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Towards Trustworthy Data-driven Modeling and Control of Unmanned Aerial Vehicles

By

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Unmanned Aerial Vehicles (UAVs) have gained significant attention and utility in various aspects of daily life, ranging from entertainment, like aerial photography, to meeting industrial demands such as delivery of goods and infrastructure inspection. As tasks and environments become more complex, advanced control algorithms are needed to ensure safe operations. While model-based control techniques have shown effectiveness in controller design, their performance heavily relies on accurate mathematical models, posing challenges in scenarios with uncertainties and disturbances. In response, data-driven methods, particularly learning-based approaches, have shown promise in accurate modeling due to their powerful approximation capabilities. End-to-end learning-based solutions have also emerged, mitigating the requirement for system knowledge in control synthesis. However, learning-based approaches, especially deep learning, are often regarded as black-box models, lacking interpretability and raising trust issues about their deployment in safety-critical systems like quadrotors. Moreover, many current studies on learning-based approaches are offline, trained before task execution, which introduces potential risks in real-world execution and compromises generalization to unseen scenarios.

This thesis aims to advance trustworthy data-driven modeling and control of quadrotors, focusing on two main parts: modeling and control design. In the modeling part, we propose a novel machine learning paradigm called Physics-informed Machine Learning (PIML) for quadrotor dynamical modeling. PIML integrates domain knowledge and empirical data to enhance the trustworthiness of the model, outperforming black-box and conventional mathematical models in terms of both modeling error and physical consistency. Our model also demonstrates improved learning capability with smaller data sets and provides interpretability through post-hoc visualization. In the control design part, we address control problems of a quadrotor subject to parametric and non-parametric uncertainties. For parametric uncertainties, we develop a novel adaptive geometric controller, of which the synthesis is based on rotation matrix rather than Euler angles or quaternions, thereby avoiding issues such as gimbal lock and unwinding

phenomena. Consequently, this controller enables aggressive maneuvers like 360° flips and elliptical helix trajectory tracking, even in the presence of uncertain mass and inertia matrix. To handle non-parametric uncertainties like wind gusts, we introduce a novel learning-based controller featuring online learning capability through the reservoir computing paradigm. We investigate the interpretability of our learning-based model through post-hoc analysis on model dynamics and parameters, providing valuable insights for understanding the model's behavior. Comparisons with offline solutions in the literature demonstrate the superior generalizability and tracking performance of our learning-based controller in facing unseen scenarios, thanks to its online learning ability. This, along with insights from post-hoc analysis, instills trust in our data-driven solution.

We anticipate a growing trend of data-driven solutions for robotics in the near future, driven by both market demands and technological advancements like Large Language Models (LLMs). Hence, infusing trust into these data-driven solutions is crucial, particularly for applications or products with potential safety implications. Although the research in trustworthy data-driven methods is still in its early stages, we acknowledge the collaborative efforts from various fields, such as robotics and machine learning, toward the common goal. These collective endeavors will ensure the successful deployment of intelligent systems in the real world, improving the lives of individuals and benefiting society as a whole. This thesis aims to contribute to this process by providing valuable insights and enlightening researchers in the field, serving as a small step in the larger journey towards advancing trustworthy data-driven modeling and control of quadrotors.