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# ROBUST DESIGN OF INTERPLANETARY TRAJECTORIES UNDER SEVERE UNCERTAINTY VIA META-REINFORCEMENT LEARNING

**Abstract**

Traditional optimal control methods represent consolidated tools to plan interplanetary trajectories in a deterministic setting. However, in real-world missions, the spacecraft motion is inevitably affected by several sources of uncertainty, which cause the actual trajectory to deviate from the reference one. Uncertainties arise due to unmodeled dynamics, inaccuracies in the orbit determination, and possibly control execution errors or missed thrust events (MTEs). Usually, a nominal trajectory is found neglecting these uncertainties. Robustness is checked a posteriori, and the nominal trajectory is improved iteratively, leading to a time-consuming and over-conservative procedure. Furthermore, ground-designed open-loop maneuvers may anyway show high sensitivity to unpredicted in-flight conditions. Several stochastic optimization methods have been proposed to directly account for these uncertainties into the trajectory optimization, the most famous being dynamic programming, model predictive control and belief-based optimization. However, these approaches generally struggle to handle a few challenges typical of robust space trajectory design, such as the uncertainty propagation through nonlinear dynamics and the presence of multiple joint stochastic constraints. Deep reinforcement learning (RL) has recently established itself as an effective and time-efficient solution method for complex control problems across different research areas, including space engineering. In deep learning approaches to spacecraft guidance, a neural network is used to map any observation of the spacecraft state to the corresponding control thrust. The problem is reformulated as a Markov decision process, and the network is trained by trial-and-error through repeated simulations of the mission scenario. Arbitrarily complex stochastic dynamics and observation models can be considered. Indeed, the exploratory behavior typical of RL algorithms, which learn through a huge number of samples, provide great robustness against variations in the environment definition. When deep RL algorithms are combined with a recurrent architecture of the network, an advanced framework, commonly referred to as meta-reinforcement learning, is obtained, which significantly boosts the average performance achieved by standard RL when dealing with non-Markov processes, which may arise from partial observability and MTE models. This paper investigates the use of deep meta-reinforcement learning for the robust design of low-thrust interplanetary trajectories. Specifically, a recurrent neural network will be trained via proximal policy optimization on a collection of environments featuring mixed sources of uncertainty. The objective is to build an internal representation of the stochastic dynamics that adapts to the considered scenario. Results in terms of optimality, constraint handling, and robustness will be compared with those returned by a more traditional fully-connected network.