IBRIDO: A Software Ecosystem for Research in Reinforcement Learning-based Receding Horizon Control[§]

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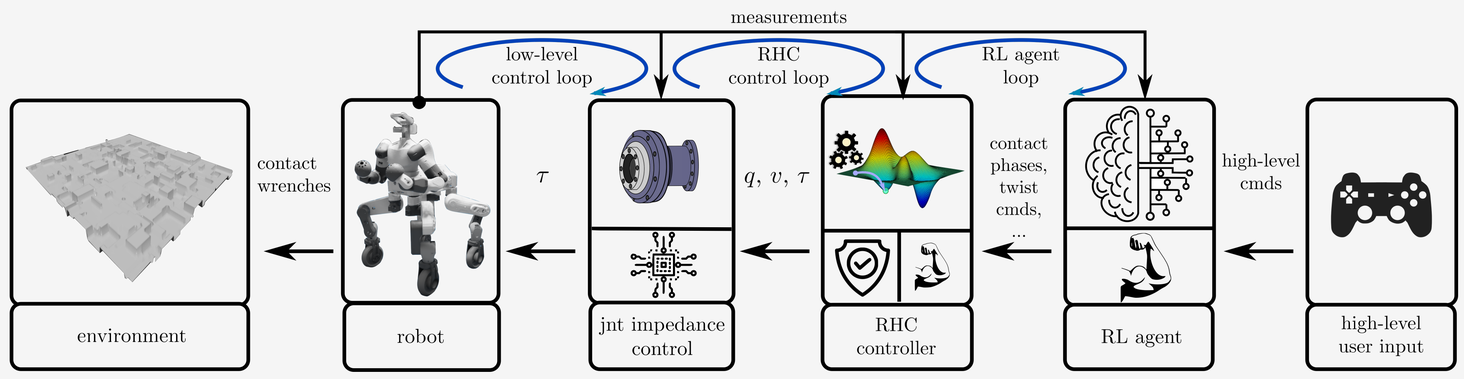
A Hybrid Approach: combining Receding Horizon Control and Reinforcement Learning

Most popular approaches:

- ▷ *Model augmentation*: improving prediction accuracy and control performance
- ▷ *Adaptive tuning* and *parameter optimization*: parameters tuning (e.g. weights, costs, constraints)
- ▷ *Safety*: learned-policy coupled with RHC controller, *safety filter*

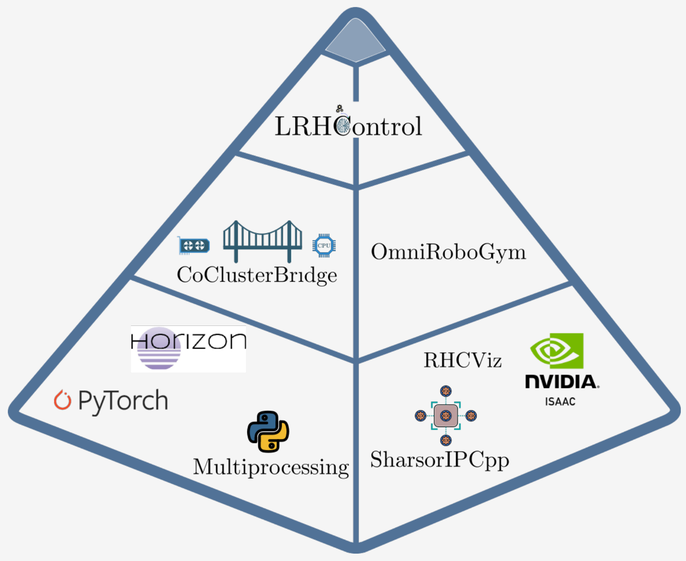
Our approach:



- ▷ *Hierarchical coupling*: agent on top of RHC controller
- ▷ RHC used as *local* and *safety-aware* controller
- ▷ Agent for high-level task achievement and RHC *performance* exploitation

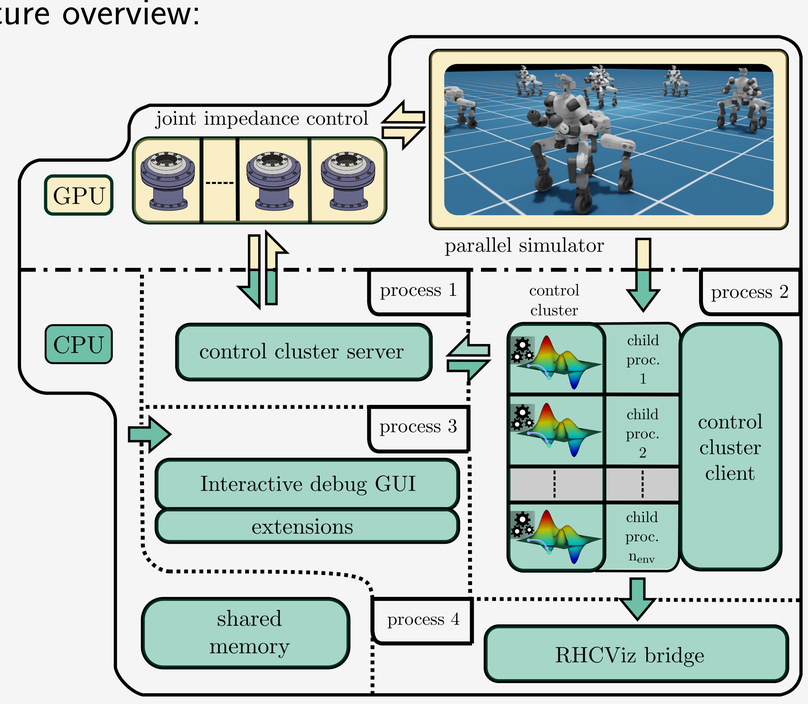
Software architecture

Software hierarchy:



- ▷ *LRHControl* → main package; sim, train env, task implementations.
- ▷ *CoClusterBridge* → coordinates connection between simulator and cluster of RHCs
- ▷ *OmniRoboGym* → wrapper on top of IsaacSim; base sim env
- ▷ *SharsorIPCpp* → shared memory backend
- ▷ Horizon (iLQR solver) → formulation of RHC controllers (CPU)
- ▷ Multiprocessing → RHCs parallelization on CPU
- ▷ GPU-accelerated simulation for data collection (IsaacSim)
- ▷ PyTorch for DL components

Architecture overview:

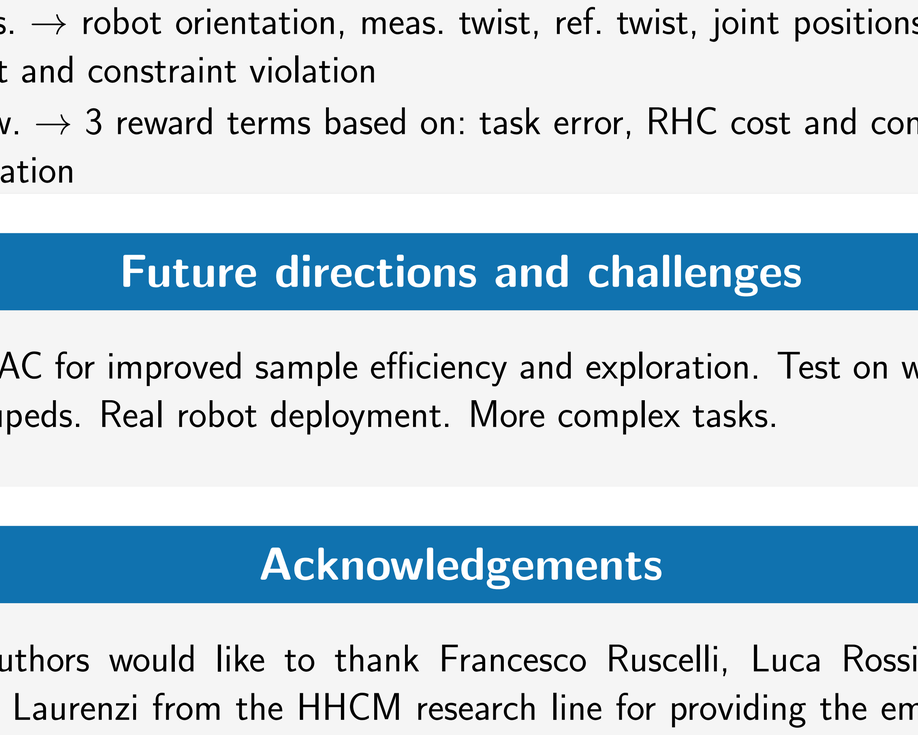


- ▷ Separate simulation and training env
- ▷ RHCs run in parallel, synchronously w.r.t. simulator
- ▷ Simulation stepping also parallel w.r.t. cluster solution
- ▷ Extensible debugging GUI for monitoring RHCs, training and for easier RL task tuning
- ▷ Single env visualization thanks to *RHCViz*

A proof-of-concept example: preliminary results

Workstation configuration used for testing:

- ▷ 32 core 13th Gen Intel(R) Core(TM) i9 - 13900KS workstation, 64 GB RAM, NVIDIA RTC 6000 Ada Generation
- ▷ Roughly 30 GB RAM necessary for running 256 RHCs + simulator (256 envs). 25% GPU usage at runtime, roughly 7 GB/48 GB



Proof of concept task:

- ▷ PPO algorithm for training
- ▷ Custom RHC controller for quadruped locomotion (closed source)
- ▷ Locomotion on flat ground exploiting RHC
- ▷ Act. → agent can command the RHC through twist commands and contact phases selection
- ▷ Obs. → robot orientation, meas. twist, ref. twist, joint positions, RHC cost and constraint violation
- ▷ Rew. → 3 reward terms based on: task error, RHC cost and constraint violation

Future directions and challenges

Test SAC for improved sample efficiency and exploration. Test on wheeled quadrupeds. Real robot deployment. More complex tasks.

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Resources and contact information

Data ↓

https://github.com/AndrePatri/IBRIDO

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