National Aeronautics and Space Administration

Multi-Spacecraft Architectures for Long Period Comet and Interstellar Object Exploration

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Program: FY21 R&TD Topics **Strategic Focus Area: Systems architecture**

Objectives and Background

The main objective of this RTD is to develop a multi-spacecraft architecture for exploring fast-moving and long-period objects such as interstellar objects (ISO), addressing the key technology risks in artificial intelligence-based autonomous guidance and control in very time constrained conditions.

The most significant challenge for ISO mission concepts, and the driver for this proposal, results from the unpredictable orbits of long-period objects, with generally high inclinations and high relative velocities. It is easier to encounter them when they cross the ecliptic but the relative velocity between a target body and the spacecraft constellation is >30 km/s. These considerations imply a short encounter duration between the spacecraft fleet and the target, requiring fast response autonomous operations while the very high speeds demand adjustments from far away. Handling these uncertainties and high-velocity challenges from a mission architecture and autonomy standpoint constitutes the uniqueness of this task.

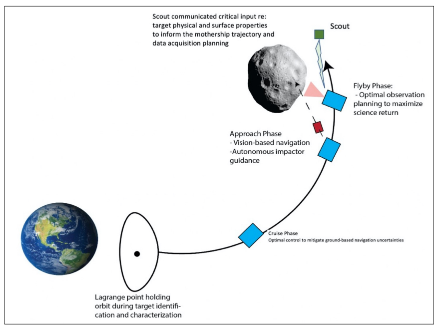
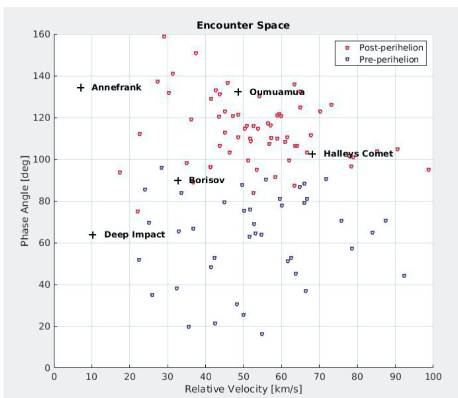


Figure 1. Flyby scenario explored in this study.

Figure 2. Space of targets that could be encountered by the flight systems considered in this study, represented in terms of relative target-spacecraft velocities and phase angle for pre- or post-perihelion approach. These targets are based on a synthetic ISO population developed by Engelhardt et al. (2017).

	Robust MPC	Naïve Learning	Robust Learning
Overview	Guidance and control based on whatever objective	Guidance and control based on whatever objective	Guidance and control based on whatever objective
Novelty	Obtain optimal target trajectory x_d w.r.t. the objective	Enable real-time computation of x_d	Enable real-time computation of x_d and robust control u that tracks x_d
Inputs	S/C and ISO state measurements at least (& available resources, e.g., fuel)	S/C and ISO state measurements at least (& available resources, e.g., fuel)	S/C and ISO state measurements at least (& available resources, e.g., fuel)
Outputs	Control input u (e.g., thrusting, repointing)	Control input u (e.g., thrusting, repointing)	Control input u (e.g., thrusting, repointing)
Remarks	Number of maneuvers, control frequency, etc. are design parameters	Number of maneuvers, control frequency, etc. are design parameters	Number of maneuvers, control frequency, etc. are design parameters
Benefits	Optimality and robustness guarantee*	Suboptimality and real-time applicability	Suboptimality, real-time applicability, and robustness guarantee*
Limitations	Computing x_d in real-time could be time-consuming	Not robust against disturbances (e.g., measurement noise)	Might fail in states and environments distinct from training samples
Tracking error	Bounded	Increases exponentially	Bounded with learning error
Online comput. load	High	Low	Low
Offline comput. load	Low	High	Higher
Scalability (multi-agent)	Not (necessarily) scalable	Scalable due to neural net	Scalable due to neural net
Robustness to d_{sc}	Robust due to feedback	Not robust	Robust due to feedback
Robustness to d_{iso}	Hard to quantify due to nonlinearity	Not robust	Robust and adaptive due to spectral normalization
Optimality	Suboptimal due to feedback	Suboptimal due to learning	Suboptimal due to feedback and learning
Safety	Guaranteed	Guaranteed when equipped with safety control	Guaranteed

Figure 3. Characteristic and performance assessment of the learning-based terminal guidance and control techniques considered in this task.



Approach and Results

Task 1 was about developing science to mission requirements flow-down and mission architecture design for a reference ISO population. We built a database for a reference population of ISOs based on input from Robert Jedicke et al. from University of Hawai'i. This database was used to compute possible trajectories, leading to the design of a reference trajectory, navigation uncertainties and target position uncertainty, serving as a basis for Task 2.
In order to ensure that the guidance and control requirements and design would be consistent with current and emerging spacecraft capabilities, we developed several reference architectures, covering a range of propulsion performance and assessed telecommunication performance among assets, and for a concept of operations covering deployment to flyby. The architecture first focused on a single spacecraft in order to define the input and output of the problem.

Task 2 derived science-driven autonomy and safety-critical autonomous guidance and control engines for the reference ISO mission designed under Task 1. We developed online trajectory generation methods with learning adaptation, which improves upon state-of-the-art off-line optimal trajectory generation for multi-spacecraft architectures. We also developed autonomous guidance and control algorithms with tight integration of machine learning. Given the above architectures and planned trajectories, the algorithms were developed for onboard trajectory adjustments as necessary to guide the spacecraft for optimal/acceptable instrument placement.

Task 3 tests this first-year algorithms in the Small Satellite Dynamics Testbed (SSDT). We tested a baseline controller only using proportional control to control to desired position and a model predictive control developed as part of Task 2 (Figures 3, 4). The simulations used a reference trajectory developed in Task 1. These preliminary tests assumed perfect knowledge of the desired ending position. Position knowledge error was injected by adding noise to the simulated spacecraft position measurements. Comparisons between the results obtained with the two control approaches are presented in Figure 5. They show that the model predictive controller is one order of magnitude more performant than the baseline controller in terms of the delivery error and for about 25% lower fuel consumption.

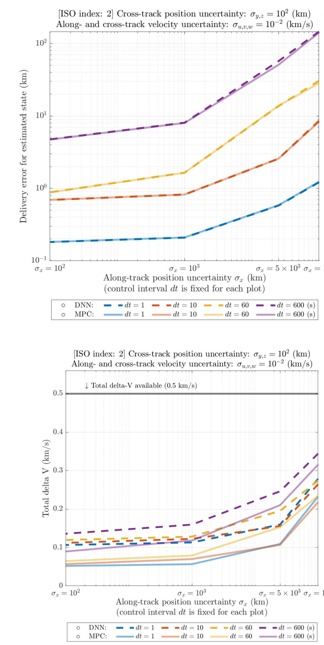


Figure 4. Example of simulation results (delivery error and delta-V required to meet that delivery performance) for the MPC controller pursued in this study (Figure 3).

Significance/Benefits to JPL and NASA

This work increases NASA and JPL's institutional capabilities in AI-based guidance and control algorithms that will be particularly beneficial to handle a variety of unknowns and uncertainties associated with a mission for an ISO. We will develop new approaches—and adapt and mature existing techniques—in AI-based autonomous guidance and control; autonomy of small-body approach; and autonomous multispacecraft formations. Much of this work would be applicable to investigating other objects in the solar system, especially for increasing the science return of fly-by missions to main belt asteroids and transneptunian objects Publications from this work can be found in the report.

Test Case	Duration	End Position Error (m)	Position Error (Mag)	Velocity Error (km/s)	Fuel Used	Comp Load (avg)
Ballistic	1 Hour	[8637.5 3456.9 -6912.0]	11.590 km	[-20.56 22.47 55.38]	0	0 µs
Perfect Knowledge	1 Hour	[-0.2170 -0.0857 0.1837]	0.2969 m	[-20.56 22.47 55.38]	1	1.553 µs
Pos Know Error: 25 km	1 Hour	[10091 -99143 88566]	133.323 km	[-20.56 22.53 55.33]	4.9795	1.579 µs
Pos Know Error: 50 km	1 Hour	[-54646 44863 112286]	132.691 km	[-20.52 22.45 55.32]	4.9840	1.680 µs
Pos Know Error: 100 km	1 Hour	[-53765 59303 -2191]	80.077 km	[-20.52 22.44 55.38]	3.0015	1.530 µs
Pos Know Error: 200 km	1 Hour	[-55565 10467 -16561]	58.918 km	[-20.52 22.46 55.39]	2.3419	1.966 µs
Pos Know Error: 1000 km	1 Hour	[69385 105874 65461]	142.509 km	[-20.59 22.41 55.34]	4.9884	1.658 µs

Test Case	Duration	End Position Error (m)	Position Error (mag)	Velocity Error (km/s)	Fuel Used	Comp Load (avg)
Ballistic	1 Hour	[8637.5 3456.9 -6912.0]	11.590 km	[-20.56 22.47 55.38]	0	0 µs
Perfect Knowledge	1 Hour	[0.8630 0.8843 0.0272]	1.2360 m	[-20.56 22.47 55.38]	0.3437	238.5 µs
Pos Know Error: 25 km	1 Hour	[-1736.1 -317.20 1078.7]	2.068 km	[-20.56 22.47 55.38]	3.4092	187.0 µs
Pos Know Error: 50 km	1 Hour	[-3650.9 -832.3 2085.7]	4.286 km	[-20.56 22.47 55.38]	3.7112	191.4 µs
Pos Know Error: 100 km	1 Hour	[-6173.0 -2202.5 3988.3]	7.672 lm	[-20.56 22.47 55.38]	3.7783	188.5 µs
Pos Know Error: 200 km	1 Hour	[-7306.2 -2784.9 4989.1]	9.275 km	[-20.56 22.47 55.38]	3.7567	189.3 µs
Pos Know Error: 1000 km	1 Hour	[-9935.5 -5244.4 5375.8]	12.455 km	[-20.56 22.47 55.38]	3.7666	187.9 µs

Figure 5. Example of SSDT simulation results for a baseline controller that only uses proportional control to control to desired position (top table) and the model predictive controller considered in this study (see Figure 4 and text) (bottom table).

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