OPTIMAL COVERAGE PATH PLANNING AND OBJECT DETECTION FOR UAV-BASED SURVEILLANCE SYSTEMS

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ABSTRACT

The development of a UAV-based surveillance system integrated with artificial intelligence (AI) poses numerous technical challenges, prominently involving two core problems: optimal coverage path planning and object detection and classification from aerial imagery. These are crucial components to ensure effective navigation and accurate target identification during UAV operations. This paper proposes a ground control system that functions as a command station, capable of generating energy-efficient and comprehensive flight paths for monitoring tasks. Simultaneously, it integrates AI models to detect and classify objects from aerial image data captured by the UAV. Simulation-based evaluations demonstrate the feasibility and potential application of the proposed solution in deploying intelligent UAV systems in Vietnam.

***Keywords**: Coverage path planning, UAV surveillance, Artificial Intelligence, object detection, classification, optimal coverage.*

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1. INTRODUCTION

In recent years, automated surveillance systems utilizing unmanned aerial vehicles (UAVs) have gained significant attention and are increasingly applied across various fields such as public security, national defense, forest monitoring, infrastructure inspection, precision agriculture, and disaster response. With high mobility and flexibility, UAVs enable the collection of high-resolution and real-time image data over wide areas, thereby effectively supporting monitoring tasks and rapid decision-making.

A critical direction in the advancement of UAV-based surveillance systems involves enabling autonomous or semi-autonomous operation, with the aim of minimizing human intervention and enhancing operational efficiency. UAV-based surveillance systems has garnered broad research interest due to its mobility, wide-area coverage, and cost-effectiveness compared to traditional surveillance methods. However, deploying such systems entails addressing multiple complex technical problems. Among them, two foundational challenges that determine the system's quality and effectiveness are: (1) optimal coverage path planning (CPP), which ensures that the UAV navigates an energy- and time-efficient trajectory while fully covering the designated surveillance area; and (2) object detection and classification in aerial images, to accurately recognize critical targets from collected image data and support automated surveillance tasks.

Coverage Path Planning (CPP) is a fundamental problem that aims to ensure a UAV can observe the entire target area while minimizing travel cost. Traditional CPP approaches often rely on spatial decomposition techniques such as Boustrophedon and Spanning Tree Coverage [1, 2]. However, these methods are primarily effective in static and structurally simple environments. In more complex scenarios such as large-scale patrol regions or environments with energy and kinematic constraints, coordinated operation of multiple UAVs becomes necessary. To address this, various optimization models for CPP have been proposed, which are typically solved using metaheuristic optimization algorithms such as Genetic Algorithms, Ant Colony Optimization, and Particle Swarm Optimization [6, 10, 11].

Recently, reinforcement learning and deep learning-based approaches have been introduced to improve adaptability in dynamic environments. These models aim to learn optimal coverage strategies directly, even under energy constraints and uncertain environmental factors. They can operate in environments with obstacles, partial observability, and concurrent multi-UAV deployment. Empirical results often show that these learning-based methods outperform classical planning techniques in terms of coverage efficiency and adaptability [8, 12-17]. Nevertheless, the high computational complexity inherent in many of these models poses a significant barrier to real-world deployment. In practice, UAV systems require fast response times and robust performance under constrained computational resources [17].

Object detection and classification from UAV-captured imagery constitute a critical component in automated surveillance systems. With the rapid advancement of deep learning, models such as Faster R-CNN, YOLO, and SSD [3, 4] have been widely adopted for processing aerial imagery acquired by UAVs. However, the inherent characteristics of UAV images such as high-altitude viewpoints, varying perspectives, high resolutions, and the typically small size of target objects, pose significant challenges for detection accuracy.

To address these issues, several studies have proposed model enhancements or incorporated additional preprocessing steps aimed at improving detection performance. In [5], the authors adopted a hard negative mining strategy to better identify difficult object instances in UAV imagery. Additionally, some research efforts have explored multimodal data fusion, integrating inputs from RGB cameras, thermal infrared sensors, and LiDAR, to enhance detection reliability under complex environmental conditions [7].

In this paper, we propose a control system capable of generating energy-efficient and fully covering flight paths for UAVs in surveillance missions. The system is deployed on a ground control station, which is responsible for the entire flight planning and data analysis process. This architecture significantly reduces the computational load on the UAV and is well-suited for real-world deployment scenarios. Moreover, the system integrates an artificial intelligence (AI) model to perform object detection and classification on images captured by the UAV.

The structure of this paper is organized as follows: Section 2 introduces the mathematical model for optimal coverage path planning (CPP) and the proposed solution methodology. Section 3 presents the AI-based object detection and classification model used for aerial imagery. Section 4 describes the system development workflow and the software tools employed. Section 5 discusses the results obtained in a simulated environment. Finally, Section 6 concludes the paper and outlines potential future research directions.

2. COVERAGE PATH PLANNING PROBLEM

Coverage path planning (CPP) for surveillance areas is a fundamental problem in autonomous UAV-based monitoring systems. The objective is to construct a trajectory that enables the UAV to fully cover the region of interest without leaving any regions unobserved, while optimizing criteria such as path length, flight time, or energy consumption. CPP is especially critical in applications such as agricultural monitoring, search and rescue operations, and border patrol, where UAVs must conduct systematic and efficient flights. The problem becomes increasingly complex when the surveillance area includes uneven terrain, obstacles, or when UAV operations are constrained by factors such as limited energy capacity, kinematic constraints, and sensor coverage range.

In this study, we focus on the two-dimensional formulation of the CPP problem, taking into account both energy constraints and sensor coverage capabilities, with the goal of generating an optimal trajectory suitable for real-world UAV surveillance deployment. We adopt the energy-efficient coverage path planning model proposed in [9], which not only ensures complete area coverage but also minimizes overall energy consumption. The model supports multi-UAV scenarios and incorporates the ability to avoid static obstacles. Moreover, the model is well-structured, scalable, and particularly suitable for implementation under practical conditions in Vietnam. Representing the surveillance area as a grid provides additional advantages: it facilitates integration with simple pathfinding algorithms, reduces computational time, and simplifies deployment within the ground control system.

Specifically, the surveillance area is discretized into a grid of square cells, each representing a discrete subregion that must be covered. The center of each cell is designated as a waypoint, which UAVs must visit under the constraint that each cell is scanned exactly once, while minimizing the total energy consumption. The model employs a cost function that integrates flight distance and travel time, allowing for a more realistic simulation of actual flight conditions. Additionally, basic kinematic constraints are incorporated to ensure the feasibility of the generated flight paths. For a detailed description of the problem formulation and the associated energy model, the reader is referred to [9] and related references.

The coverage path planning model in [9] supports the avoidance of known static obstacles by excluding unsafe cells from the feasible space. These cells are assigned significantly high energy costs, effectively discouraging their inclusion in any feasible trajectory. This formulation results in a Mixed-Integer Linear Programming (MILP) problem, where binary variables are used to indicate whether a UAV traverses a given waypoint. Linear constraints are employed to ensure path connectivity, complete area coverage, and energy minimization.

For large-scale patrol areas, deploying multiple UAVs becomes essential. A decomposition strategy is applied to partition the area into subregions, where the number of subregions matches the number of available UAVs. In other words, each UAV is responsible for covering one subregion, and the CPP model from [9] is independently applied to each of these subregions. The MILP problem defined for each subregion can be solved using various optimization solvers. In this study, energy consumption values associated with traveling between waypoints are first computed. These values may depend on multiple factors, such as the distance between waypoints, UAV speed, and turning angles. The IBM CPLEX solver is then selected for solving the MILP, owing to its effectiveness in handling medium to large scale problems, as well as its robustness and computational efficiency.

3. OBJECT DETECTION AND CLASSIFICATION

In addition to optimizing flight paths for comprehensive area coverage, the ability to detect and classify objects in aerial images captured by UAVs for surveillance, alert generation, or autonomous decision-making. This processing stage is essential in enabling the system to recognize the presence of critical targets such as humans, vehicles, suspicious objects, or anomalous events within the monitored environment.

Aerial imagery captured by UAVs differs significantly from conventional image data due to its top-down perspective, small object sizes, complex backgrounds, and substantial variations in lighting conditions, flight altitude, and terrain. Consequently, object detection and classification in this context require recognition models with strong generalization ability, fast inference speed, and high accuracy under practical operating conditions.

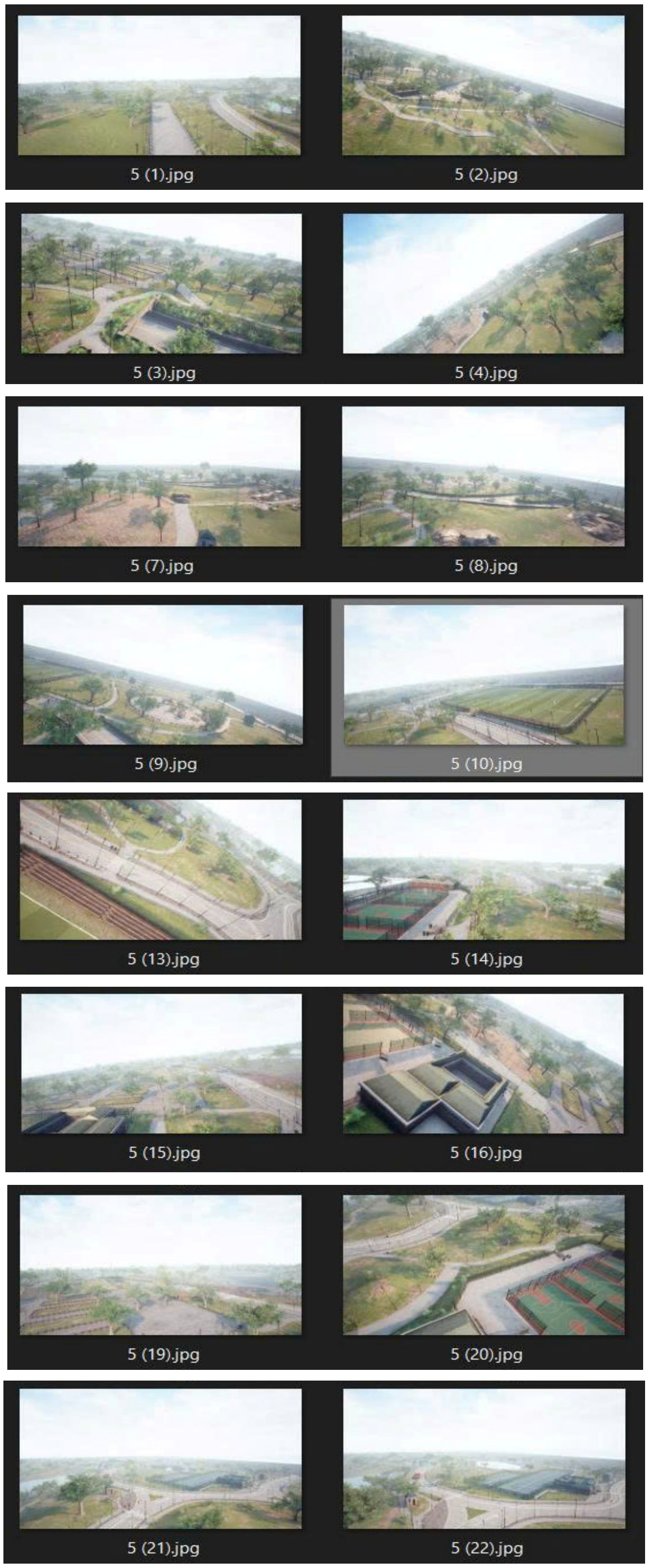

Figure 1. Samples in fine-tuning dataset for YOLOv10

In this study, we selected YOLOv10, a recent model in YOLO family, which is distinguished by its balance between real-time processing speed and detection precision. YOLOv10 is specifically designed to perform effectively even on devices with limited computational resources, such as UAVs or mobile ground control units.

Although YOLOv10 has been pre-trained on widely used datasets such as COCO, its performance in UAV-based surveillance scenarios remains limited. In such settings, images are captured from high altitudes with varying viewpoints, and target objects are often small or partially occluded. Furthermore, several domain-specific object classes commonly encountered in surveillance environments are not represented in the original training dataset, leading to suboptimal detection accuracy that falls short of practical requirements.

To address these limitations, we performed fine-tuning of the YOLOv10 model on a specialized dataset comprising 800 manually labeled images with over 2,000 annotations. The annotation set focuses on object classes that are critical in surveillance scenarios, including eight categories: human, car, motorbike, container truck, bench, house, umbrella, and crosswalk. Preprocessing steps and data augmentation techniques were applied to enhance the robustness of the dataset. Figure 1 illustrates several sample images from the dataset, while the class label distribution is shown in Figure 2.

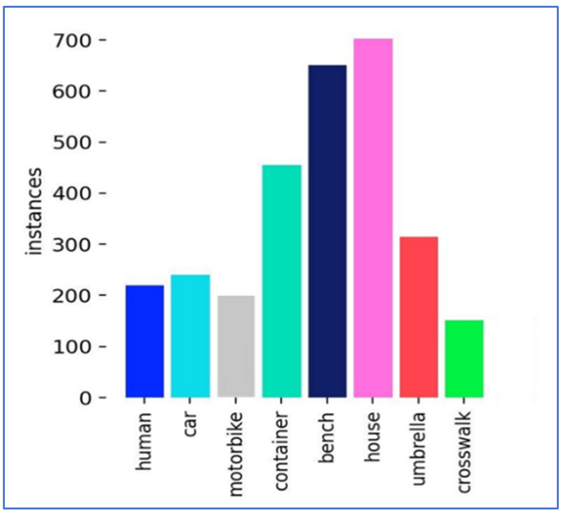

Figure 2. Class label distribution in the training dataset

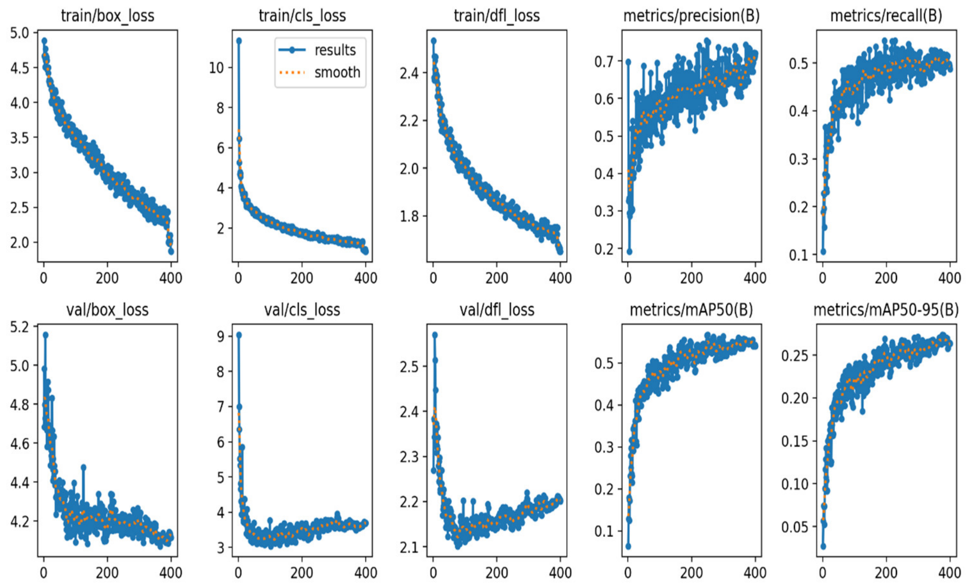

Figure 3. Fine-tuned YOLOv10 model evaluation results

Figure 3 presents the fine-tuning results of the YOLOv10 model on both the training and validation datasets. The loss metrics - including box loss, classification loss (cls_loss), and distribution focal loss (dfl_loss) - consistently decreased and stabilized across both sets, indicating an effective learning process without overfitting. In parallel, evaluation metrics such as precision, recall, mAP@0.5, and mAP@0.5:0.95 steadily improved and converged after approximately 200 epochs, demonstrating acceptable accuracy and good generalization capability of the model.

4. SYSTEM DEPLOYMENT

The UAV control system was developed following a four-stage process, which includes: (1) constructing the mathematical model and solving the CPP optimization problem; (2) developing the module for UAV communication and control; (3) implementing the module for object detection and classification based on aerial imagery captured by the UAV; and (4) integrating all components into a unified system.

Stage 1: Mathematical Modeling and CPP Optimization

The input data consists of the boundary coordinates that define the surveillance area. This area is then partitioned into grid cells, where the grid resolution matches the footprint width of the onboard UAV camera, and waypoints are defined accordingly. An energy consumption model for the UAV is constructed based on the formulation in [9], and the specific CPP problem is established. The IBM CPLEX optimization library is then employed to solve the CPP problem as a Mixed-Integer Linear Programming (MILP) formulation. The output is an ordered sequence of waypoints for each UAV that enables energy- and time-efficient coverage of the target area.

Stage 2: Development of the UAV Communication and Control Module

The optimal trajectories generated in Stage 1 are transformed and mapped to real-world geographic coordinates before being integrated into a UAV flight simulation system. The selected simulation environment incorporates several tools that facilitate UAV connectivity and control. The core tools used include:

- PX4-Autopilot**:** an open-source flight control platform that provides stabilization and autonomous navigation capabilities for UAVs. It supports a wide range of aerial vehicles and is easily integrated with simulation tools such as QGroundControl, AirSim, and ROS.
- QGroundControl**:** an open-source ground control station software used for real-time UAV monitoring and control. It offers an intuitive user interface for flight path planning, position tracking, sensor configuration, and data reception from the UAV. QGroundControl is fully compatible with PX4 and communicates with the flight controller via the MAVLink protocol.
- AirSim: an open-source simulation platform developed by Microsoft, designed to emulate the operation of UAVs and autonomous vehicles in realistic 3D environments such as Unreal Engine and Unity. AirSim supports various sensors including cameras, GPS, LiDAR, and IMU, enabling the testing and evaluation of control algorithms, computer vision, and machine learning techniques under near-real conditions. The platform integrates well with PX4 and ROS, making it suitable for incorporation into UAV development workflows prior to field deployment.

This simulation setup allows for verification of trajectory feasibility and accuracy under conditions that closely resemble real-world environments.

Stage 3: Development of the Object Detection and Classification Module

This module plays a central role in identifying key targets from UAV-captured imagery and comprises the following core functionalities:

- Image data acquisition**:** Real-time aerial images are continuously collected from the UAV's onboard camera system, ensuring a stable data stream to support subsequent object recognition processes.
- Object detection and classification**:** The fine-tuned YOLOv10 model is employed to detect and classify multiple types of target objects in the captured images. The list of object classes to be recognized is predefined based on mission requirements.
- Automated alerting**:** When an object is detected within the surveillance area, the system triggers a "target detected" alert, enabling the ground control station to promptly respond and take appropriate actions, thereby enhancing patrol effectiveness.

The object detection and classification module is a key component that enables the UAV surveillance system to operate accurately, efficiently, and adaptively under various environmental conditions.

Stage 4: System Integration

The system is implemented as a ground control station with a user-friendly interface, integrating all necessary functionalities to coordinate and monitor UAV operations during surveillance missions. This stage involves building a comprehensive management interface that includes the following capabilities: defining surveillance areas, computing optimal UAV trajectories, configuring object classes for recognition, monitoring UAV positions, performing real-time object detection and classification, and issuing alerts when targets are identified.

5. SIMULATION RESULTS AND DISCUSSION

The overall system was developed in the Visual Studio 2022 environment, with the core modules implemented in Python. The tools for simulating UAV control were configured within Windows environment equipped with WSL2 (Windows Subsystem for Linux).

Figure 4 shows the main interface of the system with a connected quadrotor-type UAV simulated in AirSim, ready for patrol deployment. Figure 5 displays the interface for defining the surveillance area, using an interactive map provided by QGroundControl. The operator can intuitively designate the patrol region with minimal effort by simply clicking on the map.

Once the surveillance area is defined, the system proceeds to compute the optimal coverage path for the UAV. Based on the optimal coverage path planning model, the system generates energy-efficient flight trajectories that fully cover the patrol area for each UAV. Figure 6 illustrates the computed optimal path, which has been transferred to the UAV control environment and is ready for mission execution.

Figure 4. Main interface of the system with the UAV successfully connected

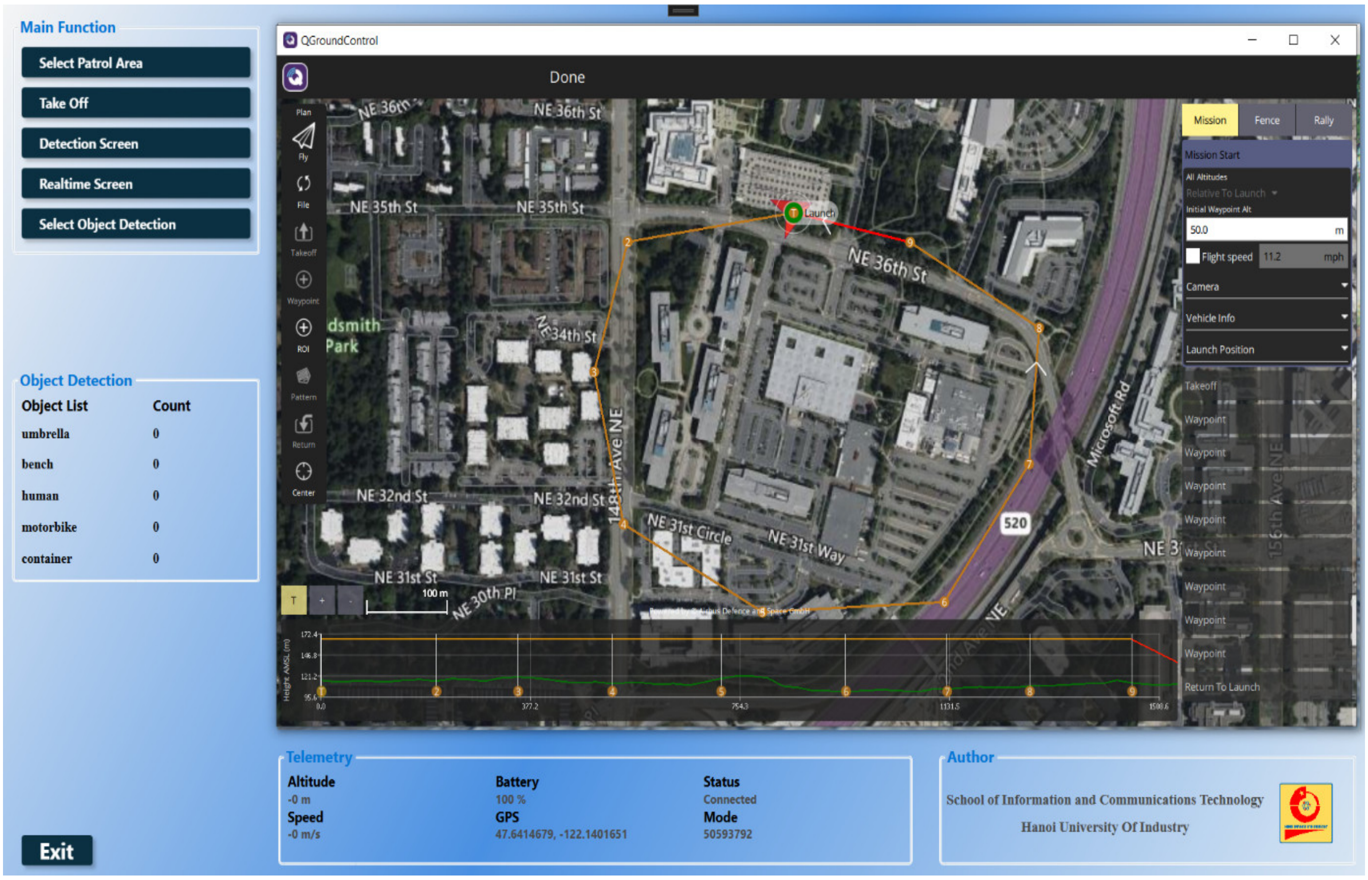

Figure 5. Interface for defining the surveillance area

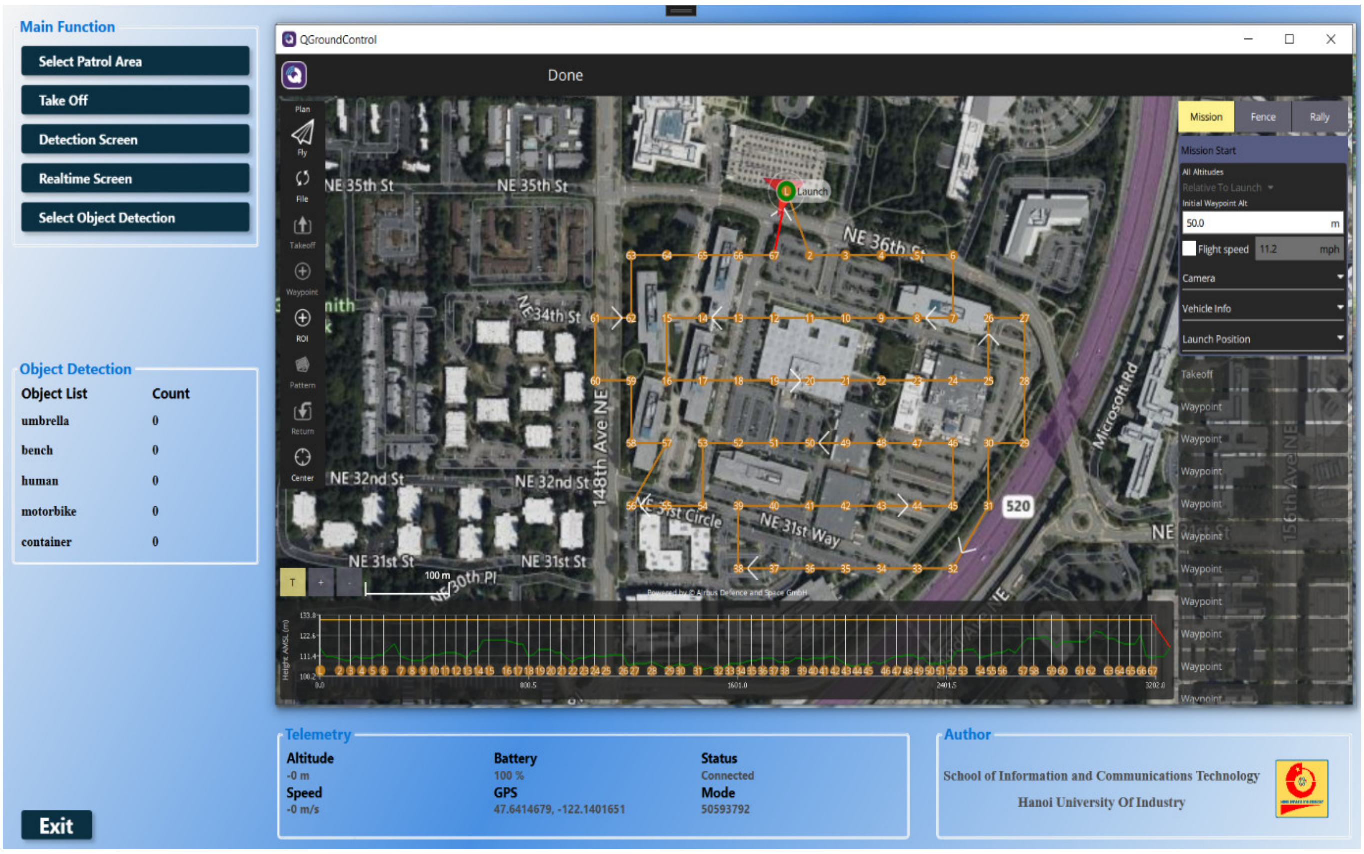

Figure 6. Coverage-optimized flight trajectory over the defined patrol zone

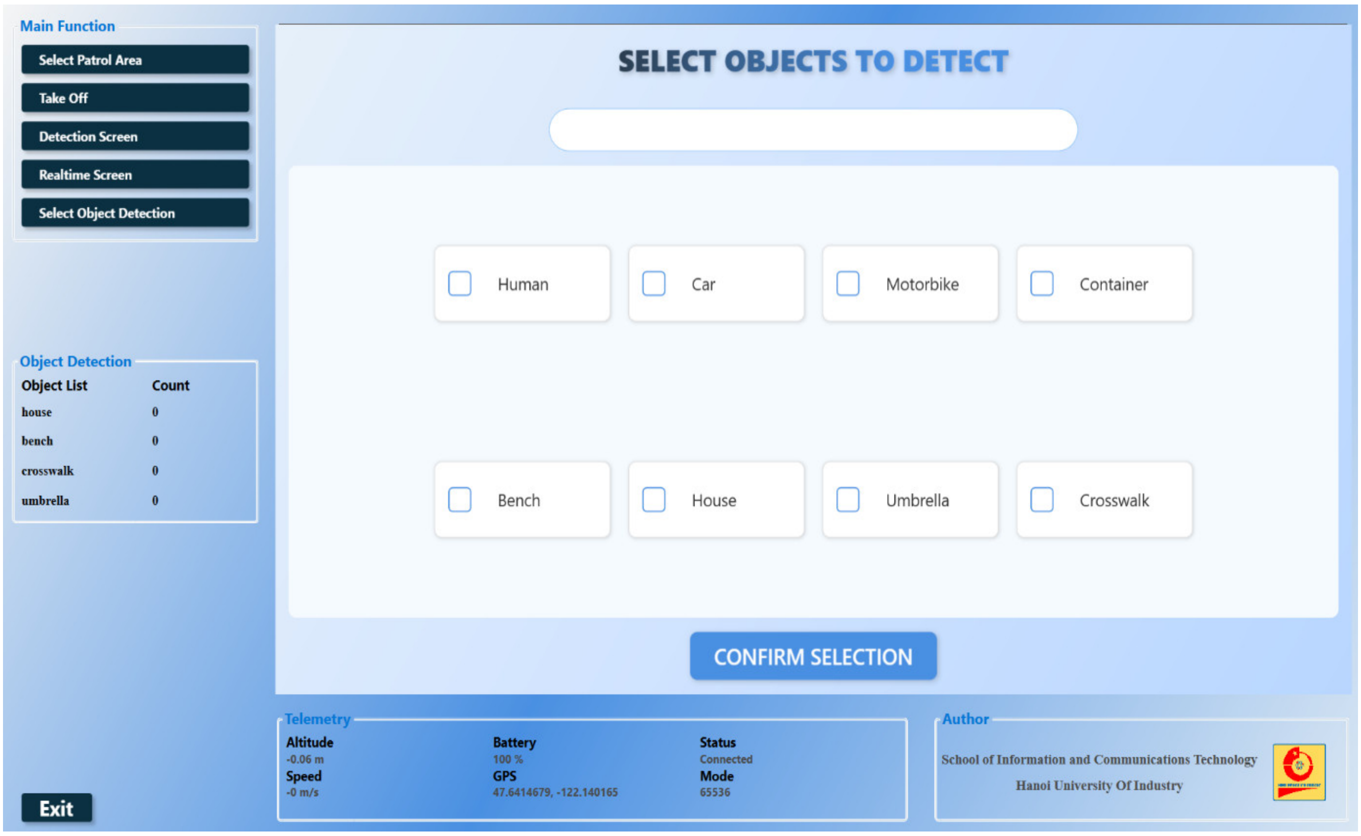

Figure 7. Object selection interface for monitoring tasks

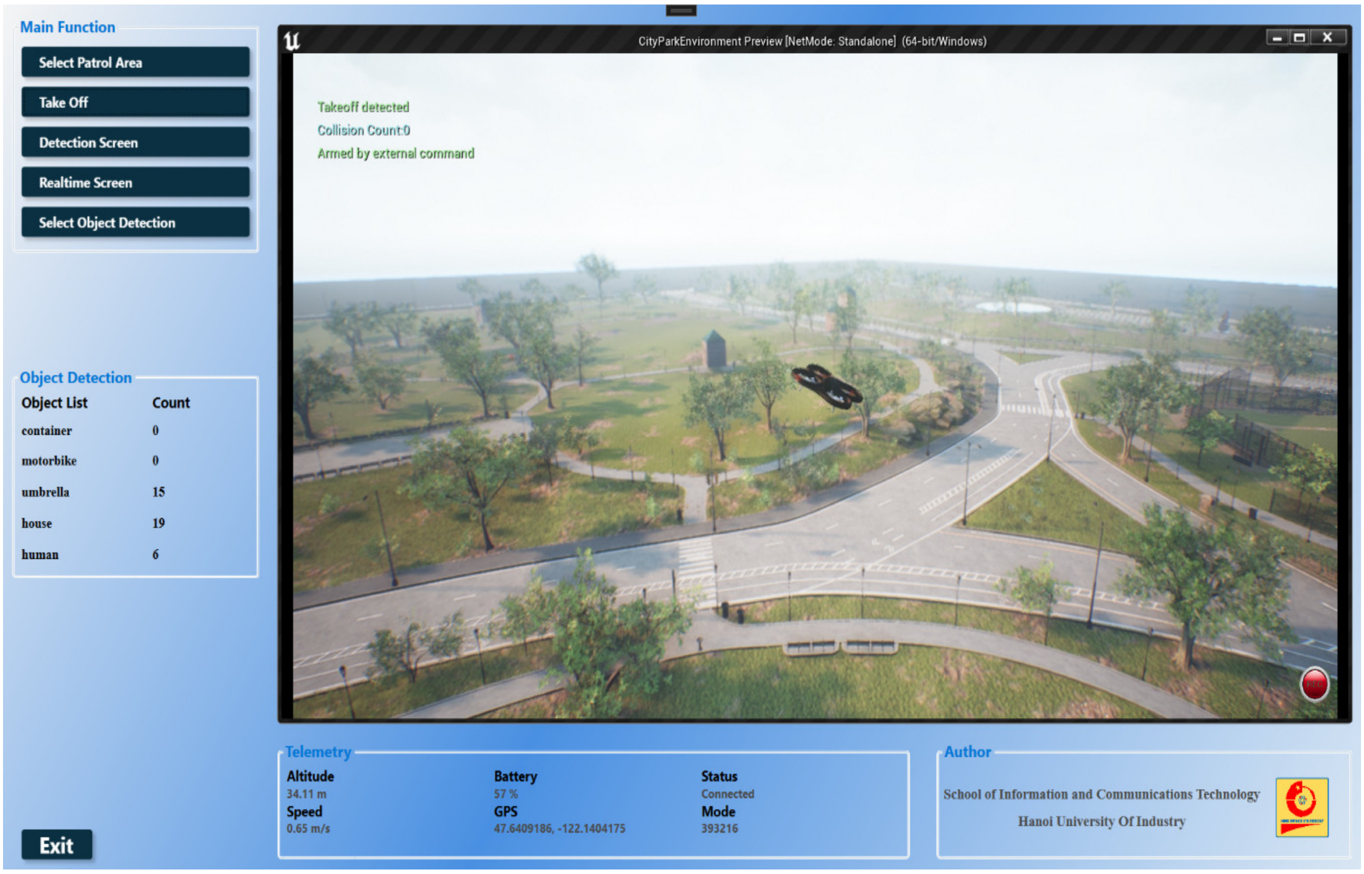

Figure 8. Visualization panel for tracking UAV simulation

Figure 9. Real-time object detection results visualized in the control interface

Figure 7 shows the interface for configuring the object classes to be detected. The ground control station allows the user to select and configure the types of objects of interest, enabling the detection and classification module to focus on the specific requirements of the mission. Depending on the surveillance objectives and the training dataset used, the list of detectable object classes can be flexibly modified or expanded. As a result, the system is not limited to the eight example categories illustrated; additional classes can be integrated if appropriate training data is available and the model is fine-tuned accordingly. This flexibility allows the system to adapt to a wide range of surveillance scenarios, including security, traffic monitoring, emergency response, and urban management.

The ground control interface provides an intuitive map-based visualization of the UAV's current position and status, enabling operators to effectively monitor the flight progress and any events that arise during the patrol mission. Figure 8 presents the system's visual interface for tracking the simulated UAV. With real-time object detection and classification functionality, the system continuously receives image streams transmitted from the UAV throughout the patrol flight. These frames are immediately processed by the fine-tuned YOLOv10 model, allowing for instant identification and categorization of objects as soon as they appear within the UAV's field of view.

The recognition results are visually displayed on the control interface (Figure 9), where each detected object is enclosed within a bounding box and labeled with its corresponding class. Simultaneously, the system triggers an audio alert to draw the operator's attention, enabling rapid situation awareness and timely response. This alert mechanism is particularly valuable in missions that require quick reactions, such as security surveillance, intrusion detection, or tracking suspicious activities.

6. CONCLUSION

This paper has introduced an artificial intelligence–enabled UAV-based surveillance system that incorporates two fundamental capabilities: optimal coverage path planning and real-time object detection and classification from aerial imagery. The proposed system is architected as a ground control station that integrates a Mixed-Integer Linear Programming (MILP) model to optimize flight trajectories, alongside a fine-tuned YOLOv10 deep learning model tailored for object recognition in domain-specific surveillance contexts. Simulation-based experimental results validate the system's operational stability, practical deployability, and suitability for practical applications in terms of performance efficiency, interface intuitiveness, and implementation feasibility. The integration of state-of-the-art simulation platforms including PX4, QGroundControl, AirSim, and Unreal Engine has significantly accelerated the development and validation cycle, enabling thorough testing prior to real-world UAV deployment. Future work will focus on enhancing the system's scalability and adaptability, particularly through the coordination of multiple UAVs operating simultaneously in dynamic environments. Additionally, efforts will be directed toward embedding lightweight AI models capable of executing inference tasks directly onboard the UAVs, thereby ensuring robust performance under constrained communication and computational resources.

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