Paper ID: 70138
oral
student

IAF ASTRODYNAMICS SYMPOSIUM (C1)
Mission Design, Operations & Optimization (1) (6)

Author: Mr. Nicholas LaFarge
Purdue University, United States, nlafarge@purdue.edu

Prof. Kathleen Howell
Purdue University, United States, howell@ecn.purdue.edu
Mr. David C. Folta
National Aeronautics and Space Administration (NASA), Goddard Space Flight Center, United States, david.c.folta@nasa.gov

ADAPTIVE CLOSED-LOOP MANEUVER PLANNING FOR LOW-THRUST SPACECRAFT USING REINFORCEMENT LEARNING

Abstract

To enable fully autonomous spaceflight and to establish a sustained human and robotic presence in deep space, rapid onboard maneuver planning is an essential technology. To meet this demand in complex, multi-body dynamical environments, several recent flight software implementations suggest iterative numerical methods to construct or update maneuver schedules to ensure mission criteria are met. For example, the autoNGC flight software system, developed by NASA Goddard Space Flight Center, implements a forward shooting scheme for onboard maneuver planning optimization. Similarly, the Orion onboard GN&C architecture leverages a differential corrections, or targeting, algorithm to alter maneuver plans based on navigation states. While targeting is demonstrated as effective for all of Orion's powered burns, it relies on sufficiently accurate startup solutions to maintain the current maneuver schedule. In the presence of large deviations or low-thrust propulsion options, an originally planned reference trajectory may prove insufficient for achieving targeting convergence. This investigation addresses this limitation by introducing a novel reinforcement learning paradigm that seeks to train a goal-oriented agent to rapidly generate accurate initial conditions for iterative guidance methods despite large deviations from a mission scenario.

Computational efficiency and algorithmic flexibility motivate the application of machine learning approaches for onboard tasks. In particular, reinforcement learning has emerged in recent years as a promising tool in onboard spaceflight guidance applications. Reinforcement learning excels in sequential decision making problems that lack a-priori knowledge of an effective control strategy, with recent applications frequently leveraging neural networks to parameterize the control function. In guidance problems, neural network controllers are demonstrated as potentially effective in overcoming challenging dynamical regions of space. However, the safety-critical nature of spaceflight poses practical barriers to onboard machine learning implementations, where neural network accuracy and explainability issues introduce risk to mission success. This investigation addresses the safety-criticality of incorporating a neural network into the guidance architecture by blending machine learning with traditional methods. In this paradigm, rather than directly controlling the spacecraft, the neural network is instead trained to estimate startup solutions for a traditional iterative approach. Directly incorporating traditional methods into the training process broadens the available solution space, reduces the impact of chaotic dynamics on the training process, and ensures all mission criteria are satisfied by the corresponding solution.