Doctoral Dissertation
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Learning-based Optimal Guidance and Control Algorithms for Robotic Systems in Unstructured Environments

By

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Declaration

I hereby declare that, the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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Abstract

Autonomous robotic systems play a critical role in complex and dynamic environments, such as space exploration missions, where safety-critical operations require high precision, adaptability, and computational efficiency. Thus, this thesis focuses on the evaluation and implementation of learning-based and classical optimization approaches for closed-loop guidance and control, aiming to enhance the performance of non-convex trajectory optimization in unstructured environments.

At first, a closed-loop trajectory planning framework integrating classical algorithms for non-convex trajectory optimization is designed. By combining state-of-the-art Interfered Fluid Dynamical Systems (IFDS) for obstacle avoidance with Bézier curves and Evolutionary algorithms (EA) for trajectory optimization, an effective and responsive closed-loop planner capable of adjusting trajectories *online* and operating within dynamic scenarios is obtained. Nonetheless, this approach encounters limitations in modeling impulsive dynamics and ensuring dynamical feasibility, restricting its applicability to safety-critical space robotic missions.

To overcome these challenges, a novel Transformer-based trajectory optimization framework is introduced, initially focusing on the open-loop setting. By leveraging the attention mechanism of Transformers, this framework effectively generates high-quality warm-start trajectories conditioned on user-defined metrics, which are subsequently optimized using state-of-the-art trust-region-based Sequential Convex Programming (SCP). The combination of these algorithms allows to integrate their strengths while mitigating their limitations. Simulations across spacecraft Rendezvous and Proximity Operations (RPO), quadrotor control, and free-flyer testbed applications demonstrate significant improvements in cost optimality, convergence speed, and success rate compared to state-of-the-art baselines.

Building on these promising results, the framework is extended to closed-loop settings, and a Transformer-based Model Predictive Control (MPC) algorithm is designed. This closed-loop algorithm effectively provides long-horizon guidance to short-horizon MPC formulations via warm-start trajectory generation and expressive Transformer-driven terminal cost formulation. Furthermore, a fine-tuning strategy based on the DAGGER paradigm is devised to mitigate the covariate shift problem, ensuring robust performance in dynamic scenarios. Both simulations and real-world experiments are used to validate the framework's ability to reduce computational burden while maintaining high planning performance, enabling safe and efficient real-time trajectory execution.

Lastly, the applicability of the framework is broadened through multi-modal learning. By incorporating diverse data sources, such as obstacle configurations and time constraints, into a multi-modal trajectory representation, a Transformer-based model that supports generalization across operational scenarios is achieved. Ablation studies are conducted to evaluate the effect of training data diversity and effective scene representation strategies on the model performance. Finally, simulations and hardware experiments on the free-flyer testbed demonstrate superior adaptation to unseen environments and varying mission requirements, achieving stable improvements in cost optimality, convergence rate, and infeasibility reduction across diverse mission scenarios.