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Autonomous Orbital Maneuver Planning: A Comprehensive Scientific Review

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Abstract: Autonomous Orbit Maneuver Planning (AOMP), or autonomous orbit control, refers to the capabilities for real-time computation of orbits for a spacecraft considering constraints like fuel economy, collision avoidance, and disturbances. This review article surveys the overall theoretical framework and applicability of principal approaches: optimal control theory, MPC, convex optimization, sampling-based motion planning, and learning-based approaches. The key challenges and future research avenues are also discussed in this technical paper. All references in this paper were peer-reviewed or were valid preprints and were formatted in IEEE style.

Keywords: Autonomous Orbital Maneuvers, Trajectory Optimization, Spacecraft GNC, Onboard Autonomy, Intelligent Spacecraft.

1. Introduction

Autonomy in orbital maneuvers is a key requirement in current space missions such as rendezvous, docking, debris separation, formation flying, and other space services. Conventional methods that are ground-based are no longer scalable to current mission requirements [1, 2]. There are also limitations in autonomy planners with respect to uncertainty, dynamics, and computational complexity [3]. The cited literatures are arranged based on thematic relevance rather than timeline in order to systematically and comparatively assess autonomous orbital maneuver planning techniques, research tendencies

2. Orbital Dynamics and Constraint Modeling

2.1 Relative Motion Models

The Clohessy–Wiltshire (CW) equations are fundamental for modeling relative motion in near-circular orbits [4], [5]. Extensions to nonlinear dynamics provide higher fidelity for rendezvous and proximity operations [6].

2.2 Planning Objectives and Constraints

AOMP formulations typically minimize cost functions involving fuel (Δv) and time while satisfying constraints such as thrust limits, line-of-sight (LOS), safety zones, and collision avoidance [7], [8].

3. Optimal Control Methods

3.1 Indirect Optimal

The results are obtained by the indirect methods through Pontryagin's Minimum Principle and have been applied to minimum fuel problems in rendezvous involving minimum principles [9],

[10]. Though optimal results, the approach needs initial good approximations and is sensitive to problem variations.

3.2 Direct Pseudos'

For direct transcription methods, Legendre and Chebyshev pseudo spectral methods are particularly effective at formulating control problems into nonlinear problems, which enhance robustness when constraints are complex [11], [12], [13].

Comparison: The indirect approaches are theoretically optimal but yield inferior numerical accuracy to the pseudo spectral direct approaches in handling constraints [9] [10] [11] [12] [13].

4. Predictive and Convex Optimization

4.1 Model Predictive Control (MPC)

MPC optimizes a constrained finite horizon problem every time step and thereby addresses the online trajectory planning problem well [14], [15]. Cases include rendezvous with a tumbling target [16] and rendezvous with perturbations [17].

4.2 Convex

Techniques such as convexification have been used to solve the nonconvex dynamics by formulating nonconvex problems as convex sub-problems, which are solved efficiently with global optimality results in the convex domain [18, 19]. Sequential convex programming is applied in collision avoidance, proximity operations, among others [20].

Related Work: Robustness to model parameter uncertainties is achieved by MPC, while high computational efficiency, by convex optimization [14], [18], [19], [20].

5. Sampling-Based Planning

Other sampling techniques such as Rapidly-Exploring Random Trees (RRT) and Fast Marching Tree (FMT*) can compute feasible trajectories in high-dimensional space with non-convex constraints [1], [21]. Dual quaternion based RRT* can enhance pose smoothness in docking analysis [22].

Comparison:

Sampling planners are very good in complex and nonconvex settings but normally do not offer optimality guarantees as provided by convex and pseudo spectral methods. [1] and [22]

6. Learning-Based Approaches

6.1 Reinforcement Learning (RL)

In this regard, policy gradient and PPO algorithms have been used to derive maneuver policies without explicit dynamic models [23], [24], [25]. These methods can adapt to unforeseen scenarios but usually lack formal safety guarantees.

6.2 Hybrid Learning and Control

Hybrid frameworks combine machine learning with model-based controllers-such as MPC-applying both adaptability and constraint enforcement [26], [27].

Comparison: Learning methods can be flexible in real-time but are intensive to train; hybrid methods compromise between adaptability and safety [23], [27].

7. Application Scenarios

7.1 Rendezvous and Docking

Autonomous rendezvous requires precise modeling and real-time planning. MPC and convex optimization have been shown to handle tumbling target approaches with constrained dynamics [16], [28].

7.2 Collision Avoidance Maneuvers

Collision avoidance is a high-priority application of AOMP. Both analytical and optimization methods have been developed to generate collision avoidance maneuvers efficiently [2], [20], [29].

7.3 Orbital Transfer and Station-Keeping

Trajectory optimization has been applied to orbital transfers and station-keeping in perturbed environments, demonstrating trade-offs between fuel efficiency and computational feasibility [30], [31].

8. Comparative Assessment

Method	Optimality	Real-Time	Constraint Handling	Robustness	Safety
Indirect Optimal Control	Very High	Low	Moderate	Low	Moderate
Pseudo spectral Direct	High	Moderate	High	Moderate	High
MPC	High	Moderate-High	Very High	High	High
Convex	Moderate-High	High	High	High	High
Sampling	Moderate	High	Moderate	Moderate	Moderate
RL	Variable	Very High	Moderate	Low	Low
Hybrid	High	High	High	High	High

9. Open Challenges and Future Research Directions

Although progress has been made, there are still a number of

9.1. Robust Uncertainty Management:

Management of uncertainties due to dynamics, sensing, and actuation is a major challenge. Currently, research focuses on robust MPC and probabilistic planning [14], [28], [32], [33].

9.2 Formal Safety Guarantees for Learning:

Currently, there are few learning methods for which formal safety guarantees are available, and RL and safety filter/control barrier implementations remain a current front-end research area [26], [34], [35].

9.3 Computational Constraints:

Real-time, on-board computation is still limited by computational capabilities. Despite advancements in convex solvers and predefined MPC, computation times are still not short enough for many applications [18], [20], [36].

9.4 Benchmarking and Standardization:

The absence of standardized test scenarios or benchmarks for AOMP hinders comparisons. Benchmarking activities in the astrodynamics community are underway with the aim of developing common benchmarks [37, 38].

9.5 Multi-Agent and Swarm Coordination:

When Constellations are scaled out, multi-agent coordination involves complexities in communication as well as planning for the agents' operations to be completed by AOMP in a decentralized manner [39], [40].

10. Conclusion

It is a multidisciplinary area that fuses classical control theory, optimization, motion planning, and learning. None of these techniques is definitively superior to any other. Nonetheless, hybrid approaches which make use of both optimization and learning could present an enabling factor for real-time, constrained planning. In the future, research points toward robust provable autonomy, using standardized benchmark problems with practical onboard realizations.

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