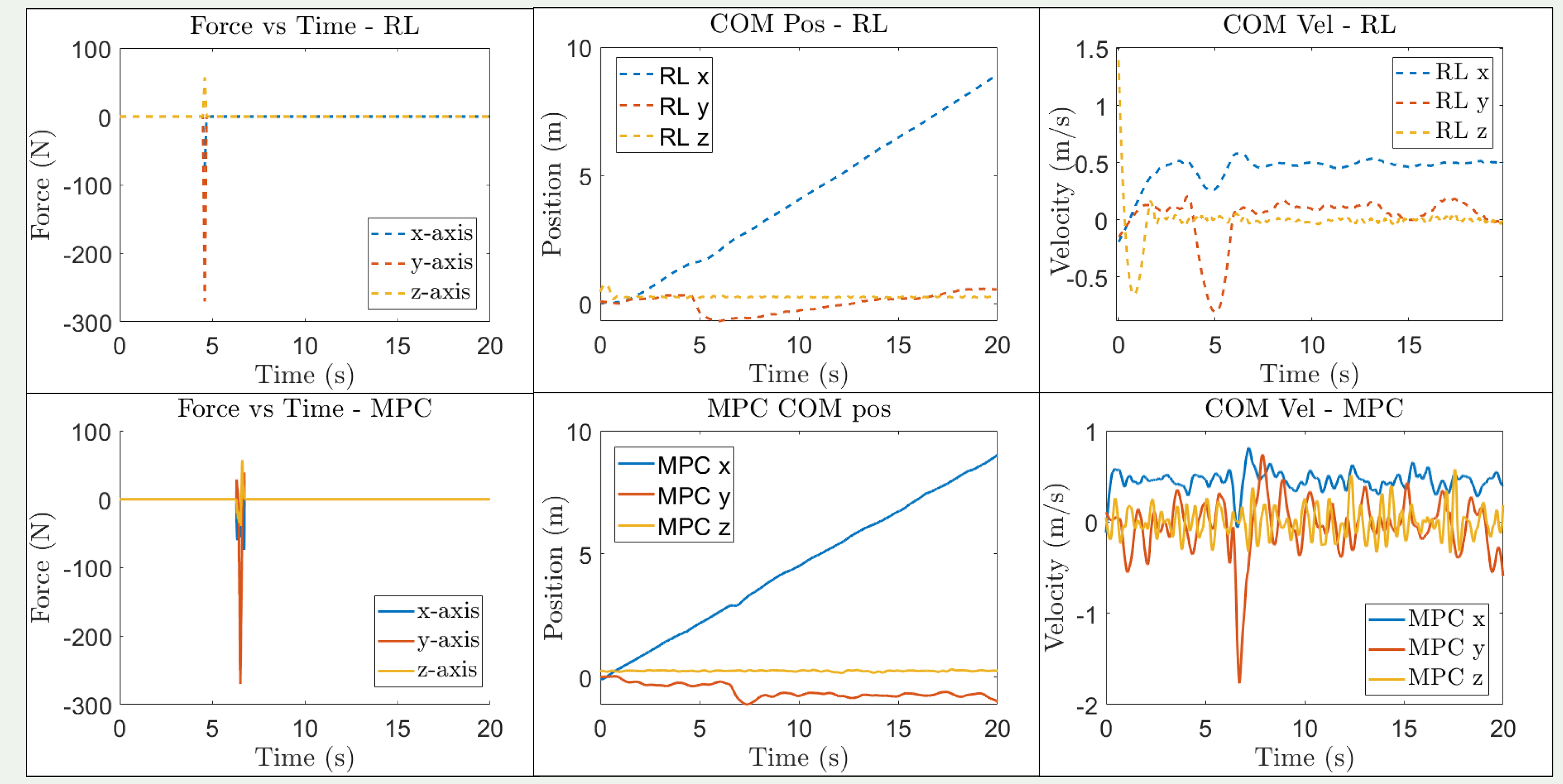
- Set a task to maintain 0.5 m/s along x-axis



Experiment 2: Perturbation along x-axis



Experiment 3: Perturbation along y-axis



Conclusion and Future Work

- Successfully implemented RL and MPC controllers on Unitree Go1 in MuJoCo-based simulation.
- RL demonstrates better disturbance rejection capabilities, largely attributed to the use of high-frequency control inputs.
- MPC is real-time and responsive, aided with complex control algorithm. MJPC offers interactive simulation, enabling fast parameter tuning. In contrast, RL, while time-intensive in training, offers a more straightforward coding approach.
- Future work will compare the two controllers under model uncertainty (flat, slippery, and uneven terrain).

References

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3. Raffin, Antonin, "RL Baselines3 Zoo", 2020
4. Brockman, Greg, et. al. "OpenAI Gym", 2016

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