



Robust Ltl-Based Optimal Path Planning For Aerial Robots in Live Power Line Maintenance

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SUMMARY: *In this paper, we present a control strategy for unmanned aerial vehicles (UAVs) used for live power line maintenance with a focus on real-time safety and effective navigation in the presence of static obstacles. The proposed method combines Control Barrier Functions (CBF) for handling the task of avoiding obstacles with Control Potential Field Functions (CPFF) that steer the UAVs towards the targeted missions, such that the UAVs can execute goal-oriented and safe behavior during the process. To represent and ensure both task-specific and safety requirements in a formal manner, we deploy Linear Temporal Logic (LTL) so that high-level control goals can be described with precise accuracy. We also include an infeasibility detection mechanism so the control system can react effectively when simultaneous goals of both safety and mission are not satisfiable based on the analysis of the workspace. The functionality of the framework is evaluated via simulations, and the UAV navigates with obstacle-free trajectories and successfully completes power line inspection tasks. The presented strategy offers a scalable and efficient method for the deployment of UAVs in critical infrastructure maintenance.*

KEYWORDS: *Linear temporal logic, obstacle avoidance, path planning, infeasibility detection.*

1 Introduction

Path planning is a key process for planning the motion trajectory of a robot system and guiding it to autonomously move towards a designated target. This technology has been widely applied to various types of mobile robot platforms such as land, air, and ocean [1-3]. The path planning problem of aerial robot platforms for complex operation scenarios such as on-site inspection and maintenance of power lines presents a higher level of complexity [4]. Robots need to autonomously navigate through dense obstacle environments such as power cables and towers, while meeting the requirements of operational efficiency and reliability. Engineering practice has shown that the large-scale deployment of such aerial robots can effectively reduce the intensity of manual operations and improve the safety level of on-site operations [5, 6].

Formal methods incorporate planning problems into a rigorous and complete mathematical theoretical framework [7]. Among various formal methods, linear temporal logic (LTL) is suitable for formalizing the objectives of temporal evolution tasks, accurately describing temporal constraint requirements such as target reachability and hazard avoidance.

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The planning method based on linear temporal logic can comprehensively generate control strategies with strict guarantee of correctness, ensuring that the execution behavior of the robot system is strictly consistent with the upper level task requirements [8]. Most existing related research equivalently transforms the LTL path planning problem into a shortest path search problem on a directed weighted graph [9]. Besides the graph-based approach, there have also been heuristic search techniques used for generating complete trajectories that conform to high-level task specifications [10]. Whilst such approaches are successful in enforcing logical task requirements, such methods are wanting when it comes to handling practical considerations like uncertain surroundings and system security—both of which are paramount in high-risk situations like live power line maintenance [11].

Apart from path correctness, the aspect of security now attracts much attention, especially in autonomous systems relying on centralized control or remote communication to perform their tasks. Such systems are vulnerable to cyber attacks, in which the attackers could intercept or deduce confidential mission information during execution [12, 13]. To mitigate such risks, the concept of opacity has emerged with the goal of keeping external observers from deducing a system’s internal states or goals from its visible actions [14]. In robotic applications, opacity mechanisms are used to protect mission-critical information so as to make it hard for observers to deduce the intents of the robot by simply following its movement or path [15, 16]. As much as existing techniques such as dynamic masking and nondeterministic edit functions have achieved success in maintaining confidentiality for static missions, they tend not to cope with the changing nature of dynamic tasks such as UAV applications [17].

To address the needs of dynamic scenes and real-time decision-taking, Control Barrier Functions (CBFs) have emerged as one of the most prevalent tools for robotic control. CBFs provide a formal method to impose safety-critical constraints—e.g., collision avoidance—during execution, leveraging concepts related to those used in the construction of Control Lyapunov Functions (CLFs) [18]. By expressing control synthesis as a quadratic program (QP) with suitable CBFs, control inputs can be computed that are guaranteed to maintain a safe distance between the UAV and surrounding obstacles. Certain forms of CBFs have been shown to be robust, with applications in scenarios involving disturbances or uncertainties given [19]. The techniques have been used in a number of domains, such as dynamic walking, multi-agent collision avoidance, and auto-lane keeping for vehicles [20]. CBFs have also been successfully integrated with LTL-based frameworks to permit the satisfaction of both temporal logic requirements as well as safety constraints [21].

In order to further enhance UAV guidance in cluttered spaces under LTL task requirements, the paper presents a control framework that integrates Control Barrier Functions (CBFs) and Control Potential Field Functions (CPFFs). CPFFs provide attractive and repulsive forces to navigate the UAV towards its destination and maintain it at a safe distance from the obstacles, so the UAV can move with smooth and continuity. With the combination of CBFs and CPFFs, the framework ensures both enforcement of task objectives in real-time and smooth trajectory planning even when task goals and safety requirements might collide. The proposed method possesses a number of noteworthy advantages: (i) static obstacles, known or unknown, can be guaranteed to be avoided, securing the UAV’s operation safety; (ii) the capability to determine task feasibility depending on the workspace structure, the distribution of the obstacles, and the priority of the tasks; and (iii) smooth control with CPFFs of relative degree one, as well as the capability to identify and recover from workspace singularities [22].

In the maintenance scenario of electrified power lines, drones need to perform sequential operation tasks under uncertain and dynamically changing environmental conditions, and

complete autonomous navigation in complex structural areas such as power lines and towers. The aforementioned framework proposes a robust and adaptive path planning method that integrates task specifications based on linear temporal logic (LTL), control barrier functions (CBF), and control potential field functions (CPFF) to ensure the safety of drone operation processes and generate smooth and continuous motion trajectories. This method organically integrates the accuracy of formal logic, the safety operation guarantee capability of CBF, and the fast response control characteristics of CPFF, and constructs a complete and closed-loop unmanned aerial vehicle path planning system. The unmanned aerial vehicle can not only achieve safe navigation and precise task objectives in complex environments, but also maintain stable operational performance in dynamic and uncertain scenarios.

2 Preliminaries and Problem Formulation

This article focuses on the research of autonomous unmanned aerial vehicle (UAV) systems characterized by the following nonlinear kinematic models:

$$\dot{x} = v \cos\theta + w_x, \dot{y} = v \sin\theta + w_y, \dot{\theta} = \omega + w_\theta \quad (1)$$

where $\mathbf{p} := [x, y]^T \in \mathbb{R}^2$ denotes the UAV's position in the inertial frame, and $\theta \in \mathbb{R}$ represents its heading angle. The terms $v \in \mathbb{R}$ and $\omega \in \mathbb{R}$ correspond to the vehicle's linear and angular velocities, respectively. The dynamics also account for process noise, modeled by independent white noise components w_x , w_y , and w_θ acting in the x , y , and θ directions. Each noise signal $w(t) \in \mathbb{R}$ is assumed to have zero mean and is statistically independent of the initial state $\mathbf{x}(0)$.

2.1 Task Specification

In this work, we express the high-level mission objectives using formulas defined in Linear Temporal Logic (LTL). An LTL formula is constructed from a set of atomic propositions (APs) Π , along with Boolean and temporal operators. These formulas can be formed based on the following syntactic rules:

$$\phi := \text{TRUE} \mid \alpha \mid \phi_1 \wedge \phi_2 \mid \neg\phi \mid \text{O}\phi \mid \phi_1 \text{U}\phi_2$$

where $\alpha \in \Pi$ is an atomic proposition. The temporal operators O (next) and U (until) represent temporal behaviors. Other operators, such as disjunction (\vee), eventually (\diamond), always (\square), and implication (\rightarrow), are derived as follows:

$$\phi_1 \vee \phi_2 := \neg(\neg\phi_1 \wedge \neg\phi_2), \diamond\phi := \text{TRUEU}\phi,$$

$$\square\phi := \neg\diamond\neg\phi, \phi_1 \rightarrow \phi_2 := \neg\phi_1 \text{U}\phi_2$$

Given a run r of the transition system (TS) \mathbf{T} , the trace of the run is denoted as $L(r) = L(q_0) L(q_1) \dots L(q_i) \dots$, where $L(q_i)$ denotes the labeling of state q_i . The run r satisfies an LTL formula ϕ if the trace $L(r)$ satisfies ϕ , i.e., $L(r) \models \phi$.

An LTL formula can also be represented using an automata-theoretic approach as a Buchi automaton (NBA), defined as a tuple:

$$\mathbf{B} := (S, S_0, \Sigma, \delta_{\mathbf{B}}, F)$$

where: - S is a finite set of states, - $S_0 \subseteq S$ is a set of initial states, - Σ is the input alphabet, - $\delta\mathbf{B} \subseteq S \times \Sigma \times S$ is a nondeterministic transition relation, - $F \subseteq S$ is a set of accepting states.

The product automaton $\mathbf{P} = \mathbf{T} \times \mathbf{B}$, formed by combining the transition system \mathbf{T} and the NBA \mathbf{B} , is defined as:

$$\mathbf{P} := (\mathbf{SP}, \mathbf{SP}_0, \delta\mathbf{P}, \mathbf{FP}, \mathbf{wP}, \mathbf{SP}, \pi)$$

where: 1. $\mathbf{SP} = Q \times S$ is a finite set of states, 2. $\mathbf{SP}_0 = \{q_0\} \times S_0$ is the set of initial states, 3. $\delta\mathbf{P} \subseteq \mathbf{SP} \times \mathbf{SP}$ is the transition relation, where $((q, s), (\bar{q}, \bar{s})) \in \delta\mathbf{P}$ if and only if $(q, \bar{q}) \in \delta\mathbf{T}$ and $(s, L(q), \bar{s}) \in \delta\mathbf{B}$, 4. $\mathbf{FP} = Q \times F$ is the set of accepting states, 5. $\mathbf{wP}: \delta\mathbf{P} \rightarrow \mathbb{R}_{\geq 0}$ assigns weights to transitions.

The product automaton \mathbf{P} represents the combined system dynamics and satisfaction of the LTL formula ϕ .

2.2 Problem Formulation

The UAV's trajectory is influenced by sampled control inputs applied at discrete time intervals. At each sampling time, the control inputs $v'(t)$ and $\omega(t)$ are updated based on local measurements to navigate the UAV while ensuring both obstacle avoidance and target reaching, despite the presence of stochastic disturbances.

This objective is formally expressed using the following LTL formula:

$$\phi = \phi^{\text{obs}} \wedge \phi^{\text{goal}},$$

where ϕ^{obs} denotes the obstacle avoidance requirement and ϕ^{goal} encodes the goal-reaching task. In the context of power line inspection, the goal is defined along the span of the power line, while obstacles represent static infrastructure such as towers and surrounding vegetation. Although the obstacle regions are modeled as spheres for tractability, their spatial configurations are representative of typical inspection environments.

The obstacle regions are modeled as static spherical regions, with centers $\mathbf{x}_{\text{obs},k}$ and safety radii $r_{\text{safe},k}$. The predicate function for avoiding the k -th obstacle is defined as:

$$h_{\text{obs},k}(\mathbf{x}(t)) = \|\mathbf{x}(t) - \mathbf{x}_{\text{obs},k}\| - r_{\text{safe},k} \geq 0$$

Similarly, the goal region is modeled as a spherical area with center \mathbf{x}_{goal} and radius r_{goal} . The predicate function for the goal region is defined as:

$$h_{\text{goal}}(\mathbf{x}(t)) = r_{\text{goal}} - \|\mathbf{x}(t) - \mathbf{x}_{\text{goal}}\| \geq 0$$

The control objective is to design an input law for the UAV system (1) that ensures satisfaction of both the obstacle avoidance and goal-reaching tasks, as specified by the LTL formula $\phi = \phi^{\text{obs}} \wedge \phi^{\text{goal}}$, despite the presence of stochastic disturbances.

Formally, the trajectory $\mathbf{x}(t)$ is required to satisfy

$$(\mathbf{x}, 0) \models \phi^{\text{obs}}, (\mathbf{x}, 0) \models_{\geq} \phi^{\text{goal}},$$

where \models denotes exact satisfaction of the safety specification, and \models_{\geq} represents relaxed satisfaction of the goal-reaching specification, accounting for deviations caused by noise and bounded uncertainty.

Definition 2.1. Consider a target point \mathbf{x}_{goal} and a safety radius r_{goal} . For the UAV starting from any initial state $[\mathbf{p}^T(t_0), \theta(t_0)]^T \in \mathbb{R}^3$, the control input is designed as $[\mathbf{v}, \omega]^T$ using local measurements in the UAV's local coordinate frame. The transformation to the local frame is given by the rotation matrix $R(\theta)$:

$$R(\theta) = \begin{bmatrix} \cos \theta & \sin \theta \\ -\sin \theta & \cos \theta \end{bmatrix}.$$

The relative position of the target and obstacles in the UAV's local coordinate frame is calculated as:

$$\mathbf{c}^i = R(\theta)(\mathbf{c} - \mathbf{p}), \mathbf{p}_{\text{obs}}^i = R(\theta)(\mathbf{p}_{\text{obs}} - \mathbf{p}).$$

The control input is then defined as:

$$[\mathbf{v}, \omega]^T = \mathcal{Q}(\mathbf{v}, d_{\text{obs}}, \beta_{\text{obs}}, d_{\text{goal}}, \beta_{\text{goal}}, \mathbf{v}_{\text{goal}}, \mathbf{a}_{\text{goal}})$$

where d_{obs} and d_{goal} represent the distances from the UAV to the obstacles and goal, respectively, and $\beta_{\text{obs}}, \beta_{\text{goal}}$ are the corresponding angular measurements. The terms $\mathbf{v}_{\text{goal}} = R(\theta)\mathbf{c}'$ and $\mathbf{a}_{\text{goal}} = R(\theta)\mathbf{c}$ represent the target's velocity and acceleration in the UAV's local coordinate frame.

To guarantee the feasibility and stability of the control design, we make the following assumptions:

Assumption 1. $E[w(k)] = 0$, $E[w(k)w(j)] = \delta_{kj}$, where δ_{kj} is the Kronecker delta function, with $\delta_{kj} = 0$ when $k \neq j$ and $\delta_{kj} = 1$ when $k = j$.

Assumption 2. The matrix function $g(\mathbf{x})g(\mathbf{x})^T$ is positive definite for all $\mathbf{x} \in D$, ensuring the control inputs are well-defined.

Assumption 3. The initial state $\mathbf{x}_0 = \mathbf{x}(0)$ is not within the zero sub-level set of any obstacle predicate function $h_{\text{obs},k}(\mathbf{x}(t))$.

Assumption 4. The trajectory that satisfies the task ϕ is bounded, i.e., there exists a constant $C > 0$ such that $\|\mathbf{x}\| \leq C$.

Assumption 5. If the goal position \mathbf{x}_{goal} is time-varying, its dynamics are known for all $t \in [a, b]$.

2.3 Control Barrier Function (CBF)

To avoid obstacles and ensure safety during UAV navigation, we adopt the Control Barrier Function (CBF) framework. Specifically, we apply a time-varying robust CBF (tRCBF) to maintain a safe distance between the UAV and surrounding obstacles throughout its flight path.

Let $b(\mathbf{x}, t)$ be a differentiable barrier function that varies with time. The superlevel set of this function defines the safety region for the UAV at time t :

$$C(t) = \{\mathbf{x} \in \mathbb{R}^2 \mid b(\mathbf{x}, t) \geq 0\}.$$

This ensures the UAV remains within a safe margin from obstacles. The tRCBF is constructed so that for all t , there exists a locally Lipschitz continuous extended class-K function α and a robustness constant ρ such that:

$$\sup_{\mathbf{u} \in \mathcal{U}} \left\{ \frac{\partial \mathbf{b}(\mathbf{x}, t)}{\partial \mathbf{x}} \cdot \dot{\mathbf{x}} + \frac{\partial \mathbf{b}(\mathbf{x}, t)}{\partial t} \right\} \geq -\alpha(\mathbf{b}(\mathbf{x}, t)) + \rho.$$

The control input \mathbf{u} is computed by solving a quadratic program (QP) that ensures the UAV stays within the safe region $C(t)$. For each obstacle, a specific CBF is used to define the minimum safety margin:

$$h_{\text{obs},k}(\mathbf{x}(t)) = \|\mathbf{x}(t) - \mathbf{x}_{\text{obs},k}\| - r_{\text{safe},k} \geq 0,$$

where $r_{\text{safe},k}$ represents the minimum safety distance to the k -th obstacle. This constraint ensures that the drone can complete various temporal tasks defined by the Linear Temporal Logic (LTL) protocol without collision risk.

2.4 Control Potential Field Function (CPFF)

Although the Control Barrier Function (CBF) can ensure the safety of drone operation, effective guidance control towards the target still needs to be implemented. To address this, this paper introduces the Control Potential Field Function (CPFF), which combines the gravitational component pointing towards the target with the repulsive component avoiding surrounding obstacles to achieve smooth and continuous trajectory planning and generation. The total potential field function $U(\mathbf{x})$ of the system is composed of both gravitational and repulsive terms, and the specific expression is as follows:

$$U(\mathbf{x}) = U_{\text{attr}}(\mathbf{x}) + \sum_k U_{\text{rep},k}(\mathbf{x}),$$

where $U_{\text{attr}}(\mathbf{x})$ directs the UAV toward the target location, and $U_{\text{rep},k}(\mathbf{x})$ accounts for the repulsion from the k -th obstacle.

The attractive component is defined as:

$$U_{\text{attr}}(\mathbf{x}) = -k_{\text{attr}} \|\mathbf{x} - \mathbf{x}_{\text{goal}}\|^2,$$

where k_{attr} is a positive gain that determines the strength of the attraction, and \mathbf{x}_{goal} represents the position of the desired goal.

The repulsive potential function is used to prevent the UAV from getting too close to obstacles. It is defined as:

$$U_{\text{rep},k}(\mathbf{x}) = \begin{cases} \frac{\eta_k}{2} \left(\frac{1}{\|\mathbf{x} - \mathbf{x}_{\text{obs},k}\|} - \frac{1}{d_{\text{safe},k}} \right)^2, \\ 0, \end{cases}$$

if $\|\mathbf{x} - \mathbf{x}_{\text{obs},k}\| \leq d_{\text{safe},k}$, otherwise, where η_k is a positive constant that governs the intensity of the repulsive force, and $d_{\text{safe},k}$ defines the obstacle's influence radius. This formulation ensures that the UAV is repelled when entering the proximity of an obstacle, thereby reducing the risk of collision.

The control input for the UAV is derived from the gradient of the total potential field:

$$\mathbf{u} = -\nabla U(\mathbf{x}).$$

This mechanism can enable the drone to continuously converge and approach the target position, while smoothly avoiding surrounding obstacles.

To meet the obstacle avoidance constraints and task reachability requirements under the LTL protocol, this paper formalizes the task as follows:

$$\phi = \phi^{\text{obs}} \wedge \phi^{\text{goal}}.$$

Based on the above mechanism, the control input constructed can keep the drone within the safe and feasible range defined by tRCBF constraints, while CPFF achieves directional guidance motion for the target. Under the conditions of external disturbances and environmental uncertainty, it can still meet the requirements of safety constraints and temporal task constraints in real time.

In response to the performance deficiency of unmanned aerial vehicles being prone to falling into local optima in dynamic environments, this paper introduces a disturbance compensation term in the control input to further improve the dynamic operating performance of the system:

$$\mathbf{u}_{\text{cpf}} = \mathbf{u} + \delta,$$

where δ is a bounded disturbance that helps the UAV escape undesired positions and continue advancing toward its goal. This adjustment enhances the system's robustness in navigating complex environments.

2.5 Combined Control Strategy

The proposed control framework integrates the advantages of Control Barrier Function (CBF) and Control Potential Field Function (CPFF) to generate control inputs that satisfy safety constraints. The control law can be expressed as:

$$\mathbf{u}(t) = \lambda(\mathbf{x}(t))\mathbf{u}_{\text{CBF}}(t) + (1 - \lambda(\mathbf{x}(t)))\mathbf{u}_{\text{CPFF}}(t),$$

where $\lambda(\mathbf{x}(t))$ is a state-dependent weighting function that adjusts the contribution of each control strategy. When the UAV is near obstacles, the function emphasizes safety by favoring the CBF-based control; when obstacles are farther away, the CPFF component dominates to guide the UAV toward its goal.

The weighting function is defined as:

$$\lambda(\mathbf{x}(t)) = \begin{cases} 1, & \text{if } \|\mathbf{x}(t) - \mathbf{x}_{\text{obs},k}\| \leq r_{\text{safe},k}, \\ 0, & \text{otherwise.} \end{cases}$$

This switching mechanism ensures a smooth transition between safety critical control and target oriented motion, enabling the drone to adaptively respond to dynamic changes in the surrounding environment.

This article integrates the Control Barrier Function (CBF) and Control Potential Field Function (CPFF) through context aware approach. The proposed hybrid control can ensure the safe passage of unmanned aerial vehicles in dense obstacle spaces, while efficiently reaching designated target positions, fully meeting the core requirements of complex work scenarios such as live power line maintenance.

2.6 Infeasibility Detection within the Control Framework

Although the proposed control framework is designed to satisfy the LTL specification $\phi = \phi^{\text{obs}} \wedge \phi^{\text{goal}}$, certain workspace configurations may render the task infeasible. The above

infeasible working conditions are mainly caused by two factors: (1) the spatial distribution and layout of obstacles, which can easily simultaneously hinder task accessibility and violate safety constraints; (2) The inherent performance limitations of the control strategy itself. This article integrates an infeasible real-time detection mechanism within the proposed framework to achieve adaptive dynamic adjustment of drone control behavior.

This mechanism evaluates the feasibility of the current temporal task online by determining the intersection state between the reachable area of the target and the accessible feasible set. The specific judgment conditions are as follows:

$$C(t) = \{\mathbf{x} \in \mathbb{R}^2 \mid \text{hobs},k(\mathbf{x}) \geq 0 \text{ for all obstacles } k\}.$$

The mechanism checks whether the intersection of the safe regions defined by $C(t)$ and the goal region satisfies the LTL task ϕ^{goal} :

$$flg(\phi^{\text{goal}}) = \left(\bigcap_k C(t) \neq \emptyset \right),$$

returning True if the task is feasible, or False otherwise.

Based on this detection, the system classifies scenarios as:

- Feasible: The UAV can achieve both obstacle avoidance and goal-reaching.
- Infeasible: It is impossible to satisfy both tasks, prioritizing obstacle avoidance.
- Possibly Feasible: The UAV may be able to partially satisfy both tasks during some intervals.

Adapting Control Inputs Based on Detection Results:

In feasible scenarios, the UAV follows the standard CBF-QP approach to ensure obstacle avoidance while striving to reach the goal.

In possibly feasible cases, a relaxed CBF-QP with slack variables ϵ is employed to allow flexibility in obstacle avoidance, while still attempting to reach the goal:

$$\mathbf{u}, \epsilon \quad \min K_1 \|\mathbf{u}\|^2 + K_2 \epsilon^2,$$

subject to:

$$\frac{\partial \mathbf{b}(\mathbf{x}, t)}{\partial \mathbf{x}} \cdot \mathbf{u} + \frac{\partial \mathbf{b}(\mathbf{x}, t)}{\partial t} \geq -\alpha(\mathbf{b}(\mathbf{x}, t)) - \epsilon.$$

In infeasible scenarios, the UAV abandons the goal-reaching task and focuses entirely on safety, using the CBF method to maintain operation within the safe region.

Dynamic Control Strategy:

The combined control law dynamically balances between obstacle avoidance and goal-reaching based on the feasibility result:

$$\mathbf{u}(t) = \lambda(\mathbf{x}, \text{hobs}(\mathbf{x})) \cdot \mathbf{u}_{\text{CBF}}(t) + (1 - \lambda(\mathbf{x}, \text{hobs}(\mathbf{x}))) \cdot \mathbf{u}_{\text{CPFF}}(t),$$

where $\lambda(\mathbf{x}, \text{hobs}(\mathbf{x}))$ is a weighting function that shifts between obstacle avoidance (CBF) and goal-reaching (CPFF) based on the UAV's proximity to obstacles.

This integrated detection mechanism can ensure real-time adaptive response of unmanned aerial vehicles to the status of the workspace environment, implement safety priority control logic, and continuously complete target approach and sequential task execution under the premise of feasible tasks.

3 Application in Live Power Line Maintenance

To verify the actual operational performance of the proposed control framework, this paper constructs a typical simulation scenario for unmanned aerial vehicle (UAV) power line inspection. The UAV needs to navigate along linear power infrastructure and avoid static obstacles such as towers, vegetation, and other environmental obstacles.

Modeling the workspace as a two-dimensional plane environment, setting horizontal power lines, and placing a single static obstacle at coordinates (2,5); The target point for drone inspection is set at (8,8), corresponding to the key inspection points that need to be reached on the power line, and the following linear temporal logic (LTL) formula is used to formalize the inspection task:

$$\phi = \square(\text{avoid obstacles}) \wedge \diamond (\text{inspect the power line}),$$

where the safety condition \square enforces persistent avoidance of obstacles, and the liveness condition \diamond ensures the inspection task is eventually completed.

According to the LTL task protocol mentioned above, the Control Barrier Function (CBF) module solves the forward invariant safety zone around the obstacle, calculates the collision free control input online, and controls the potential field function (CPFF) to couple the gravitational and repulsive forces, guiding the drone to approach the inspection target while actively avoiding dangerous areas.

The motion trajectory of the drone is obtained by dynamically weighted fusion of CBF and CPFF: (1) When the distance between the drone and the obstacle is far, CPFF occupies the dominant control position, smoothly driving the drone along the inspection path towards the target; (2) When the drone gradually approaches the danger zone, CBF switches to the dominant control item. Through the above control process, while strictly satisfying safety constraints, the drone can still continue to advance towards the target along the inspection path.

3.1 Simulation Example

To verify the effectiveness of the control framework proposed in this article, a simulation experiment of unmanned aerial vehicle navigation was conducted in a typical two-dimensional plane environment for power line inspection. The simulation parameters were set as follows: (1) Modeling the power line as a horizontal linear operation path that the unmanned aerial vehicle needs to follow for inspection; (2) Set up static obstacles at coordinates (2,5) to simulate tower structures and environmental interference around the line; (3) The drone departs from the initial position on the left side of the inspection area and heads towards the target point (8,8) under obstacle avoidance constraints; (4) The control input of the drone is obtained by jointly solving the Control Barrier Function (CBF) and Control Potential Field Function (CPFF), ensuring that it satisfies both safety constraints and LTL mission specifications.

The simulation results in Figure 1 intuitively verify the feasibility and superiority of the proposed framework. The motion trajectory of the drone depicted in Figure 1 indicates that the drone can achieve autonomous navigation in complex environments and effectively avoid the risk of obstacle collisions.

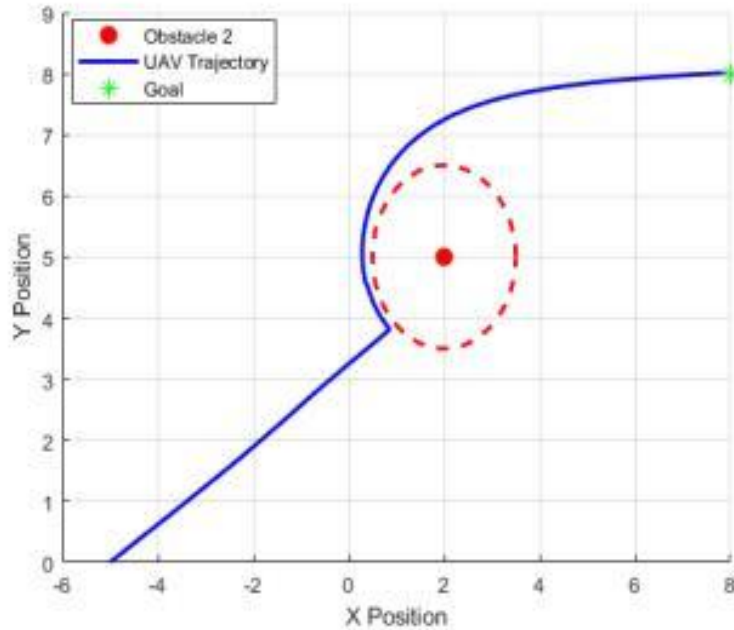


Figure 1: UAV trajectory in the live power line maintenance scenario.

As shown in Figure 1, the blue curve represents the trajectory of the drone, which starts from the initial position on the left and continues to move towards the designated inspection target at coordinates (8,8). The red circle centered around (2,5) is the static obstacle, and the outer dashed boundary is the corresponding safety margin area. From the simulation results, it can be seen that the drone can adaptively adjust its motion trajectory in real time, actively avoiding obstacles while continuously approaching the target position smoothly.

The above motion characteristics fully reflect the synergistic optimization effect of Control Barrier Function (CBF) and Control Potential Field Function (CPFF). CBF ensures system safety through dynamic obstacle avoidance mechanism, while CPFF provides stable target guidance control for unmanned aerial vehicles. The final planned path has a smooth transition, reliable safety guarantee, and excellent operational performance even in complex environments with limited space and dense obstacles.

3.2 Discussion of Results

This simulation experiment shows that when obstacles are extremely close to the inspection trajectory, the Control Barrier Function (CBF) can implement hard constrained real-time obstacle avoidance through the safety buffer zone, significantly reducing the risk of collision during operation and improving the overall operational safety level. The Control Potential Field Function (CPFF) can continuously guide the unmanned aerial vehicle to pass through the power line along an efficient path, achieving optimal approach control.

The motion trajectory of the drone can dynamically and adaptively adjust the environmental state, achieving a smooth transition between safety constraint execution and target oriented motion behavior. Switching between control modes is critical in realistic situations, where the positions of obstacles as well as external constraints can vary. The framework also manages more sophisticated configurations with multiple close obstacles to critical points of inspection, proving its capability to balance multiple goals.

Overall, the findings validate that integrating CBFs and CPFFs results in a robust and flexible control policy. The UAV is able to perform its task with obstacle avoidance even in

constrained, uncertain spaces. While the simulation employs a simplified model of obstacles for the sake of computational efficiency, the underlying structure is transfer- able to aerial inspection tasks subject to the same spatial and safety limitations. While the current test is for a single test case, the methodology is well positioned for extension to more complex, dynamic spaces in further work.

4 Conclusion

The work presented in this paper proposed a strong control framework for live power line maintenance by UAVs, with both safety and task efficiency a priority. The framework employs Control Barrier Functions (CBFs) for the guarantee of real-time obstacle eva- sion and Control Potential Field Functions (CPFFs) for goal-oriented movement. The framework, therefore, supports UAV operation in complex scenes with effective inspec- tion tasks. The use of Linear Temporal Logic (LTL) for the specification of the mission also adds a rigorous assurance layer, which guarantees the satisfaction of both safety and task goals even in the presence of uncertainty. The simulation results show that the proposed control framework can comprehensively optimize the performance of safety constraint execution while completing the timing inspection task.

Future research will introduce event driven control mechanisms to further improve real-time control efficiency and expand to dynamic disturbances and strong uncertain environments, further enhancing the practical deployment and application capabilities of unmanned aerial vehicle systems engineering.

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