Autonomous closed-loop guidance using reinforcement learning in a low-thrust, multi-body dynamical environment*

*Reinforcement Learning Course Project Report

Ali Baniasad
Department of Aerospace Engineering
Sharif University of Technology
Tehran, Iran
ali_baniasad@ae.sharif.edu

Mehrdad Boroushaki
Department of Energy Engineering
Sharif University of Technology
Tehran, Iran
boroushaki@sharif.edu

***Abstract*—Onboard autonomy is an essential component in enabling increasingly complex missions into deep space. In nonlinear dynamical environments, computationally efficient guidance strategies are challenging. Many traditional approaches rely on either simplifying assumptions in the dynamical model or on abundant computational resources. This research effort employs reinforcement learning, a subset of machine learning, to produce a 'lightweight' closed-loop controller that is potentially suitable for onboard low-thrust guidance in challenging dynamical regions of space. The results demonstrate the controller's ability to directly guide a spacecraft despite large initial deviations and to augment a traditional targeting guidance approach. The proposed controller functions without direct knowledge of the dynamical model; direct interaction with the nonlinear equations of motion creates a flexible learning scheme that is not limited to a single force model, mission scenario, or spacecraft. The learning process leverages high-performance computing to train a closed-loop neural network controller. This controller may be employed onboard to autonomously generate low-thrust control profiles in real-time without imposing a heavy workload on a flight computer. Control feasibility is demonstrated through sample transfers between Lyapunov orbits in the Earth-Moon system. The sample low- thrust controller exhibits remarkable robustness to perturbations and generalizes effectively to nearby motion. Finally, the flexibility of the learning framework is demonstrated across a range of mission scenarios and low-thrust engine types.**

***Index Terms*—Reinforcement learning-based, computationally efficient closed-loop control enables autonomous low-thrust guidance in complex deep-space missions, showcasing flexibility across diverse scenarios without relying on explicit dynamical models.**

I. Introduction

Advancements in onboard autonomy are enabling new opportuni- ties for establishing a sustained human and robotic presence in deep space. In complex multi-body dynamical environments, such as in the Earth–Moon neighborhood, onboard applications for low-thrust spacecraft are particularly challenging. This investigation demonstrates Reinforcement Learning (RL), a subset of Machine Learning (ML), to be an effective approach for automated closed-loop guidance in these challenging regions of space. Onboard autonomous guidance requires a computationally efficient approach that addresses nonlinearity in the dynamical model and offers flexibility as requirements change inflight. In satisfying these criteria, RL provides a model-agnostic approach for training a neural network controller that is applicable to multiple problems, and potentially suitable for onboard use.

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II. Problem formulation

The three-body problem serves as a suitable dynamical model that is representative of observed natural motion in cislunar space. While the proposed guidance framework does not depend on any particular model, the planar Circular Restricted Three-Body Problem (CR3BP) serves as a useful environment for preliminary evaluation because it both represents a challenging region of space that is relevant to upcoming missions while sufficiently low-fidelity for initial analysis of the guidance scheme. Additionally, low-thrust propulsion is included to demonstrate algorithmic performance despite limited control authority and pronounced nonlinearities. While the proposed guidance scheme directly supplies a control history, an alternative concept of operations leverages the trained neural network to produce an initial guess for other numerical methods, such as targeting or optimization schemes. A sample direct multiple shooting algorithm is included in this analysis to demonstrate the added value of the neural network to the onboard targeting capability.

A. Dynamical model

The CR3BP is a model for the motion of an infinitesimal mass moving under the influence of two celestial bodies. In this model, two spherically symmetric gravitational bodies, P_1 and P_2 form the primary system as they move in circular orbits about their common barycenter, B; P_3 moves freely with respect to the barycenter. The motion of P_3 is governed by the following equations of motion:

$$\ddot{x} - 2\dot{y} = \frac{\partial U}{\partial x} + u\frac{\partial U}{\partial \dot{x}} \tag{1}$$

$$\ddot{y} + 2\dot{x} = \frac{\partial U}{\partial y} + u\frac{\partial U}{\partial \dot{y}} \tag{2}$$

where U is the effective potential function and u is the dimensionless thrust parameter. The effective potential function is defined as:

$$U = \frac{1}{2}(x^2 + y^2) + \frac{1-\mu}{r_1} + \frac{\mu}{r_2} \tag{3}$$