MOMVO-Based Trajectory Generation For Multi-Target Search By A Swarm of UAVs

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***Abstract*—The dynamic and complex nature of managing drone swarms presents significant challenges in path planning, synchronization, and real-time control. This research paper introduces a novel framework aimed at addressing these challenges by leveraging the Multi-Objective Multi-Verse Optimization (MOMVO) algorithm for individual drone trajectory planning within a swarm. Furthermore, the paper discusses the integration of advanced computer vision techniques for object detection and classification, crucial for applications in surveillance and reconnaissance. By incorporating state-of-the-art software tools and frameworks, such as SITL, QGC, PX4, ROS 2, Gazebo, etc. the study enhances the drones' communication, control, and simulation capabilities ensuring high-precision simulations and in-depth real-time analysis of UAV swarm behaviours, thereby enhancing the reliability and applicability of the findings. Our experimentation provides better results than the existing algorithms without compromising on computation efficiency and time. MOMVO presents an average path length of 120.589 units and a computation time of 3.74 seconds. We not only address the current challenges in UAV coordination and object detection but also aim to lay the groundwork for future advancements in autonomous aerial systems.**

Keywords—swarms, path planning, MOMVO, trajectory, computer vision, object detection, surveillance, SITL, QGC, PX4, ROS 2, Gazebo, computation efficiency.

I. INTRODUCTION

In recent years, unmanned aerial vehicles have become one of the most promising innovations for military and civil use due to their promising weight and size, mobility and cost characteristics [1]. Robotics path planning, which can be perceived as the navigation part specifically directed on the subsidies of the vehicles hitting the barrier, can be defined as a navigation mission that is the route on which a robot or other unattended vehicle moves from share to face [2]. The main problem of the vehicle's navigation is to find a route from the current robot's location to a designated mission head rendezvous in the most efficient, safe, and without a conflict of trajectory. However, the issue is challenging when the flight territory of the UAV Navigation is very versatile and adds sporadically changing barriers and dangers. In such circumstances, the recognition of the conflict-free route is not easy and, as a result, is not a cheap task [3].

Between the last two decades, unmanned aerial vehicles have shown great prospects in implementing autonomous or semi-autonomous missions. Applications in practical conditions begin to spread with great speed [4]. To achieve this autonomy, several barriers need to be eliminated. Trajectory planning is one of the most important components of the autonomous control of unmanned aerial vehicles [5]. The vehicle trajectory planning is used to compute a series of valid movements or proper actions that enables the robot to move from a starting location to the target destination. In some planning issues, the spatial configuration of obstacles may experience temporal changes. As a result, the constraints within the environment, namely, mobile obstacles, must be dynamic constraints that path planning must obey while acting, and there are the requirements and perceptions of the vehicle. Moreover, almost all of the real path planning problems can be accurately described as the trade-off of competing objectives containing the cost and quality aspects.

Now, performing all of this but with multiple UAVs poses a challenge. Swarming of drones is a concept that has been introduced by advances in drone technology, in which a group of drones work together in synchrony to efficiently complete tasks. These tasks can be anything from object recognition to object tracking to performing choreographies in the sky. Swarms of drones cooperatively complete missions more economically and effectively in comparison to a single drone system [6]. Drone swarms are a great example of how a well-coordinated swarm might truly make a difference—Drones flying in formation may assist in locating and rescuing individuals in an emergency, improving existing farming practices to generate more crops, and conducting more extensive inspections in industrial settings.

Using the Multi-Objective Multi-Verse Optimisation (MOMVO) algorithm for strategic path planning, a swarm of unmanned aerial vehicles which might be utilized for effective surveillance operations. During their flight, our UAVs advance from a designated start point to a predetermined end point whilst maintaining adherence to a formation that has been dynamically set. Additionally, implementing Computer Vision into the UAV formation's configuration guarantees that the drones maintain a desired spatial orientation and proportionality at all times.

Further, each UAV in the cluster is equipped with modern camera systems that are very helpful in object recognition and classification in the field of view. The drones, while on the surveillance mission, can use the cameras and enhanced image processing to detect a potential target or an object of interest. In cases involving the military, this system becomes reliable and is a valuable move to gather information promptly. These drones are intelligent enough to occupy roles that are very rare for the larger flying system, which is aiding in intelligence. They can feed information to the military on how the situation is, thus helping make informed decisions.

This paper makes several contributions to the field, including:

1. The novel implementation of MOMVO for strategic path planning of UAV swarms. This demonstrates an innovative approach to efficient and effective navigation in complex environments.
2. The use of computer vision techniques for dynamic formation control that enhances the spatial coordination of drone swarms, a significant improvement over traditional control methods, and the development and integration of advanced image processing algorithms for drones to identify and categorize objects within their operational range, particularly useful in surveillance and reconnaissance missions.
3. The research prominently uses sophisticated software tools like SITL, QGroundControl, and PX4, ensuring high-precision simulations and in-depth real-time analysis of UAV swarm behaviours, thereby enhancing the reliability and applicability of the findings.
4. We achieve better results than the existing algorithms without compromising on computation efficiency and time. Our algorithm works with an average path length of 120.589 units as compared to the current algorithms getting average path lengths of 128.098 units and 135.708 units.

The remainder of this paper is structured as follows: Section II covers a brief literature review on similar algorithms used, Section III explains the problem formulation behind this study, Section IV lists the software tools used for the simulation purposes, Section V proposes the workflow, Section VI showcases the results obtained from the simulations, and finally, Section VII concludes the paper.

II. LITERATURE REVIEW

This section presents a brief overview of the existing research on path planning with collision avoidance in dynamic environments. Table I summarizes all the methods used for similar research objectives by researchers recently.

According to Table 1, the recent research in this field falls into four primary categories: Sampling Based, Node Based, Machine Learning Based and Metaheuristics Based algorithms. Sampling based algorithms [7-9] necessitate prior knowledge of the environment to gather and process collision free data. Node based methods [10-12] find routes within a graph structure. In these algorithms, the predefined nature of the graph influences the applicability for unknown scenarios. They also face the issue of very high compute times, especially in complex environments or large-scale scenarios. Machine Learning Based algorithms [13-15] commonly use techniques like Reinforcement Learning for the purpose of Single-UAV Path Planning [13] or Multi-UAV Path Planning [14]. Metaheuristic based algorithms [16-18] use a variety of techniques to efficiently explore search spaces and find solutions.

Machine Learning and Metaheuristics techniques are the most extensively used approaches in recent years. These approaches offer a balance between exploration and exploitation to find near-optimal solutions in high-dimensional spaces.

We consider our work to follow a more optimal approach, considering all the shortcomings from the following techniques and resulting in better efficiencies and accuracies. We combine the usage of advanced algorithms like MOMVO for Path Planning and Computer Vision for object detection to create a robust algorithm that has the perfect balance of processing speed and accuracy.

TABLE I: SUMMARY OF LITERATURE REVIEWS FOR UAVS PERFORMING PATH PLANNING WITH COLLISION AVOIDANCE

Class of Algorithms	Literature	Technique Used
Sampling Based Algorithms	[7]	Path Planning of UAV Based on Voronoi Diagram and DPSO
	[8]	An Improved Artificial Potential Field Method for Path Planning and Formation Control of the Multi-UAV Systems
	[9]	Feedback RRT algorithm for UAV path planning in a hostile environment
Node Based Algorithms	[10]	A* Algorithm for the Shortest Trajectory Planning of UAV in the Presence of Obstacles
	[11]	R5DOS Model Improved A* for UAV Path Planning in a 3D Environment
	[12]	Improved D* Lite Algorithm Based Quick UAV Path Planning in Hazardous Environments
Reinforcement Learning	[13]	Reinforcement Learning (RL) Based Approach for UAV Path Planning in Rapidly Changing Environments

Based Algorithms	[14]	Multi-UAV Path Planning by Deep Q-Learning in Communication Denial Environment
	[15]	Transformer Based Reinforcement Learning for Scalable Multi-UAV High Area Coverage
Metaheuristics Based Algorithms	[16]	UAV Trajectory Planning in Large Areas by incorporating Multi-Mechanism Improved Gray Wolf Optimization (NAS-GWO)
	[17]	3D Path Planning of UAV based on All Particles Driving Wild Horse Optimizer Algorithm (APD WHO)
	[18]	UAV Path Planning in a 3D Environment using Hybrid A*FPA (Flower Pollination Algorithm)

III. PROBLEM FORMULATION

Unlocking the potential of drone swarms is hampered by formidable coordination and control issues. Foremost are the path planning difficulties, synchronisation, and wastage of resources. While huge progress has been achieved in enhancing drone technology and the corresponding software tools, there is an urgent necessity for a framework that would enhance the deployment and management of drone swarms.

First, one crucial problem that this research attempts to tackle is individual drone trajectory planning optimization in a swarm. Therefore, for our specific case study, we choose to rely on MOMVO that enables choosing a solution considering multiple parameters such as mission time, energy consumption, and obstacle avoidance. By choosing to develop the MOMVO approach, we will potentially find a way to enhance path planning and influence making within a swarm. Another integral element of the route that needs to be preserved is the formation among drones to jump while staying in the same formation. Thus, finding strategies for formation control is another issue we address in this work.

Moreover, drones also need to not only detect but also classify objects in the area where they are operating. The ability to differentiate among objects is especially important for application in surveillance and reconnaissance. To accomplish this task, it is necessary to apply computer-vision methods. The use of multiple software tools and frameworks, including PX4, ROS 2, and Gazebo, will be required to enhance communication, control, and simulation of drones. Nevertheless, it is still hard to guarantee real-time communication and control, as the process is prone to extensive time delays due to the need for processing in dynamic and unstable conditions.

In essence, the objective of this research is to develop a systematic and comprehensive solution that addresses these challenges. Thus, through the appropriate software tools and methodologies, the proposed framework of MOMVO-based trajectory generation for multi-target search on a swarm of drones seeks to maximize the use of drone swarms to increase productivity, safety, and situational awareness in more sectors. The workflow of the proposed system which is discussed in Section V is as follows.

IV. METHODOLOGY

An elaborate framework is presented to manage drone swarm coordination considering its complexities. MOMVO-based path planning is used to manage the movement of drones to navigate from start to end. These formations are established by inputting a pattern image and generating coordinate points through computer vision techniques. These drones are equipped with cameras, undertaking the crucial task of detecting and categorizing targets or objects within their operational scope. Their primary mission revolves around functioning as surveillance drones, diligently scouring the designated area, identifying potential targets, and subsequently classifying them. This effort allows for surveying, detecting and classifying target objects for further action by military personnel, and it significantly facilitates the successful implementation of their tasks through the implementation of surveillance and reconnaissance from an aircraft. It is another step in a different direction with a number of interconnected stages, each of which carried significant benefits to the overall success and performance of the solution.

The pipeline can be broken down into four major parts:

- MOMVO Implementation for Path Planning in Single UAV
- Multi-UAV Trajectory Coordination Using MOMVO
- Integration of Computer Vision for Object Detection
- Computer Vision-Based Formation Flying

We will discuss each of them in subsequent sections.

A. *MOMVO Implementation for Path Planning in Single UAV:*

The objective of this phase is to use the MOMVO algorithm to optimize trajectory planning for a single UAV. The process involved incorporating MOMVO into the simulation environment of Gazebo and PX4. Consequently, the UAV was in a position to decide the optimal path and traverse it considering such numerous factors as mission time and energy, among others. The results concretely confirmed efficient route planning, as supported by the Gazebo simulation result. At the same time, an indication of the enhanced safety measures and the reduced power used was provided.

MOMVO is an optimization algorithm that draws inspiration from the multiverse concept. By conceptualizing a "multiverse" of potential solutions, MOMVO explores diverse solution spaces to find a set of Pareto-optimal solutions, which represent the trade-offs between conflicting objectives. Through iterative updates and evolutionary mechanisms, it navigates the solution landscape to find out the most optimal solution.

Our implementation of MOMVO is explained in Algorithm 1 below.

Algorithm1 Multi-Objective Multi-Verse Optimization(MOMVO)

Start
1. Set control parameters: nd, xs, ys, zs, xd, yd, zd, lbx, lby, lbz, ubx, uby, ubz, arch_size, pop_size, max_iter, obstacle_params, ds.
2. Initialize population for X, Y, Z within bounds, first member linear from start to destination.
3. Initialize iteration counter to 0.

While (iter < max_iter + 1) **do**
   3.1. Update position bounds for each coordinate.
   3.2. **For** each universe in population do
         If (universe is inside search space):
            calculate fitness
         End If
      End For
   3.3. Sort fitness values.
   3.4. Find nondominated solutions.
   3.5. Normalize inflation rates.
   3.6. Update archive with nondominated solutions.
   3.7. **If** (archive is full):
         reduce archive size
      End If
   3.8. Increment iteration counter.

End While
4. Select the best solution from the archive.
5. Generate path using cubic spline interpolation.
6. Visualize path in 3D space and optionally save waypoints.

End

Now using the MOMVO algorithm explained in algorithm 1, a drone plans its path and generates a trajectory in real-time based on its starting location, target location, and the positions of obstacles. It generates 100 intermediate waypoints that the drone needs to go through to reach its target location. Algorithm 2 below explains this process.

Algorithm 2 Drone Control in Offboard Mode Using PX4

Start
1. Input: Waypoints from MOMVO, Vehicle commands, Control modes from PX4.
2. Output: Command series for the drone, Log commands, Transition to offboard mode.

Initialization:
   Initialize ROS node 'OffboardControl'.
   Setup publishers for OffboardControlMode, TrajectorySetpoINT, VehicleCommand.
   Read waypoints from the MOMVO-generated file.
   Set the setpoint counter to 0.

While (not rospy.is_shutdown()) **do**
   Increment setpoint counter
   If (setpoint counter == 10):
      Switch to Offboard mode
      Send an arm command
   End If
   Publish offboard control mode.
   Publish trajectory setpoints based on waypoints.
   If (setpoint counter requires vehicle transition):
      Update setpoint
   End If
   Log waypoint number and setpoint counter.

End While

End

B. Extending the MOMVO Algorithm for UAV Swarm Coordination

The primary aim is to adapt MOMVO to enable efficient trajectory planning for UAV swarms, ensuring optimal pathfinding that accounts for environmental variables, mission objectives, and the intrinsic dynamics of swarm behaviour. Extending the MOMVO algorithm for multi-UAV coordination is the focus here. The methodology involved adapting MOMVO to generate trajectories for multiple UAVs simultaneously. Additionally, a control system was implemented to maintain consistent spatial separation between UAVs. The results highlighted successful coordinated flight patterns in simulations, indicating synchronized movements and stable separation between UAVs.

The process works the same way, except now ‘n’ number of drones that will have the MOMVO path planning algorithm running individually, where we would be specifying the start locations, obstacles’ positions, and end locations for each drone and perform intra-collision avoidance within the swarm.

C. Integration of Computer Vision for Object Detection

The integration of computer vision technologies marked a significant advancement in the project, enabling UAVs to perform real-time object detection and engage in autonomous formation flying based on visual cues. We have performed Real-Time Object Detection with the You Only Look Once (YOLO) algorithm. The deployment of the YOLO was a strategic choice, balancing speed and accuracy to meet the demands of dynamic UAV operations. This phase involved configuring UAV-mounted cameras to feed live video into the YOLO algorithm, which was optimized for UAV computing constraints while maintaining high detection accuracy. The integration process addressed challenges such as varying light conditions, object scale, and movement speed, ensuring reliable object detection in diverse operational contexts.

Algorithm 3 Working of the object Detection Model

Start
Load trained yolov5 model φ
Take frame F from drone feed
If (object detected on F):

name, confidence, bbox = φ (F)
calculate centroid from bbox
save centroid, name, confidence in a json file
End If
End

D. Computer Vision-Based Formation Flying

This algorithm translated visual inputs into actionable waypoints, guiding UAVs into predetermined formations with precision. The process entailed the creation of a comprehensive visual language, encompassing various formation patterns and the corresponding navigational coordinates required to achieve them. Extensive testing validated the algorithm's effectiveness, demonstrating its capability to dynamically adjust formations in response to real-time visual data.

Algorithm 4 Drone Swarm Pattern Formation and Simulation

Start
1. Input: Image for analysis, number of drones, grid unit size, hover height, file path.
Initialization:
Load the image.
Set number of drones, hover height, and grid size.
Initialize variables for grid, pattern contours, and drone coordinates.
Detect Origin:
Convert image to grayscale.
Apply binary thresholding.
If(contours are found):
Select potential origin
Else
Exit with an error "No suitable origin found."
End If
Pattern Points Identification:
Convert image to HSV color space.
Create masks for specific colors.
If (a large green contour is found):
Identify it as the pattern contour
Calculate equidistant points for drone positions in pixel coordinates
Else
Exit with an error "No suitable pattern contour found."
End if
Grid Unit Calculation:
Detect and approximate the grid contour.
If (grid contour is found):
Calculate its perimeter and area
Determine grid size in pixels
Else
Exit with an error "No suitable grid contour found."
End If
Pixel to Meter Mapping:
Convert drone positions from pixel to meter coordinates.
Pattern Visualization:
Draw origin, grid, pattern contour, and points on the image.
Data Saving:
Save drone positions in meter coordinates to a JSON file.
ROS Node for Simulation:
Initialize and start ROS node.
Subscribe to model states.
Publish target positions to drones.
Load pattern data from JSON file.
Continuously publish drone positions as goals.
Simulation Execution:
While (not rospy.is_shutdown()) **do**
Run the ROS node simulation.
If (simulation ends or is interrupted):
Shut down the ROS node
End If
End While
End

Through rigorous testing in simulated environments, our methodology proves effective in addressing the key issues of synchronization, resource management, and operational versatility in drone swarm technology. The detailed algorithms provide a clear and actionable roadmap, making the deployment of drone swarms more feasible and efficient in practical scenarios, thereby unlocking their full potential in varied applications from surveillance to reconnaissance.

V. Simulation And Results

The simulations and research used to build this novel architecture and framework are briefly explained in this section, along with its final results and discussion. The adaptation process began with a thorough analysis of the original MOMVO algorithm, identifying key areas for modification to suit UAV operational contexts. A custom control system was developed to maintain a consistent separation between UAVs, a critical factor in preventing collisions and ensuring coherent swarm movement. This system dynamically adjusted each UAV's trajectory based on real-time spatial data, utilizing a combination of predictive modeling and reactive adjustments to maintain optimal formation integrity.

Simulations played a pivotal role in the development process, with Gazebo-Classic and ROS2 providing a realistic and flexible environment for testing. The simulation setup involved creating multiple instances of drones, orchestrated to operate under a unified ROS2 Agent, facilitating seamless communication and control across the swarm. This environment enabled the execution of complex flight patterns and operational scenarios, providing invaluable data for refining both the adapted MOMVO algorithm and the UAV control system. All scripts for the same are developed using Python programming language.

A. Performance Against Other Algorithms:

This section presents a comparative analysis of our method with existing approaches, focusing on key performance metrics and real-world implementation challenges. It is observed that MOMVO showcases robust performance, outperforming both Sampling and Node-based Algorithms. To showcase this, we present results comparing

MOMVO with Artificial Potential Field (APF) [8] and A* [10].

1. Artificial Potential Field:

It gets trapped into the local minima multiple times when many obstacles are used, as it lacks mechanisms for global exploration. Figure 1 showcases the trajectory planned by APF.

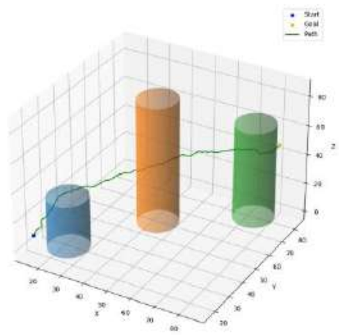

Fig 1. Trajectory Planning by Artificial Potential Field

2. A* Algorithm:

It needs all the data before you can run the algorithm. It provides very good results but is not suitable in real life due to the large space size, memory consumption and its search bias. Figure 2 showcases the trajectory planned by A*.

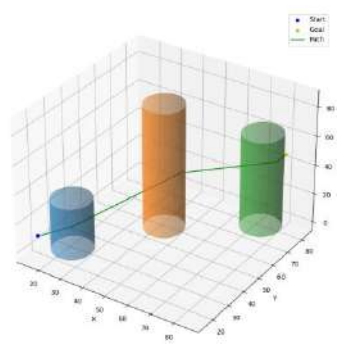

Fig 2. Trajectory Planning by A* Algorithm

MOMVO is more practical than these methods as it efficiently explores the search space. It stores only the best solutions in the archive keeping the memory optimized as well. It can adapt to changes in the environment very easily by dynamically changing the search strategy as well.

Now, we turn our attention to comparing MOMVO with algorithms which are used for path planning in present-day, specifically metaheuristic algorithms like MOGWO (Multi-Objective Grey Wolf Optimization) [19] and NSGA II (Non-Dominated Sorting Genetic Algorithm II) [20], which are widely recognized methods in the field of Path Planning.

The three algorithms were run for 100 iterations with obstacles on the same locations to ensure a fair comparison. Each algorithm was evaluated under identical conditions to assess their performance in terms of path length and computation time. The best parameters were chosen for all the algorithms after extensive grid-search and the final experimental setup was run with the parameters shown in Table II. Table III showcases the outcomes of the experimental simulations and Fig 3. presents the visual representations of the trajectory planning paths generated by the three algorithms for obstacle avoidance.

TABLE II: PARAMETERS CHOSEN FOR ALGORITHMIC EVALUATION

Algorithm	Parameters	Values
MOMVO	Archive Size	100
	Wormhole Existence Rate	0.3
	Travelling Distance Rate	0.7
NSGA II	Crossover Probability	0.75
	Mutation Probability	0.3
	Mutation Rate	0.03
MOGWO	Grid Inflation	10
	Number of Grids per Dimension	4
	Leader Selection Pressure	2
	Extra Repository Member Selection Pressure	0.1

TABLE III: COMPARISON OF RESULTS BETWEEN MOMVO, NSGA-II & MOGWO ALGORITHMS BASED ON PATH LENGTH & COMPUTATION TIME

Algorithm	Path Length		Computation Time (s)
MOMVO (Multi-Objective Multi-Verse Optimizer)	**Average**	120.589	3.74
	Standard Deviation	6.316	
NSGA II (Non-Dominated Sorting Genetic Algorithm II)	**Average**	128.098	3.32
	Standard Deviation	12.585	
MOGWO (Multi-Objective Grey Wolf Optimization)	**Average**	135.708	3.81
	Standard Deviation	18.735	

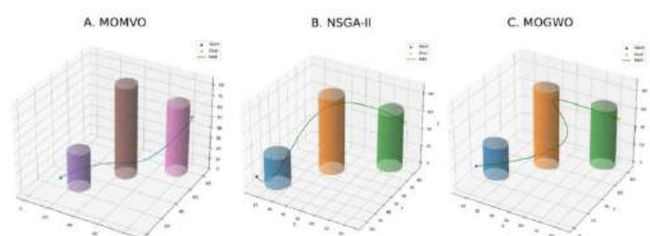

Fig 3. Paths Generated by MOMVO (A), NSGA-II (B) and MOGWO (C) under identical conditions.

MOMVO presents an average path length of 120.589 units and a computation time of 3.74 seconds. The standard deviation for path length was observed to be 6.316 units, indicating consistent and reliable results. It is visible that MOMVO outperforms both NSGA II and MOGWO in terms of path length and demonstrates competitive computation times.

B. *MOMVO Path Planning for a Single UAV:*

Having established the comparative performance of our algorithm, we now delve into its specifics, starting with the real-world application of MOMVO in single UAV path planning, which is represented by Fig 4. Showcasing the multiple stages of real-time path planning procedure done by MOMVO.

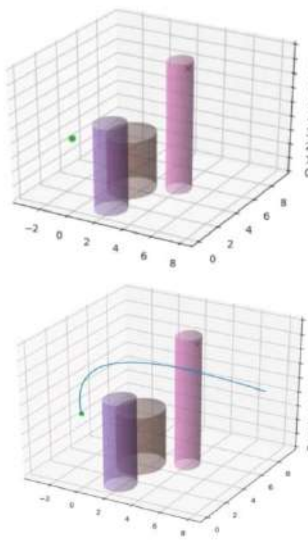

Fig 4. Real-time Path Planning by MOMVO

In Fig. 5, we can observe similarity between our planned and actual trajectories, as well as the trajectory produced by QGroundControl (QGC) simulation. The similarity of these trajectories suggests the efficiency of our path planning procedure and its use in real world situations as well. We use QGC as a real-world simulator to validate this. By running our paths in a simulated real-world environment, we ensure that our planning algorithms accurately reflect real-world results.

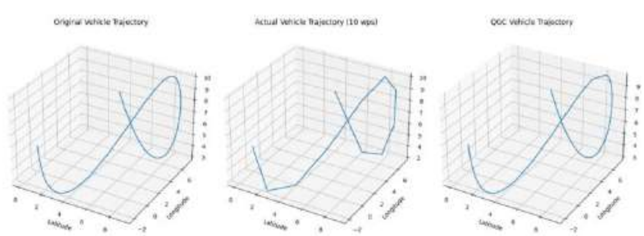

Fig 5. Planned, Actual and Observed Trajectory of the UAV in QGroundControl.

C. *Multi-UAV Trajectory Coordination:*

Expanding on single UAV path planning, we extend our analysis to multi-UAV scenarios, focusing on trajectory coordination. In Fig. 6, we can observe the flight of 3 UAVs simultaneously. This highlights the collaborative communication between the UAVs to avoid collisions. Through real-time communication, they all change their trajectories to avoid collisions while ensuring optimal paths. This approach guarantees a safe and efficient flight for all UAVs involved while navigating complex environments.

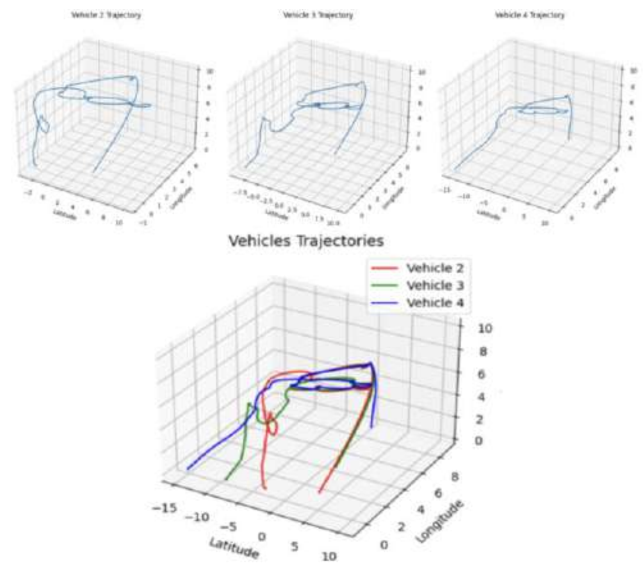

Fig 6. Multi-UAV Trajectories in a Simulated Environment.

D. *Target Search using YOLOv5s:*

Having explored the complexities of multi-UAV trajectory coordination, we now shift our focus to another vital aspect of autonomous systems which is Target Search. Different sets of experiments were conducted to achieve a high confidence score for object detection. The object detection model was run on the drone's camera feed. We created our own custom dataset by taking images of the objects from the drone's camera.

Fig 7. Detection of the Target from the Drone's Camera.

In Fig. 7, we can observe the accurate detection of the object and formation of a bounding box around the target object by the drone's camera during flight, and Fig 8. presents the various performance curves of the YOLOv5s model, where (A) and (B) show the box and object loss of the training set respectively, and (C) and (D) are the mean Average Precision (mAP) scores.

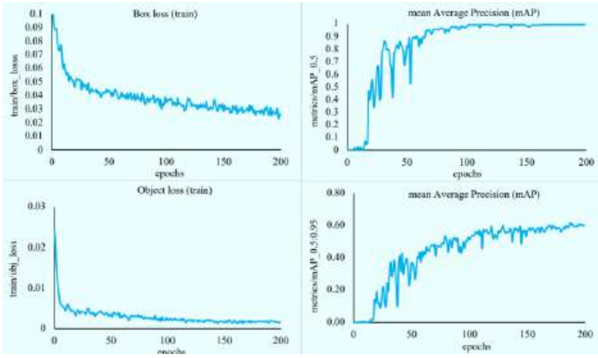

Fig 8. Performance curves of YOLOv5s Model

VI. Conclusion

This research has demonstrated a comprehensive approach to advancing UAV swarm technology, combining the MOMVO algorithm with innovative applications of computer vision. Through the exploration of various aspects outlined in the methodology, from single UAV path planning to multi-UAV coordination and object detection, this study has addressed crucial challenges in autonomous aerial systems. The implementation of MOMVO for path planning in a single UAV context showcased its efficacy in optimizing trajectories, providing a foundation for further exploration in swarm coordination. Extending this algorithm for multi-UAV coordination has shown promising results, indicating the potential for scalable and efficient swarm behavior. Integration of computer vision techniques, particularly YOLOv5s for object detection and formation flying, has demonstrated enhanced situational awareness and precise navigation capabilities.

Overall, this study contributes to the advancement of UAV swarm technology by offering a systematic framework that combines theoretical development, simulation testing, and practical implementation. By addressing current challenges in UAV coordination and object detection, this research sets a solid foundation for future advancements in autonomous aerial systems, paving the way for safer, more efficient, and versatile UAV operations.

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