Heuristic Search and Receding-Horizon Planning in Complex Spacecraft Orbit Domains*

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Abstract

Spacecraft missions to small celestial bodies face sensitive, strongly non-Keplerian dynamics that motivate the employment of automated sampling-based trajectory planning. However, the scarcity of onboard computing resources necessitates careful formulation of heuristics for efficiently searching the reachable sets, which exhibit complex and finely-detailed structure. We examine a global search heuristic that combines aspects of simulated annealing and hill-climbing to locate sparse regions of the planning domain that simultaneously satisfy numerous geometric and timing constraints associated with remote sensing objectives for points of interest on the central body surface. Subsequently, we demonstrate the use of a receding-horizon implementation of this maneuver-planning strategy to produce mission profiles that fulfill sets of such goals.

Introduction

Traditional space mission design is anchored in Keplerian motion, which allows for any orbital state to be immediately associated with its conic section, an easily-described one-dimensional manifold of the six-dimensional orbit state space. A conventional ruleset exists for piecing these unchanging orbits together with impulsive thrust maneuvers to take a spacecraft from one desired state to another; this is applicable to many actual systems that contain only small perturbations relative to a spherically symmetric gravity field. However, missions to closely study small celestial bodies such as asteroids and comets — important targets for planetary science, planetary defense, and eventual resource exploitation — face constant exposure to strong perturbations from Keplerian motion, driven by highly nonspherical gravity fields and proportionally large third-body gravitation and solar radiation pressure. The resultant highly non-periodic motion causes conic sections to no longer be an apt basis for even short-term trajectory design (Russell 2012).

An alternate class of mission design strategies for non-Keplerian orbit environments exists, relying heavily upon exploitation of periodic orbits that sparsely populate the phase space; given an exhaustive precomputed database of these structures, efficient onboard mission design can be posed as a graph search (Trumbauer and Villac 2014). Unfortunately, a lack of accurate apriori system knowledge can, when combined with large navigation uncertainties and dynamical sensitivity, rapidly result in highly off-nominal conditions or even mission failure, hampering this far-sighted approach. Further, the independent matter of relating system dynamics to ultimate mission goals and constraints is equally nontrivial. The sum of these complications motivates yet another distinct approach to mission design: sampling-based planning in the form of an efficient heuristic search of the spacecraft's complexly structured reachable set (Komendera, Scheeres, and Bradley 2012).

Applied onboard in a receding-horizon fashion, this trajectory design strategy could allow flexible and opportunistic responses to rapidly-growing errors and meet spaceflight autonomy requirements seen as pivotal to enabling ever more ambitious exploration missions (Pavone et al. 2014), synergistically complementing onboard automation of other planning tasks such as management of subsystems for communications and science instrument operations.

Planning Domain

A classic control input paradigm of intermittent impulsive-thrust maneuvers remains appropriate and practical despite the target systems' starkly atypical orbit dynamics. This defines a single-maneuver planning domain $\Delta\mathcal{V}$ whose center is designated by the initial velocity vector. The reachability map M applies a hierarchy of system dynamics, consisting first of the strongly non-Keplerian orbit dynamics (here either those of the small, elongated asteroid Itokawa or the low-orbiting Martian moon Phobos) and then the mission objectives (here the tracking of the duration over which the trajectory satisfies observation requirements given visually in figure 2). In the final step, an objective function maps into the score space $\mathcal{S}(t)$ by which an an automated planner designates the next action to be taken; after variably truncating the time horizon to maximize score, the reachability map is $M : \Delta\mathcal{V} \longrightarrow \mathcal{S}$. Augmentation of $s(t) \in \mathcal{S}(t)$ with another computed value $\hat{Q}_{max}$ creates a gradient, representing how closely an unsuccessful trajectory passes by a potentially hard-to-locate observation region, that aids the search for maxima on M; see figure 1.

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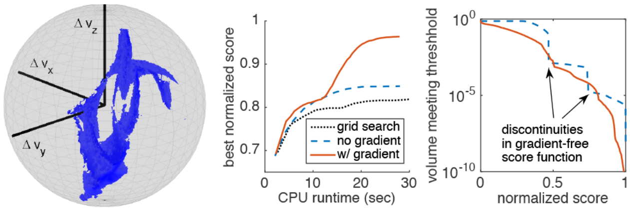

Figure 1: Left: Level surface of augmented objective function in M. Center: Monte Carlo mean performance of search heuristics. Right: Sparseness of high-scoring regions.

Heuristic Search

The nonintegrability of the dynamical model necessitates a sampling-based approach for charting M. A heuristic-based iterative mesh refinement strategy is used to drastically improve the efficiency of this process relative to a simple grid search (Komendera, Scheeres, and Bradley 2012; Surovik and Scheeres 2015). Beginning with an initial random or grid sample of maneuvers $\Delta \mathbf{v_i} \in \Delta\mathcal{V}$, scores $s \in \mathcal{S}$ are computed via numerical integration. Next, Delaunay Triangulation is used to build this small sample of points in M into a mesh, i.e. a set of tetrahedral "simplex" volume elements each bounded by four vertices, to allow inference of its continuous structure. The search heuristic then operates on the mesh, assigning each j-th simplex a weight W_j based upon the extent to which the numerically propagated results of its vertices indicate that it contains relevant missing detail. Finally, a random sample of simplex IDs is taken to determine the locations of the next maneuver sample set. This process of meshing, propagation, and heuristic search is repeated until a specified final sample size is reached.

Weights are assigned such that the random sample of discrete elements functions in a roughly continuous manner.

$$W_j = V_j \cdot \underset{j}{\text{mean}}\{\Delta t\} \cdot \max_j \left\{ s + \hat{Q}_{max} \right\}^\wedge \left(2^{8\tau}\right) \qquad (1)$$

The first factor, simplex volume V, normalizes the uneven sample distribution while the second, the mean trajectory lifespan, scales sample probability density in accordance with the varying temporal depth of M and the final factor biases the search in proportion to the gradient-augmented score. As the refinement completion factor τ increases from 0 to 1, the exponent of the bias term causes it to be progressively amplified, causing the global search to hone in on maxima in a manner akin to Simulated Annealing or Rapid Random Trees (though the notion of paths does not apply to this search domain). Monte Carlo mean results of searches of a typical planning domain are plotted in figure 1.

Receding-Horizon Planner

To complete a set of several observation objectives, this maneuver design scheme is applied in a receding-horizon fashion (Surovik and Scheeres 2014), as has frequently been deemed appropriate for aerospace vehicle motion planning scenarios in highly dynamic environments. A *horizon prospect function* $p_h(\mathbf{x}(t))$ is formulated to account for two additional subtleties of planning: maneuver timing (selection of trajectory lifespan Δt) and consideration of prospects beyond the planning horizon. The current implementation of p_h enforces a preference for arc termination at altitudes in the range associated with the observation regions, providing favorable structure of the next M. Each planning cycle thus uses a heuristic search to identify an available action and trajectory lifespan $(\Delta t, \Delta \mathbf{v})$ that maximize $s \in \mathcal{S}(t; \Delta\mathcal{V})$, providing a balance of short-term progress with long-term prospects. Repeated application of this scheme produces mission profiles that fulfill all goals, as seen in figure 2, while its sampling-based nature implies an ability to accommodate any possible dynamical model and mission requirement set, limited solely by onboard computational power.

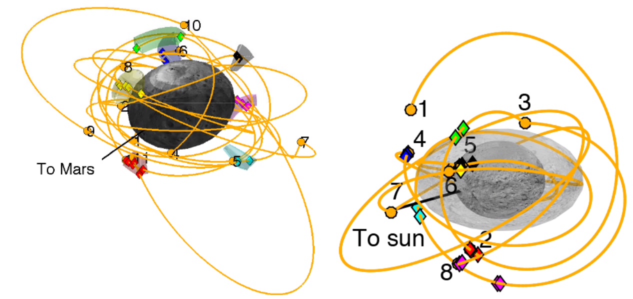

Figure 2: Rotating-frame solution at Phobos and inertial-frame solution at Itokawa; diamonds denote start/end of successful observations, demonstrating satisfaction of viewing geometry (colored regions) and Sun-phasing requirements.

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