A Modular Ecosystem for Research in Learning-based Receding Horizon Control

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Abstract— Robotics research in manipulation and locomotion is undergoing a transformative shift towards the use AI-based tools, where purely learning-based control policies and pipelines are starting to take over the field. Despite being shown to be capable of remarkable robustness and performance even when applied to real-world environments, some key inherent limitations such as safety guarantees, interpretability, etc.. persist. For this reason, it is the authors' belief that more classical control approaches should not be considered outdated yet. We thus advocate for a hybrid approach, combining offline data-based policy design, specifically through Reinforcement Learning (RL), with classical online Motion Planning, i.e. Receding Horizon Control (RHC). Even though this kind of hybrid approaches are not entirely new, to the authors' knowledge, there is no specific tool currently available for search in this domain. To this purpose, we developed a modular software ecosystem, hereby synthetically presented in its main components and features. We care to stress that the framework is currently under active development, and features might not be stable or could be lacking. To facilitate usability and diffusion, we made all the core components open source under the GPLv2 license. To showcase the potential of the framework, we furthermore briefly present a proof-of-concept example combining a high-level RL agent coupled with a lower-level MPC controller for the execution of a simple locomotion task on our wheeled quadruped robot Centauro.

I. BACKGROUND: TRAJECTORY OPTIMIZATION, DEEP REINFORCEMENT LEARNING AND COMPUTING ADVANCEMENTS

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II. LEARNING-BASED MPC AND RESEARCH TOOLS

[13] [14] [11]

III. FRAMEWORK OVERVIEW AND RATIONALE

IV. CHALLENGES AND FUTURE WORK

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