Monte Carlo Tree Search for Autonomous Small Body Science Operations*

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Abstract. Future small spacecraft missions to asteroids and comets will require on-board planning and scheduling capabilities to increase responsiveness and handle long periods without communication to the ground. This work explores policy-based decision-making agents for on-board planning and scheduling. Specifically, this work explores Markov decision process problem formulations and Monte Carlo tree search, an online tree search algorithm, to formulate and solve a small body science operations problem where the objective is to maximize the amount of spectroscopy map and number of surface image targets collected and downlinked. A hyperparameter search is conducted for Monte Carlo tree search, and a heuristic rollout policy based on the traveling salesman problem is presented.

Keywords: Spacecraft Autonomy · Small Bodies · Monte Carlo Tree Search · Markov Decision Processes.

1 Extended Abstract

On-board planning and scheduling will become a requirement as more ambitious missions are launched into deep space, particularly for small spacecraft missions to asteroids and comets where responsiveness and the ability to operate without ground intervention is desired. Past missions have flown on-board planning tools that utilize iterative repair to modify ground-based plans [3, 4, 2]. However, reinforcement learning has recently been posed for on-board planning and scheduling in both Earth-orbiting [7, 5] and small body missions [1, 8]. Reinforcement learning uses thousands of environment interactions to train decision-making agents that map states to actions (i.e. policies) to maximize a numerical reward signal, which encapsulates the objectives of the mission. Reinforcement learning offers a closed-loop planning solution, which is beneficial for on-board planning and scheduling on missions where responsiveness is desired.

Past work demonstrating reinforcement learning for planning and scheduling considers on-board data storage but typically does not account for downlink, power, and fuel resources. Spacecraft attitude and its impact on these resource states is also not modeled. The authors of this work have developed a small body science operations problem that incorporates these resource constraints in past work [6]. The problem is depicted in Fig. 1. However, deep Q-learning was applied to solve the problem and was found to be lacking in performance. Therefore, this work will apply the lessons learned in the Earth-orbiting domain to the small body domain, demonstrating how Monte Carlo tree search can be used to solve the planning problem. Monte Carlo tree search is parameterized over various numbers of exploration constants, simulations-per-step, and depths of search. A heuristic rollout policy that solves a traveling salesman problem is also implemented.

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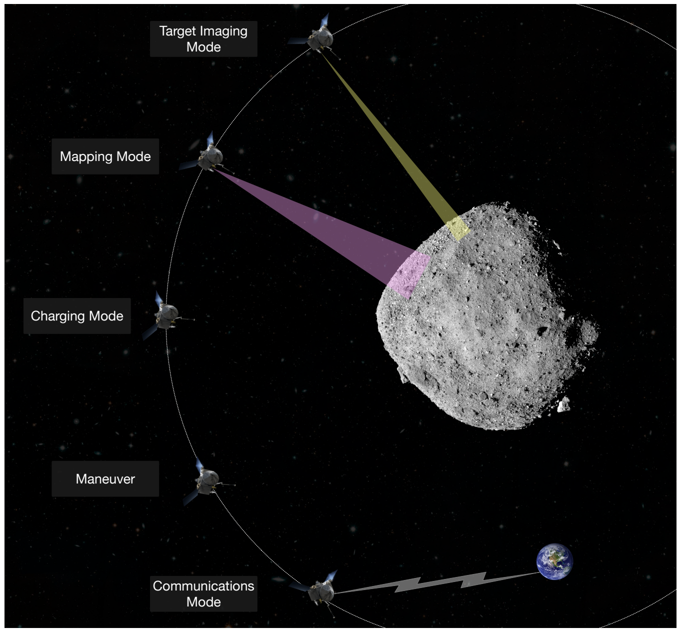

Fig. 1. Small Body Science Operations Problem

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