AUTONOMOUS PATH PLANNING FOR UAVS

Project Reference No.: *49S_BE_4390*

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Keywords:

Collision Tolerant, Mechanical Gimbal, Inspection, drone cage, unmanned sewage inspection, UAV path planning, A* algorithm, Artificial Potential Fields, YOLOv8, obstacle avoidance, deep learning,ROS, Gazebo simulation, autonomous navigation, dynamic environments

Introduction:

UAVs are increasingly used for infrastructure inspection, pipeline monitoring, and surveillance in environments that are too dangerous for humans to enter safely. The core challenge in making these vehicles truly autonomous is path planning, and no single algorithm handles it well enough on its own. A* finds optimal routes on known maps but cannot react when obstacles move, while APF adjusts in real time but gets trapped at local minima in complex environments. This project combines both methods into a single hybrid framework, using A* for global route generation and APF for real-time local avoidance, with YOLOv8 object detection added so the system understands what it is avoiding rather than just reacting to positions. The complete three-layer system was built and validated inside a ROS-Gazebo simulation environment that models realistic UAV flight dynamics and moving obstacle agents. The longer-term goal is deployment on a physical quadcopter, with the simulation results serving as the baseline that hardware testing will build on.

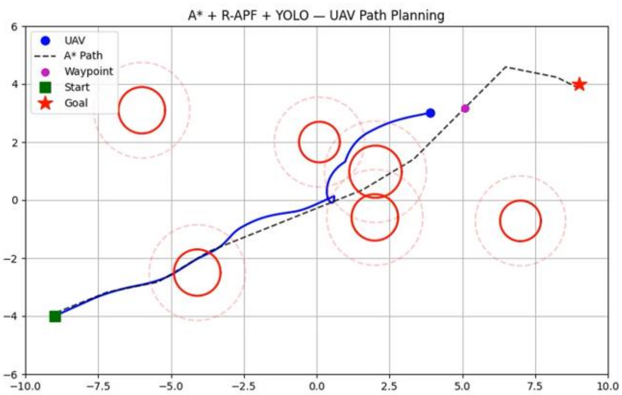

Figure 1: Hybrid Path Planning with global Local guidance.

Objectives:

1. To understand the importance and necessity of path planning in UAVs
2. To learn the popular path planning algorithms

3. To implement traditional path planning methods (e.g., A*) as a baseline for UAV navigation and analyze their limitations.
4. To develop a hybrid path planning framework combining A* global planning and APF local avoidance into a single system capable of handling both static and dynamic obstacles in a UAV flight environment.
5. To integrate YOLOv8 object detection into the planning pipeline so that avoidance behaviour adapts based on what an obstacle actually is, not just where it is located.
6. To validate the proposed algorithm through simulation experiments and compare its performance with traditional methods in terms of reaching the goal state in less time.
7. To integrate and test the algorithm on a small quadcopter platform for real-world demonstration.

Methodology:

1. Literature survey (review path planning algorithms): This initial step involved thoroughly researching existing path planning techniques, such as A* and RRT, to understand their principles, strengths, and weaknesses before designing a new approach.
2. Baseline implementation (implement A* algorithm): A foundational A* search was implemented first to establish a basic, functional path planner against which the performance and complexity of subsequent, more advanced algorithms could be measured.
3. Performance analysis (identify limitations of A*): This phase involved rigorous testing of the A* implementation, specifically noting its lack of efficiency and inability to handle real-time dynamic obstacles or non-grid-based motion smoothly.
4. Constraint integration (apply UAV constraints): Real-world limits specific to the UAV, such as its maximum flight range, turning radius, and required obstacle clearance distance, were mathematically incorporated into the planning model.
5. Algorithm development (design real-time path planning method): The core task was creating a novel method by integrating A* and Artificial Potential Fields that addresses the identified limitations by integrating prediction, dynamic tangent calculation, and force-based guidance for smooth, real-time path generation.
6. YOLOv8s was trained on a custom aerial dataset covering three obstacle classes using the Ultralytics framework with standard augmentation including horizontal flipping, mosaic composition, and HSV color jitter, then exported to ONNX format for inference.
7. Simulation & testing (validate algorithm): The newly developed algorithm was rigorously tested using computational models to verify its ability to find safe paths effectively in both static environments (fixed buildings) and challenging dynamic environments (moving objects).

    1. Performance comparison (compared with traditional methods): The final algorithm's efficiency, speed, and safety were measured directly against the baseline A implementation and other standard techniques to show how much better it is.

2. Prototype demonstration (implemented on small quadcopter): The final successful method was tested on a small quadcopter to confirm it's performance and reliability in the real hardware test environment.

Result and Conclusion:

The hybrid A*/APF system was tested across 50 randomized simulation trials at varying obstacle densities, and it finished 94% of them successfully. Standalone A* managed 78% and standalone APF came in at 71%, so the hybrid outperformed both by a meaningful margin. APF alone failed most often in dense scenarios where repulsive forces from clustered obstacles cancelled each other out and left the vehicle with nowhere to go. A* alone failed whenever a moving obstacle crossed the pre-computed path mid-flight, since the planner had no mechanism to react once the route was set. Running both together in the same loop removed both failure modes without adding significant computational overhead. YOLOv8 reached an overall mAP@0.5 of 0.89 across the three obstacle classes trained on the custom aerial dataset. UAV detection came in highest at 0.92 precision, which was the most operationally critical number because a false positive on that class triggers an unnecessary speed boost and wastes battery mid-mission.

In Conclusion, this project built and tested a three-layer autonomous navigation framework combining A* global planning, APF reactive avoidance, and YOLOv8 object classification inside a ROS/Gazebo simulation, with each layer covering a gap the other two cannot handle alone. The hybrid system achieved a 94% mission success rate across 50 randomized trials, outperforming standalone A* and standalone APF by 16 and 23 percentage points respectively, while keeping path length overhead at just 8.1%. YOLOv8 delivered an overall mAP@0.5 of 0.89 across three obstacle classes, with UAV detection precision reaching 0.92, which was critical because the speed-scaling behaviour is only as good as the trigger that fires it. Compared against four published hybrid UAV planners, this framework achieved the highest reported mission success rate, with classification-driven speed adaptation being the one feature that prior systems did not include. Everything here was demonstrated in simulation, and closing the gap to real outdoor flight through hardware-in-the-loop testing is the work that comes next.

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Future Scope:
The future scope of this project includes:

1. Training the YOLOv8 model on night footage, rain, fog, and direct sunlight conditions would open up 24-hour all-weather operation, which is a hard requirement for infrastructure inspection and border surveillance applications where missions cannot be scheduled around ideal visibility.

2. Integrating the framework with a ground control station that displays live obstacle logs, APF vectors, and the planned path in real time would give a human operator meaningful situational awareness without requiring them to intervene in every avoidance decision, striking a practical balance between autonomy and human oversight.

3. If the current single-drone framework is extended to a swarm, multiple UAVs could divide a search area among themselves and cover ground far faster than any one vehicle, which is directly relevant to disaster response scenarios where time is the difference between finding a survivor and not.

4. Connecting the system to a MAVLink-compatible flight controller and running hardware-in-the-loop tests would close the sim-to-real gap in a controlled way, producing a version of AeroPath AI that is genuinely deployable on commercial quadrotor platforms rather than living only in Gazebo.