A Perception-Decision-Control Framework for Dynamic Obstacle Avoidance of UAVs

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Abstract. Unmanned aerial vehicles (UAVs) face significant challenges in dynamic obstacle avoidance despite their broad applications in agriculture, logistics, and emergency response. Existing methods, such as sampling-based RRT and graph-based Dijkstra algorithms, often struggle with dynamic environments and complex multi-objective tasks. This study proposes an integrated "perception-decision-control" framework to address these limitations. The framework incorporates multi-sensor fusion (LiDAR, vision, IMU) for robust environmental perception, linear temporal logic (LTL) for task decomposition and constraint formalization, and an improved Dijkstra algorithm with safety constraints for real-time path planning. A PID-based tracking controller ensures precise trajectory execution, achieving a 95% success rate in dynamic obstacle avoidance scenarios, with trajectory errors below 0.30.3 meters. Experimental validation on a quadrotor platform demonstrates enhanced adaptability to illumination variations and computational efficiency (45 FPS on embedded hardware). The system provides a comprehensive solution for autonomous UAV navigation, balancing safety, real-time performance, and mission complexity. Future work will focus on adaptive control strategies and multi-agent coordination to further improve robustness in large-scale environments.

Keywords: Unmanned Aerial Vehicle, Obstacle Avoidance, Linear Temporal Logic, Dijkstra Algorithm, PID Control

1 Introduction

With the rapid development of unmanned aerial vehicle (UAV) technology, UAVs have been widely adopted in agricultural plant protection, logistics distribution, surveying, emergency rescue, and other fields due to their unique advantages [1]. As low-altitude technologies advance, UAV application scenarios are becoming increasingly diverse. However, safety constraints such as obstacle avoidance during flight operations have emerged as critical challenges restricting their broader adoption [2]. Consequently, motion planning and control of UAVs under safety constraints has become a key research direction in this field [3–4].

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1.1 Existing Obstacle Avoidance Methods

UAVs utilize sensors such as LiDAR, vision systems, and ultrasonic sensors for real-time environmental perception to detect obstacles and update flight paths. Current obstacle avoidance algorithms fall into three categories:

(1) Sampling-based methods (e.g., Rapidly-exploring Random Tree (RRT)) construct search trees through random sampling for path planning [5–6].

(2) Graph-based methods (e.g., A* algorithm) model environments as graph structures for optimal path searches [7–8].

(3) Potential field-based methods treat UAVs as particles moving in virtual force fields, addressing local optima and formation safety issues [9–10]. These methods primarily focus on offline planning for static obstacles.

1.2 Advantages of Temporal Logic Approaches

Traditional algorithms struggle with complex tasks requiring sequential multi-target visitation or time-constrained operations [11–12]. Temporal logic methods provide effective solutions for such problems. Linear Temporal Logic (LTL) translates mission objectives and safety constraints into logical formulas, enabling UAV path planning [13]. Recent studies highlight its advantages. Studies use temporal logic for task modeling and improve robustness through Büchi automata relaxation [14–15]. Studies [16] proposes an LTL-based method incorporating task priorities and resource constraints. References [17–18] present distinct path planning strategies for UAVs with known/unknown dynamics.

1.3 Research Challenges and Solutions

Existing LTL - based methods frequently overlook safety constraints and dynamic performance [19–20]. To overcome these limitations, this work presents an integrated “perception - decision - control” framework. It establishes a discrete environment model via visual perception for real - time obstacle/target detection in environmental perception, decomposes complex missions through LTL formalization and generates obstacle - avoidance paths using a safety - constrained Dijkstra algorithm in task planning, and designs PID - based tracking control laws to ensure precise trajectory following in motion control [21].

Implementing an integrated perception - decision - control flight control system holds significant value. It enhances UAV autonomy as traditional flight control systems relying on predefined paths have limited responsiveness to environmental changes, and the integrated system endows UAVs with environmental adaptability for autonomous obstacle avoidance and dynamic path adjustment. It improves adaptability in complex environments since visual perception enables precise obstacle identification, reducing GPS dependency and enhancing applicability in urban, forested, or other complex terrains, and the integration of LTL with path planning algorithms further boosts mission flexibility [22–23]. It elevates flight safety as environmental modeling and obstacle - avoidance safety constraints reduce collision risks and ensure operational safety, and PID control along with error feedback achieves accurate trajectory tracking, minimizing deviations and enhancing flight stability. Moreover, it increases mission efficiency as task decomposition optimizes flight strategies, the Dijkstra algorithm generates optimal paths to improve execution efficiency, and real - time flight control adjustments reduce energy consumption and hasten task completion.

1.4 System Architecture

The proposed hierarchical framework, depicted in Fig. 1, encompasses a deep learning - based perception module that conducts obstacle detection and feature extraction, an LTL task modeling module which generates reference trajectories via a safety - constrained Dijkstra algorithm, and a PID tracking control module that executes high - precision trajectory tracking. Fig. 2 shows the UAV platform in the laboratory and some basic parameters of the UAV.

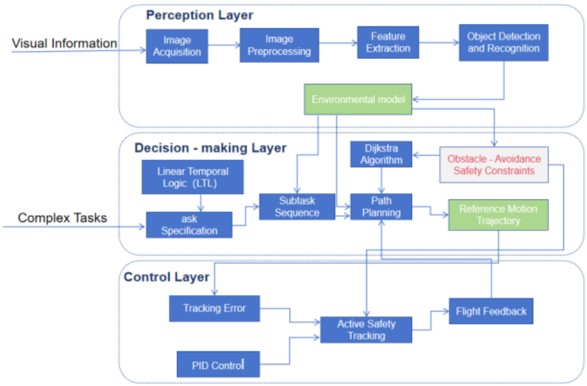

Fig. 1. Overall system architecture

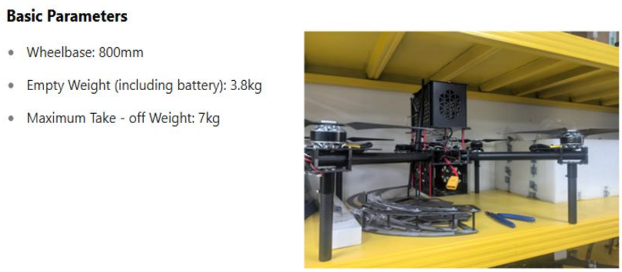

Fig. 2. Experimental UAV platform

2 Feasibility Analysis

2.1 Visual Perception for UAVs

The UAV visual perception system uses depth cameras to capture environmental images, enhanced through preprocessing techniques (denoising, grayscale conversion, contrast enhancement) to ensure effective feature extraction. Deep learning algorithms such as Convolutional Neural Networks (CNNs) and YOLO are used for object detection and recognition, facilitating precise environmental awareness. However, it has key limitations including a significant dependence on illumination conditions (resulting in errors in low - light, glare, or dynamic environments) and high computational demands that impact real - time performance. To address these, improvement strategies involve implementing multi - modal sensor fusion (LiDAR + IMU), optimizing efficiency through lightweight neural networks, and enhancing adaptability via data augmentation and adaptive learning.

2.2 Obstacle-Avoidance Motion Planning

The framework applies Linear Temporal Logic (LTL) for task specification and a safety - constrained Dijkstra algorithm to generate obstacle - free trajectories. However, it has critical limitations: in large - scale environments, it suffers from high computational complexity and relies heavily on perception accuracy, being sensitive to false positives and negatives. To address these issues, several enhancements can be made. Integrating the A* algorithm or Dynamic Window Approach (DWA) can improve efficiency; applying reinforcement learning helps optimize for dynamic obstacles; and using multi - sensor fusion can enhance environmental awareness.

2.3 Safety-Critical Flight Control

The PID - based control system attains trajectory tracking by means of real - time error correction. However, it encounters challenges such as being sensitive to nonlinear disturbances like wind and terrain variations and relying heavily on sensor precision, rendering it vulnerable to noise. To tackle these challenges, advanced solutions can be adopted. Implementing adaptive PID or Model Predictive Control (MPC) helps enhance control performance. Employing sensor fusion of IMU, GPS, and vision along with Kalman filtering improves sensor data reliability. Additionally, deploying error compensation through advanced filtering algorithms optimizes the control system.

3 Specific Solution

3.1 The Specific Implementation of Visual Perception in UAVs

Unmanned aerial vehicle (UAV) visual perception is a crucial technology for UAVs to interact with the environment. The specific implementation of UAV visual perception consists of the following steps. Firstly, image acquisition. UAVs utilize depth cameras to capture real - time environmental images. Depth cameras can provide not only the appearance information of the scene but also depth information, which is essential for UAVs to understand the spatial layout of the surrounding environment. Secondly, image preprocessing. After obtaining the images, preprocessing steps such as denoising, grayscale conversion, and contrast enhancement are carried out. Denoising helps to reduce the noise interference in the images, improving the clarity. Grayscale conversion simplifies the image data while retaining the main features. Contrast enhancement makes the differences between different parts of the image more obvious, facilitating subsequent processing.

Thirdly, feature extraction. In this step, features like edges, corner points, and textures in the images are extracted. Edges can represent the boundaries of objects, corner points are important for object positioning and recognition, and textures can provide additional information about the surface characteristics of objects. These features are the basis for further object detection and recognition.

Finally, object detection and recognition. Deep - learning algorithms such as Convolutional Neural Networks (CNNs) and YOLO are employed. CNNs can automatically learn the hierarchical features of objects through multiple convolutional and pooling layers, while YOLO is a real - time object detection algorithm that can quickly identify various objects in the environment, such as obstacles and roads, enabling UAVs to make appropriate decisions based on the recognition results. The reference image can be seen in Fig. 3.

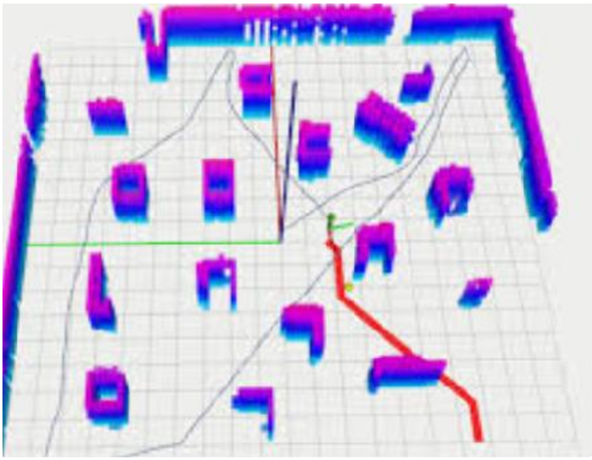

Fig. 3. Visual Perception for UAVs

3.2 The Specific Implementation of UAV Obstacle - Avoidance Motion Planning

The specific implementation of UAV obstacle - avoidance motion planning consists of the following steps. Firstly, task specification. Linear Temporal Logic (LTL) is used to transform complex tasks into formal descriptions that can be understood and processed by computers. It clarifies the task objectives as well as the temporal and logical relationships among various tasks, providing a clear guideline for subsequent planning. Secondly, task decomposition. Complex tasks are subdivided into a series of relatively simple and operable subtasks according to certain rules and logic. This makes it easier to handle and plan each subtask separately, improving the efficiency and accuracy of planning. Thirdly, Dijkstra algorithm design. The traditional Dijkstra shortest - path algorithm is improved based on obstacle - avoidance safety constraints, enabling it to calculate the shortest path that meets safety conditions while taking into account the presence of obstacles. Finally, path planning and obstacle avoidance. The improved algorithm is used to generate the optimal tracking path, ensuring that the UAV can avoid obstacles during flight and fly safely along the planned path. The reference image can be seen in Fig. 4.

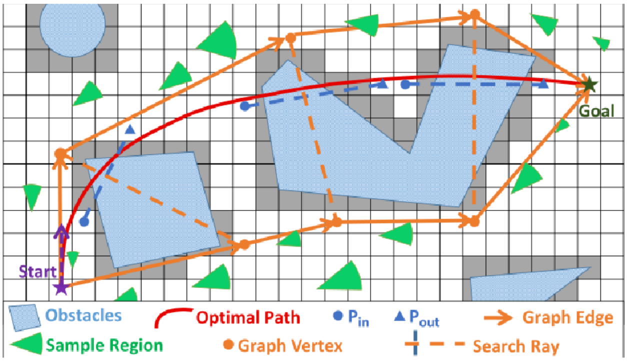

Fig. 4. Overall system architecture

3.3 The Specific Implementation of UAV Safety Control

The specific implementation of UAV safety control consists of the following steps. Firstly, tracking error calculation. Accurate sensors are used to obtain the actual state information of the UAV, such as position, speed, and attitude, and compare it with the pre - set target state information to calculate the tracking error between them. These error data serve as the basis for subsequent control adjustments. Secondly, PID control. The PID controller takes into account position error, speed error, and time factors comprehensively. The position error reflects the deviation between the current position of the UAV and the target position, while the speed error represents the difference between the actual speed and the desired speed of the UAV. According to the current error situation, the PID controller dynamically adjusts the control input in accordance with the control laws of proportional (P), integral (I), and derivative (D) to reduce the error. Thirdly, active safety control. Using the control commands output by the PID, the tracking control module precisely adjusts the flight direction, speed, and attitude of the UAV. Adjusting the flight direction ensures that the UAV moves towards the target path; speed adjustment guarantees that the UAV flies at an appropriate speed; and attitude adjustment keeps the UAV stable during flight. Finally, flight execution and feedback. During the flight, the UAV continuously adjusts its motion trajectory in real

- time according to environmental changes and its own state. At the same time, it provides real - time feedback of its actual state information to the control system, which makes optimization adjustments based on the feedback information and continuously tracks the optimal path to ensure the safe and stable flight of the UAV. The reference image can be seen in Fig. 5.

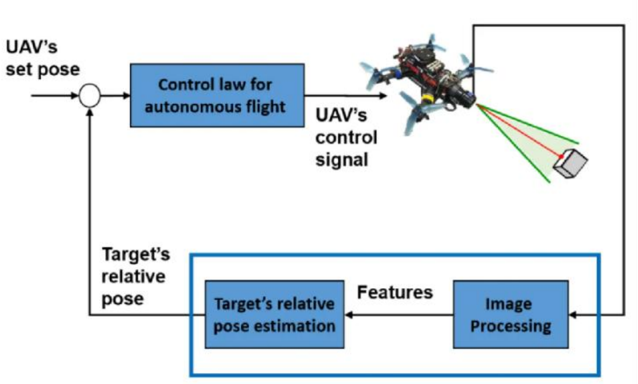

Fig. 5. Safety-Critical Flight Control

4 Conclusion

4.1 Key Contributions

This study puts forward an integrated perception - decision - control architecture for UAV autonomous flight systems, enabling closed - loop optimization from environmental perception to motion control. The framework exhibits three key advancements: it enriches environmental understanding through deep learning - based visual perception, boosts obstacle - avoidance efficiency using the LTL - guided Dijkstra algorithm for path planning, and ensures flight stability via PID - based trajectory tracking control. Although the system grapples with challenges such as high computational demands, poor environmental adaptability, and insufficient control precision, these limitations can be alleviated by implementing multi - sensor fusion, conducting algorithmic optimization, and adopting adaptive control strategies. Evidently, the proposed approach substantially improves UAV autonomy in complex operational situations.

4.2 Future Directions

Future research will zero in on three primary areas: optimizing obstacle - avoidance algorithms for dynamic environments under algorithm enhancement; strengthening robustness via multi - sensor fusion techniques in perception improvement; and implementing adaptive PID or Model Predictive Control (MPC) to ensure stability in control advancement.

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