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DEEP LEARNING FOR GLOBAL TRAJECTORY OPTIMIZATION IN MULTIPLE-ASTEROIDS EXPLORATION MISSIONS: A REINFORCEMENT LEARNING APPROACH

Abstract

In recent years, there has been a growing interest in asteroid exploration, with notable missions like DART and OSIRIS-REx seeking to test planetary defence methods and collect asteroid samples, respectively. However, despite having identified over one million asteroids, our knowledge remains limited since only a handful have been visited thus far. By exploring multiple asteroids with a single spacecraft, we can gain a more comprehensive understanding of planetary building materials and enhance our knowledge of the universe formation. Multi-phase trajectory optimization is a crucial part of aerospace missions to multiple asteroids, posing technical challenges due to the non-linearity of the problem and its combinatorial structure. In fact, as the search space grows larger, the complexity of the global sequence search increases, leading to significant computing difficulties. The traditional way for solving global trajectory optimization problems involves using hard-coded heuristics. Some of the competition-winning strategies in various edition of the Global Trajectory Optimization Competition (GTOC) focus on using evolutionary algorithms as global optimizers and indirect optimization methods as local optimizers. Even though the results are promising, both optimization methods have major weaknesses. Evolutionary algorithms are often tweaked by domain experts to fit the nature and the peculiarities of the problem at hand. In addition, the solutions are often suboptimal due to difficulty of the problem. On the other hand, indirect optimization methods require good initial guesses of the costates. Furthermore, they may struggle due to discontinuities in the state and control variables, leading to computational inefficiency and convergence issues. This limits the robustness of the method and makes evaluating a large set of transfers a difficult and time-consuming task. In light of these facts, the contribution of this work is two-fold. First, we propose a deep reinforcement learning approach to automate the search for trajectory scheduling. Then, a physics informed neural network is used in an inner-loop to speed up the convergence of the indirect method. This is performed by forcing the neural network to learn a mathematical law that governs the optimal control problem. This results in a reduction of the domain of the possible solutions that minimize the loss function of the network and a great improvement of its generalization power. The procedure is then applied to the problem proposed in the last GTOC competition. By comparing our results with those of well-established algorithms, we show that our approach is a promising direction for solving global trajectory optimization problems.