Towards Robust Spacecraft Trajectory Optimization via Transformers

Progress Report

Perera ITM - 210460V

August 24, 2025

Overview

Orbital Mechanics

Spacecraft rendezvous builds on classical orbital mechanics. In the two-body problem under Newtonian physics, each spacecraft follows a Keplerian orbit (an ellipse or conic) about the central body. Rendezvous involves planning a path from the chaser's initial orbit to the target's orbit. For nearby (close-range) motion, a target-centered rotating frame (often called Hill's or LVLH frame) where the axes are defined relative to the target's motion (radial, along-track, normal) is typically used. In this frame, Clohessy-Wiltshire (Hill's) equations give a linearized relative motion model under the assumption of a circular reference orbit. Clohessy and Wiltshire's original guidance formulation (used in Gemini rendezvous) assumes small separation and yields simple linear equations for the chaser's relative position and velocity [3] . In practice, the relative state is represented either as a Cartesian RTN state (relative position and velocity vectors in the target-centered frame) or via Relative Orbital Elements (ROE), which are combinations of the servicer's and target's orbital elements and serve as integration constants of the linearized dynamics [2] .

Optimal rendezvous maneuvers are typically solved as boundary-value problems in the full two-body dynamics. The classic approach is Lambert's problem: given two positions (initial and final) and a time-of-flight, find the conic transfer orbit that connects them under gravity. Lambert's theorem states that the transfer time depends only on the geometry of the two points and the orbit's semi-major axis [4] . Solving Lambert's problem gives the impulsive maneuvers for minimum-time or minimum-fuel transfers, and is used for preliminary trajectory planning.

Autonomous Rendezvous Transformer (ART) [2]

The Autonomous Rendezvous Transformer (ART) is a Transformer-based framework designed for trajectory optimization, specifically applied to spacecraft rendezvous. Its primary goal is to enhance traditional sequential optimizers by providing learning-based warm-starts, thereby leveraging the benefits of data-driven approaches while ensuring the satisfaction of hard constraints. ART was developed to address limitations in existing AI-based methods for trajectory optimization in autonomous dynamical systems. Current AI techniques often either completely replace traditional control algorithms, leading to a lack of constraint satisfaction guarantees and expensive simulations, or merely imitate traditional methods through supervised learning. ART aims to overcome these issues by integrating modern generative models with traditional optimization.

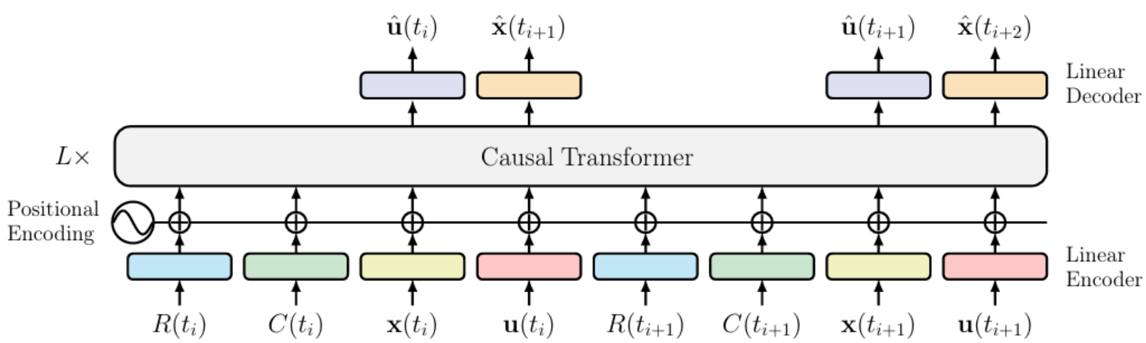


Figure 1: ART Architecture from [2].

The architecture processes trajectories represented as sequences of performance parameters, states, and controls. A trajectory (τ) is defined as:

$$\tau = \big(P(t_1), x(t_1), u(t_1), \ldots, P(t_N), x(t_N), u(t_N)\big),$$

where P includes performance parameters like reward-to-go (R), indicating future optimality, and constraint-to-go (C), signifying the expected feasibility or constraint satisfaction. For robust scenarios, this representation is extended to include a target state.

ART processes the last K timesteps of an input trajectory, where K is the context length. Each timestep includes multiple modalities such as reward-to-go, constraint-to-go, state, and control, with an optional target state for robust scenarios. Each element is encoded into an embedding space using modality-specific linear transformations, followed by the addition of positional encodings to preserve temporal information.

The encoded sequence is passed to a GPT-based architecture composed of Transformer blocks. These blocks use self-attention to relate different elements within the sequence. To maintain temporal causality, a masking mechanism ensures that each element attends only to past elements, preventing information leakage from the future.

After processing, ART generates future states and controls in an autoregressive manner. The Transformer outputs are projected through decoders to obtain the predicted trajectory.

During inference, ART operates in two modes: (i) predicting states directly or (ii) predicting controls and propagating states through a dynamics model for feasibility.

Methodology Overview [1]

The study extends the Autonomous Rendezvous Transformer (ART) in [2] to generate robust warm-starts for chance-constrained spacecraft trajectory optimisation. The approach combines a learning-based trajectory generator (ART), a runtime acceptance check, and optimisation-based refinement via Sequential Convex Programming (SCP) to ensure reliability in Low Earth Orbit rendezvous scenarios.

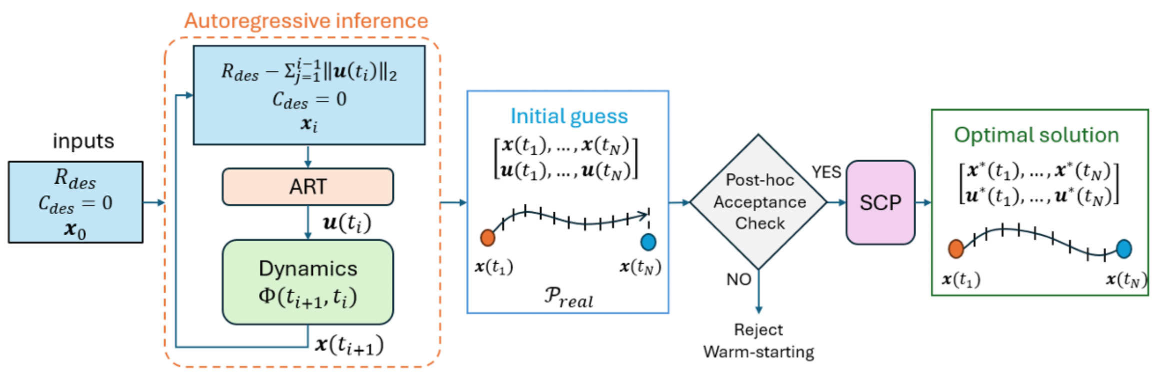


Figure 2: Pipeline of ART inference for non-convex chance-constrained trajectory optimization [1].

1. Dataset

Two large datasets were created: one deterministic and one chance-constrained, each containing approximately 115,000 trajectories. A multi-stage optimisation pipeline produced these trajectories, involving a convex two-point boundary value problem, a deterministic collision-avoidance step, and a full chance-constrained problem ensuring passive safety.

2. Model and Training

ART uses a GPT-style Transformer to model trajectories as sequences of states, controls, and performance indicators. It learns from the generated datasets using a teacher-forcing strategy to minimise prediction error. The model was implemented in PyTorch with standard training techniques.

3. Inference

At test time, ART generates an open-loop trajectory autoregressively. It predicts controls and propagates states using a dynamics model (*dynamics-in-the-loop*) to maintain feasibility. Two state representations were considered: RTN (Radial-Tangential-Normal) and ROE (Relative Orbital Elements).

4. Post-hoc Acceptance Check

A lightweight filter evaluates the quality of ART-generated trajectories using error metrics on performance parameters. If a trajectory fails this check, the method falls back to a conservative warm-start from a convex solver.

5. Optimisation Refinement (SCP)

The accepted ART-generated trajectory serves as a warm-start for SCP, which iteratively refines it into a dynamically feasible and constraint-satisfying solution. Chance constraints are linearised around reference trajectories during this process.

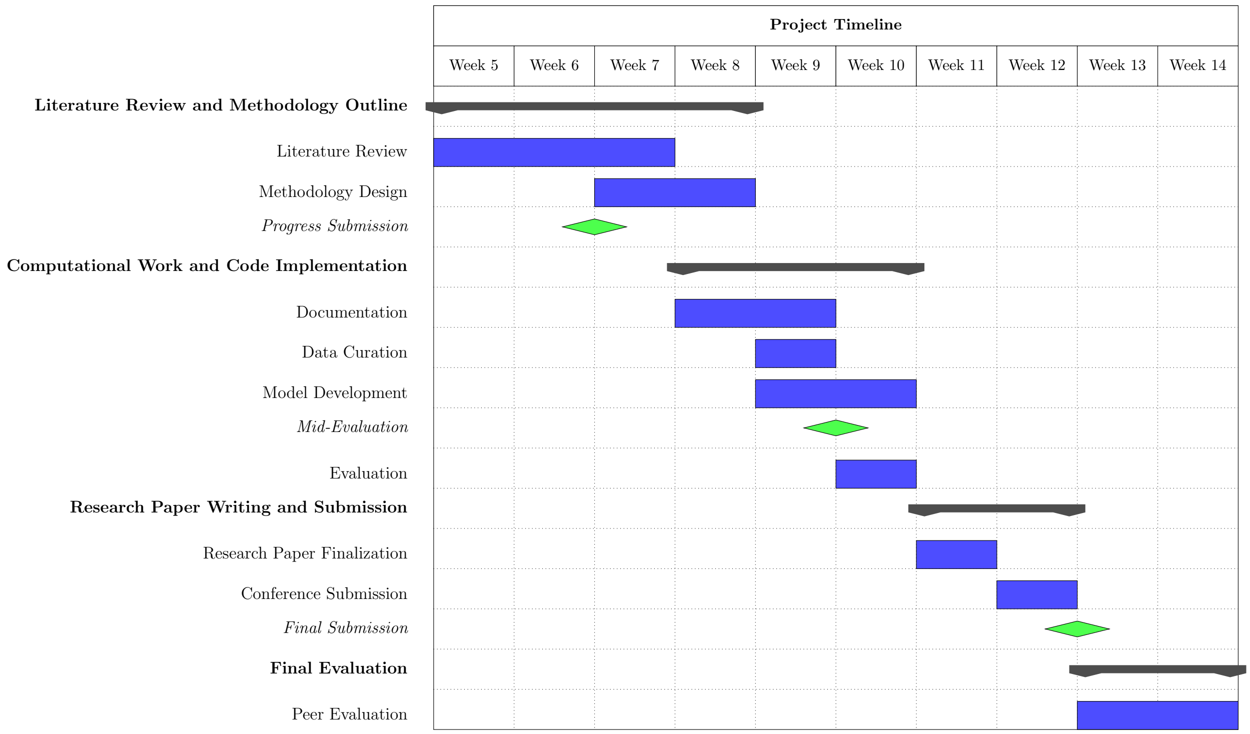
6. Experimental Evaluation

Experiments benchmark ART-based warm-starts against traditional convex warm-start approaches. Metrics include suboptimality improvement, convergence rate, runtime, and feasibility. Results show ART significantly improves convergence speed and solution quality while reducing infeasibility rates.

7. Implementation

The method was implemented using PyTorch and HuggingFace Transformers. Full details and hyperparameters are provided in the paper's appendix.

Project Timeline



References

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