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Physics-Informed Data-Driven Dynamic Modeling for Quadrotor Motion Control

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Введение. Accurate modeling of quadrotor dynamics is essential for ensuring stability and performance in a wide range of applications, from environmental monitoring to search and rescue. However, traditional modeling approaches, which rely on simplified physical equations, often struggle to capture complex aerodynamic interactions and external disturbances such as wind. These limitations lead to inaccuracies, especially under non-nominal conditions like rapid maneuvers or turbulent environments. Data-driven modeling has emerged as a promising solution to these challenges by leveraging real-world data to learn complex dynamic behaviors. Among these methods, physics-informed neural networks stand out by combining data-driven learning with physical laws, such as the principles of rigid-body dynamics and aerodynamics. This hybrid approach allows models to generalize better, even with limited data, while maintaining physical consistency. By integrating physics-informed modeling techniques, we aim to achieve more accurate and robust quadrotor models that enhance navigation stability. This will be demonstrated through improvements in both model-based and learning-based control strategies that employ the learned models in the control loop.

Основная часть. The primary goal is to enhance the robustness and reliability of quadrotor modeling and study its effect on the performance of model-based and learning-based control approaches. The key objectives include:

- Analyzing machine learning techniques for modeling quadrotor dynamics, especially in uncertain environments.
- Integrating data-driven models into control strategies to evaluate their impact on accuracy and performance.
- Developing a ROS2-based research framework for autonomous quadrotor navigation, including simulation, real-time communication, and visualization.

The study divides the problem into two key areas: data-driven dynamic modeling and control strategy integration. Various modeling approaches are examined:

- **Analytical models,** which rely purely on first principles to derive the dynamics model. The complexity of these models varies based on which effects are included. Two such models were studied: a nominal model that incorporates rigid-body dynamics with simple rotor models and an analytical model that incorporates aerodynamic effects such as ground effect, rotor drag, and fuselage drag.
- **Gray-box models**, which combine analytical dynamics with neural networks to correct errors. Two such models were studied, adding a residual term—a neural network that predicts the error of the analytical model—to the two previous analytical models [1].
- **Black-box models**, which rely solely on neural networks for dynamic estimation.
- **Physics-informed models**, which incorporate domain knowledge into the loss function of neural networks to enhance physical consistency, thereby improving efficiency and accuracy, in what’s called physics-informed neural networks [2].

These six models were implemented using PyTorch and trained on the NeuroBEM dataset [3]. Performance was evaluated through training and testing on separate data subsets.

To test the impact of data-driven modeling, in general, and the physics-informed modeling approach, in particular, on control performance, two control methodologies were explored:

- **Model-Based Control**: Differential Flatness-Based Control (DFBC [4]) is enhanced by integrating predicted dynamic corrections from the data-driven models.
- **Learning-Based Control**: Reinforcement learning (RL) policies are trained in a simulated environment that incorporates a realistic dynamic model. This approach ensures robustness and adaptability to real-world uncertainties.

Various controllers, including DFBC, RL-based control, and Model Predictive Control (MPC), were evaluated in trajectory-following tasks under different conditions. Results demonstrated that integrating data-driven models significantly improves tracking accuracy and stability.

To facilitate testing and deployment of the developed models, a comprehensive ROS2-based software framework was implemented. This framework seamlessly integrates data-driven modeling techniques with both simulation and real-time control environments, ensuring consistency and robustness. The framework consists of:

- A simulation module for high-fidelity dynamic modeling and visualization.
- A control module supporting both model-based and learning-based controllers.
- A trajectory generation module for planning and optimization.
- A communication module enabling integration with real quadrotors.

The modular design of the software allows for easy adaptation and testing of different modeling approaches, streamlining the integration of advanced data-driven techniques into practical applications.

Выводы. This study presents a framework integrating data-driven modeling, in general, and physically consistent modeling, in particular, into control strategies to achieve robust and reliable motion control for quadrotors in uncertain environments. Utilizing a data-driven approach inspired by physics-informed neural networks, the dynamic behavior of quadrotors was learned from collected data, enhancing control performance and creating a realistic simulation environment with ROS2. A reinforcement learning-based control strategy was then developed to guide the quadrotor along desired trajectories while ensuring stability. Extensive evaluations demonstrated the effectiveness of this approach, showing significant improvements in tracking accuracy and robustness in both simulations and real-world conditions. The developed software framework plays a crucial role in bridging theoretical modeling with practical deployment, ensuring that advanced data-driven techniques can be readily tested and applied in real-world scenarios.

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