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Low Thrust Trajectory Optimization in Cislunar and Translunar Space

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Low-thrust propulsion technologies such as electric propulsion and solar sails are key to enabling many space missions which would be impractical with chemical propulsion. With exhaust velocities 10x higher than chemical rockets, electric propulsion systems can deliver a spacecraft to its target state for a fraction of the fuel. Due to the low thrust, the control must remain active for weeks or even years. When three-body dynamics are considered, the change in dynamics over the course of a trajectory can be extreme. This greatly complicates low-thrust mission design and navigation in cislunar and translunar space, making it an area of active research.

Deterministic strategies for trajectory design and optimization rely on linearizing the problem and solving a series of linearized problems. In regimes with simple or slowly-varying dynamics, the linearization holds “true enough”, and we can easily arrive at a solution. However, three-body environments readily provide real cases where the linearization for all but the most carefully-chosen problem descriptions break down. This thesis presents a few modifications to existing algorithms to improve convergence.

This thesis then uses this fast, robust method for trajectory optimization to generate training samples for a machine learning approach to optimal trajectory correction. We begin with one optimal low-thrust transfer. Then, we optimize thousands of transfers in the neighborhood of the nominal transfer. These transfers are described in the language of indirect optimal control, with the optimal control given as a function of Lawden’s primer vector. We see that for a slightly

different initial condition, the states and the costates both follow a slightly different trajectory to the target. A feedforward artificial neural network is trained to map the difference in states to the difference in costates, with a high degree of accuracy.

Finally, we explore a potential application of this neural network: spacecraft that can navigate themselves autonomously in the presence of errors. We propose this as a method for future spacecraft that can optimally correct their trajectories without ground contacts. We demonstrate neural network navigation in two simplified dynamical environments: two-body heliocentric gravity, and the Earth-Moon circular restricted three body problem.