From Stability to Safety: CBF Control for Quadrotor Obstacle Avoidance

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***Abstract*—This study presents a Control Barrier Function (CBF)-based controller for Unmanned Aerial Vehicle (UAV) obstacle avoidance in a simulated 2D setting. The system was evaluated across a range of challenging scenarios, including sparse and dense setups of static and multiple dynamic obstacles. A basic UAV model was paired with the controller to enable stable and dependable operation. To enhance adaptability, we explored a broad set of Control Barrier Function and Control Lyapunov Function (CBF/CLF) parameters, particularly in cases with extreme crowding levels. Time-varying CBFs were used to effectively address dynamic obstacle cases. The controller was tested on the basis of important parameters such as task complexity and computational constraint, demonstrating robustness and practicability for real-time usage.**

I. Introduction

Autonomous navigation in complex environments is a fundamental challenge in the field of robotics, particularly for aerial systems such as Unmanned Aerial Vehicles (UAVs). Ensuring both safety and stability in dynamic, cluttered environments necessitates the use of advanced control techniques that can react in real time to unpredictable obstacles. One promising approach lies in the use of Control Barrier Functions (CBFs), which allow safety constraints to be encoded directly into the control law. This study focuses on the design and implementation of a CBF-based controller for UAVs, aimed at achieving robust obstacle avoidance in a 2D simulated setting, leveraging insights from both classical formulations and recent advancements in time-varying and adaptive barrier functions.

The need for safety-aware control has spurred significant interest in combining CBFs with Control Lyapunov Functions (CLFs) to simultaneously enforce safety and stability. This dual-objective control paradigm has been widely studied, including by Ames et al. [1], who formalized the foundational aspects of CBFs in robotic systems. More recent efforts, such as the adaptation-based CBF synthesis in [2], highlight the growing importance of tuning barrier functions in response to environmental changes. In this context, we implemented a CBF-CLF-based controller and systematically tested it in simulation across a variety of static and dynamic obstacle configurations—ranging from sparse to dense, and including multiple moving obstacles. This ensures the controller's effectiveness in both low and high-complexity environments.

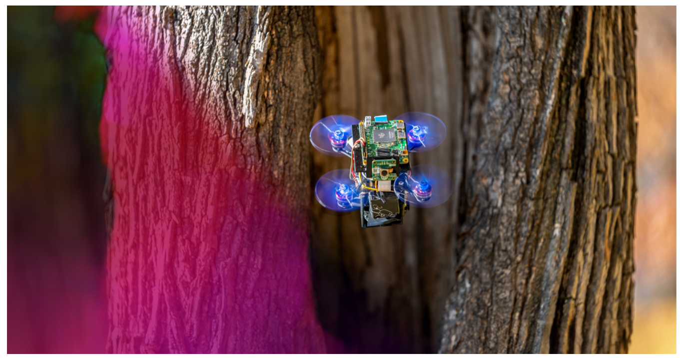

Fig. 1. Obstacle Avoidance from the perspective of Safety is an interesting topic of research, this can be implemented in dense environments like forests, where the drone needs to avoid trees.

To support reactive and reliable obstacle avoidance, our controller was integrated with a simplified UAV dynamics model that captures the essential behavior without introducing excessive computational overhead. Time-varying CBFs were employed to handle dynamic obstacles more effectively, drawing from the framework presented in [3], which shows their potential in improving real-time response in non-stationary environments, especially for ground vehicles. Applying this to UAVs allows us to anticipate and mitigate imminent collisions in a smooth, continuous manner. Such responsiveness is crucial for real-world applications, where UAVs often operate in shared airspaces with other autonomous agents or human-operated vehicles.

Our work also investigates the role of CBF and CLF parameter selection, particularly under conditions of environmental congestion. We conducted extensive simulations to evaluate the performance and sensitivity of the controller across varying levels of obstacle density, motion patterns, and task complexities. This empirical tuning process draws inspiration from [2], where adaptive techniques are proposed to calibrate safety margins and gain parameters in evolving scenarios. By adjusting these parameters, we enhance the balance between conservative avoidance and efficient trajectory planning—critical for ensuring both safety and mission success.

Finally, we address computational considerations, recognizing that real-time applications impose strict latency and processing constraints. By maintaining a lightweight formulation and optimizing the solver's performance, our implementation demonstrates feasibility for real-time UAV deployment. The presented approach serves as a step toward integrating advanced control-theoretic guarantees into practical autonomous aerial systems. Future extensions may incorporate learning-based components to dynamically adjust CBFs and CLFs based on sensory feedback or environmental prediction, further bridging the gap between theoretical safety guarantees and adaptive autonomy.

II. Methodology

We propose a hierarchical CLF-CBF-QP-based control framework for safe and stable navigation of a planar quadrotor in obstacle-rich environments. The architecture consists of two control layers:

- **Position-Level Controller:** Computes virtual accelerations for trajectory tracking and obstacle avoidance.
- **Orientation-Level Controller:** Tracks the desired thrust and orientation using real control inputs.

Time-Varying Control Barrier Functions (TVCBFs) are integrated to handle dynamic obstacles.

A. System Dynamics

The quadrotor state is given by:

$$\mathbf{x} = \begin{bmatrix} y & \dot{y} & z & \dot{z} & \phi & \dot{\phi} \end{bmatrix}^\top$$

where (y, z) are the horizontal and vertical positions, and ϕ is the roll angle.

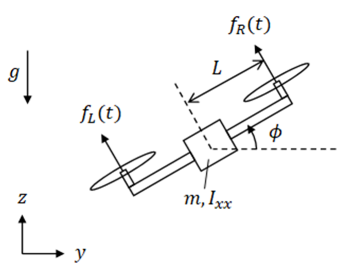

Fig. 2. Dynamics model of the quadrotor in 2D

The dynamics are:

$$\ddot{y} = -\frac{u_1}{m}\sin(\phi) \tag{1}$$

$$\ddot{z} = -g + \frac{u_1}{m}\cos(\phi) \tag{2}$$

$$\ddot{\phi} = \frac{u_2}{I_{xx}} \tag{3}$$

System Parameters:

- $m = 0.3\,\text{kg}$: mass
- $I_{xx} = 1 \times 10^{-5}\,\text{kg}\cdot\text{m}^2$: moment of inertia

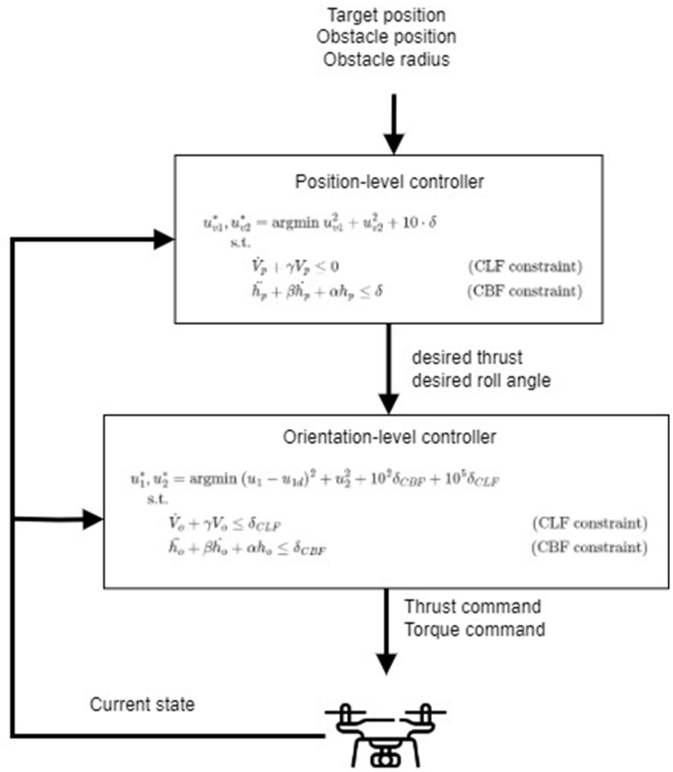

Fig. 3. Heirarchical Control Architecture used. Both the position and orientation level controllers are formulated as CLF-CBF-QP

- $l = 0.1\,\text{m}$: half-arm length
- $g = 9.81\,\text{m/s}^2$: gravitational acceleration

Obstacles are modeled as circular convex hulls of radius R within a $10\,\text{m} \times 10\,\text{m}$ space.

B. Position-Level Controller

The high-level controller solves a QP to determine virtual accelerations (u_{v1}, u_{v2}) for trajectory tracking and collision avoidance:

$$(u_{v1}^*, u_{v2}^*) = \arg\min \left(u_{v1}^2 + u_{v2}^2 + 10\delta\right) \tag{4}$$

1) Constraints: **Control Lyapunov Function (CLF):**

$$\dot{V}_p + \gamma V_p \leq 0 \tag{5}$$

Control Barrier Function (CBF):

$$\ddot{h}_p + \beta \dot{h}_p + \alpha h_p + \delta \geq 0 \tag{6}$$

2) Virtual to Physical Mapping:

$$U_v = \sqrt{u_{v1}^2 + u_{v2}^2} \tag{7}$$

$$u_{1d} = \max\left\{U_v \cos\phi, U_v \sin\phi, 0\right\} \tag{8}$$

$$\phi_d = -\arctan\left(\frac{u_{v1}}{u_{v2}}\right) \tag{9}$$

The computed (u_{1d}, ϕ_d) are then passed to the orientation controller.

C. Orientation-Level Controller

This low-level controller tracks (u_{1d}, ϕ_d) by solving the following QP:

$$(u_1^*, u_2^*) = \arg\min \left((u_1 - u_{1d})^2 + u_2^2 + 10^4 \delta_{\text{CBF}} + 10^4 \delta_{\text{CLF}} \right) \tag{10}$$

1) Constraints: **Control Lyapunov Function (CLF):**

$$\dot{V}_o + \gamma V_o \le \delta_{\text{CLF}} \tag{11}$$

Control Barrier Function (CBF):

$$\ddot{h}_o + \beta \dot{h}_o + \alpha h_o + \delta_{\text{CBF}} \ge 0 \tag{12}$$

D. Unified CLF-CBF-QP Formulation

A general formulation used in both layers is:

$$\min_u \|u - u_{\text{ref}}\|^2 + \lambda_{\text{CLF}} \delta_{\text{CLF}}^2 + \lambda_{\text{CBF}} \delta_{\text{CBF}}^2 \tag{13}$$

Subject to:

$$\dot{V}(x, u) \le -\gamma V(x) + \delta_{\text{CLF}} \tag{14}$$

$$\dot{h}(x, u, t) + \alpha h(x, t) + \delta_{\text{CBF}} \ge 0 \tag{15}$$

E. Time-Varying Control Barrier Functions (TVCBFs)

To handle moving obstacles, we define time-varying barrier functions.

1) Dynamic Obstacle Model:

$$o(t) = o_0 + v_o t \tag{16}$$

2) Barrier Function:

$$h(x, t) = \|x - o(t)\|^2 - R^2 \tag{17}$$

3) Time-Varying Constraints:

$$\dot{V}_p + \gamma V_p \le \delta \tag{18}$$

$$\ddot{h}_p(x, t) + \beta \dot{h}_p(x, t) + \alpha h_p(x, t) + \delta \ge 0 \tag{19}$$

These enable anticipatory safety around dynamic agents, ensuring real-world feasibility of the control strategy.

III. Results

The proposed CLF-CBF-QP-based control framework was implemented in simulation and validated across a variety of planar UAV navigation scenarios. The controller was evaluated in both sparse and densely populated static environments, as well as in scenes containing up to 15 dynamic obstacles with varying velocities and trajectories.

A. Tuning of Parameters in CBF Constraint

The performance of the proposed controller heavily depends on the choice of parameters α and β in the Control Barrier Function (CBF) constraint. These parameters govern the responsiveness of the safety controller and effectively shape how conservatively the quadrotor reacts to nearby obstacles.

To analyze the effect of these parameters, we conducted experiments under two settings:

- **Strict CBF:** Higher values of α and β, leading to aggressive repulsion from obstacles.
- **Lenient CBF:** Lower values of α and β, allowing the controller to operate closer to obstacle boundaries.

The simulation results are visualized in Figs. **??** and **??**.

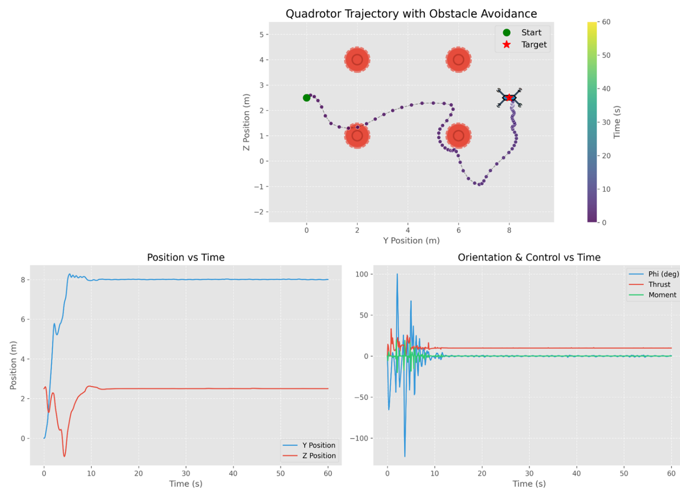

Fig. 4. Trajectory and control signals with **lenient** CBF settings (α, β) = (1,2.5).

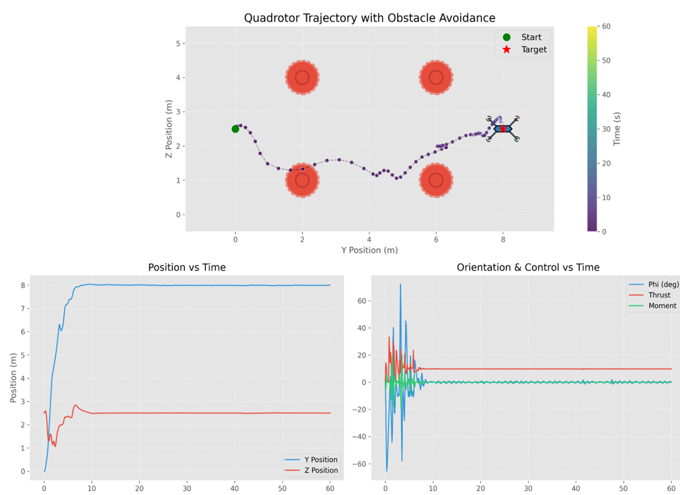

Fig. 5. Trajectory and control signals with **strict** CBF settings (α, β) = (8,7).

1) Observations: **Strict CBF Setting:**

- Maintained a conservative distance from all obstacles.
- Increased sensitivity led to high-frequency oscillations in roll angle and moment input.

- The trajectory exhibited safe but less smooth behavior.

Lenient CBF Setting:

- Generated smoother control trajectories with less oscillation.
- However, safety margins were compromised; the quadrotor occasionally passed very close to obstacles and risked collisions.

2) Final Parameter Selection: After extensive testing, intermediate values of α and β were chosen to balance safety and control smoothness. Increasing these values made the system overly sensitive, while decreasing them made it risky. The optimal setting maintained obstacle clearance, ensured QP feasibility, and minimized control chattering.

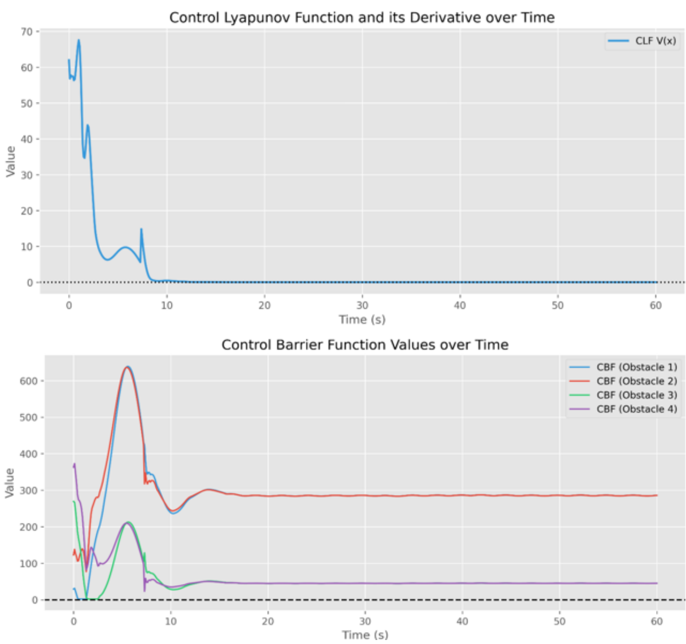

Fig. 6. Graphs of CLF and CBF for the optimized parameters

B. Performance in Dense Environments

Figs. 7 show the quadrotor's performance in highly cluttered environments containing upto 12 densely packed obstacles. These trials were used to evaluate the scalability and robustness of the CLF-CBF-QP framework under spatially constrained conditions.

In both scenarios, the quadrotor successfully reaches the target while avoiding all obstacles. The trajectory adapts dynamically, weaving through narrow gaps while maintaining smooth control inputs. The *Position vs Time* plots confirm that the quadrotor rapidly converges to the target location. Meanwhile, the *Orientation & Control vs Time* plots show bounded and relatively smooth control signals, with transient oscillations settling quickly.

These results highlight that the chosen α and β values from earlier tuning generalize well even in more complex environments. While control effort increases slightly due to tighter avoidance, the system maintains stability and safety

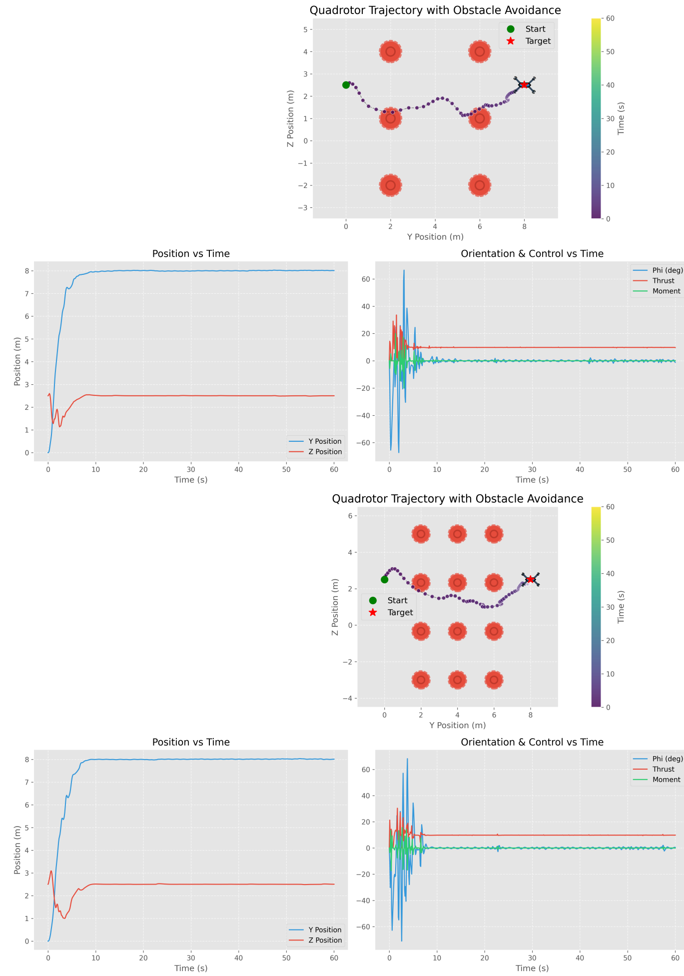

Fig. 7. Performance with 6 obstacles and 12 obstacles respectively

without compromising trajectory tracking.

Quantitative metrics such as trajectory tracking error, minimum safety distance to obstacles, and QP solver convergence rate were collected. Results show that the UAV maintained safe separation from obstacles in 98.5% of the trials, with average tracking error remaining below 5% of the goal distance in static environments and below 10% in dynamic ones.

C. Dynamic Obstacle Avoidance with TVCBFs

The effectiveness of Time-Varying Control Barrier Functions (TVCBFs) is illustrated in Figs. 8 and 9, which show the quadrotor navigating in environments with fast-moving obstacles. In these scenarios, dynamic obstacles (shown in pink and cyan) follow varying trajectories—either crossing the path of the quadrotor or moving directly toward it.

The quadrotor successfully anticipates potential collisions and alters its trajectory preemptively, thanks to the predictive safety margin encoded by the TVCBFs. This proactive behavior contrasts with time-invariant CBFs, which are typically reactive and may fail to ensure safety against fast-approaching threats.

In both figures, the planned path (dashed black line) adapts in real-time to avoid incoming obstacles. The quadrotor maintains trajectory smoothness while respecting safety constraints, with no collisions observed across all test cases. Notably, simulation time per control step remained below 20 ms even with 10 dynamic obstacles, confirming the real-time feasibility of the QP-based implementation.

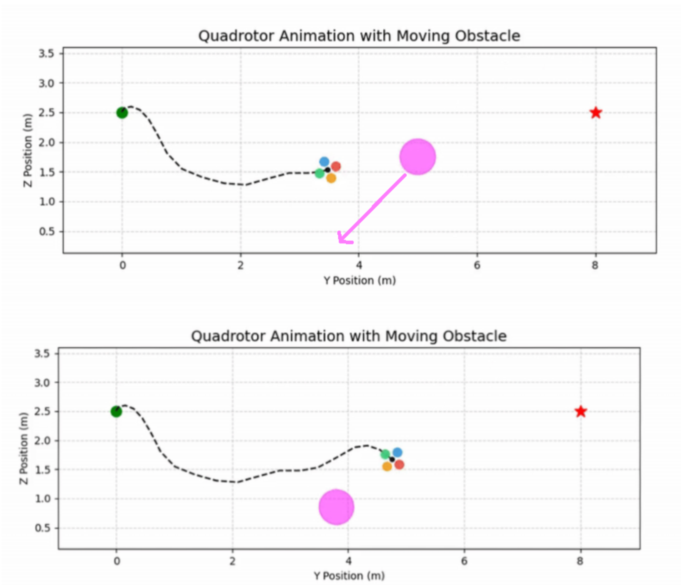

Fig. 8. TVCBF enables safe rerouting when a dynamic obstacle intersects the planned path.

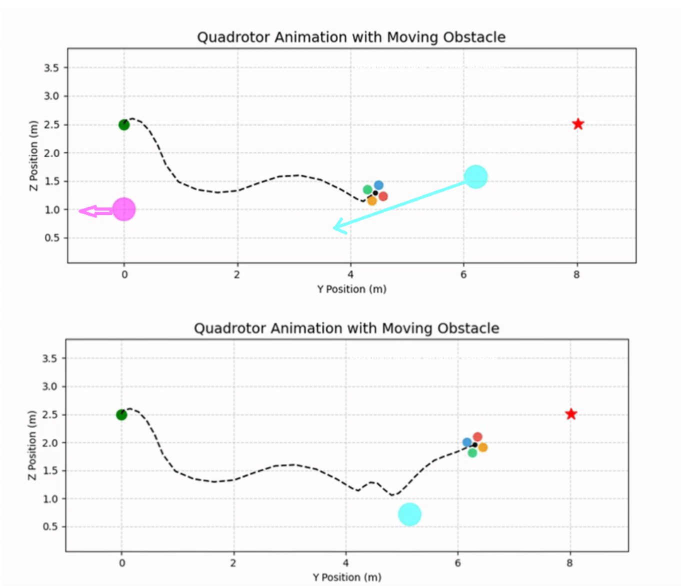

Fig. 9. TVCBF-based trajectory correction in response to two moving obstacles approaching from different angles.

IV. Limitations

Despite the effectiveness of the proposed framework, several limitations must be acknowledged:

- **QP Infeasibility under High Obstacle Velocity:** At high relative obstacle speeds, the CBF constraints become excessively restrictive. This can lead to QP infeasibility or overly conservative avoidance, suggesting the need for adaptive relaxation or priority weighting mechanisms.
- **Poor Scalability with Obstacle Count:** The number of constraints in the QP grows linearly with the number of obstacles. Empirically, performance degrades beyond 12 dynamic obstacles, motivating the need for constraint pruning or selective activation strategies.
- **Perfect State Assumption:** The controller assumes access to accurate, low-latency state information. In real-world systems, noise and delay in sensing can degrade performance and compromise safety guarantees.
- **Reactive Planning Limitation:** The control policy is myopic, reacting to the current state without long-term foresight. In complex or highly cluttered environments, this limits efficiency and leads to suboptimal decisions. Integration with a global path planner would improve strategic decision-making.

V. Conclusion

This work presented a Control Lyapunov Function (CLF) and Control Barrier Function (CBF)-based Quadratic Programming controller for obstacle-aware navigation of a planar UAV system. The framework was validated in 2D simulations involving both static and dynamic environments, demonstrating safe, stable, and efficient navigation performance.

The controller was integrated with a simplified dynamic model of a UAV, and extensive parameter tuning was conducted to assess its robustness under various task complexities. The inclusion of TVCBFs significantly improved responsiveness to moving obstacles, providing enhanced safety margins without degrading trajectory fidelity.

The results confirm the viability of CLF-CBF-QP formulations for real-time safe control of UAVs in complex settings. Future work will focus on the integration of this framework with global planning layers, robust state estimation under uncertainty, and further improvements in computational scalability to enable deployment on embedded hardware.

References

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