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BSK-RL: MODULAR, HIGH-FIDELITY REINFORCEMENT LEARNING ENVIRONMENTS FOR SPACECRAFT TASKING

Abstract

Reinforcement learning (RL) is a highly adaptable framework for generating autonomous agents across a wide domain of problems. While RL has been successfully applied to highly complex, real-world systems, a significant amount of the literature studies abstractions and idealized versions of problems. This is especially the case for the field of spacecraft tasking, in which even traditional preplanning approaches tend to use highly simplified models of spacecraft dynamics and operations. When simplified methods are tested in a full-fidelity simulation, they often lead to conservative solutions that are suboptimal or aggressive solutions that are infeasible. As a result, there is a need for a high-fidelity spacecraft simulation environment to evaluate RL-based and other tasking algorithms.

To fulfill this need, this paper introduces BSK-RL. BSK-RL is an open-source Python package for creating and customizing reinforcement learning environments for spacecraft tasking problems. It combines Basilisk — a high-speed and high-fidelity spacecraft simulation framework — with abstractions of satellite tasks and operational objectives, all within the standard Gymnasium API wrapper for RL environments. The package is designed to meet the needs of RL and spacecraft operations researchers. Environment parameters are easily reproducible, customizable, and randomizable. Environments are configured in a highly modular way: satellite state and action spaces can be specified, mission objectives and rewards can be defined, and the satellite dynamics and flight software can be configured, implicitly introducing operational limitations and safety constraints. Heterogeneous multi-agent environments can also be created for more complex mission scenarios that consider communication and collaboration. Finally, training and deployment in the environment are demonstrated for an Earth-observing satellite with safety constraints, benchmarking the speed and performance of the environment.